Creative AI: a New Avenue for Semantic Web?

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Abstract. Computational Creativity (or artificial creativity) is a multidisciplinary field, researching how to construct computer programs that model, simulate, exhibit or enhance creative behaviour. This vision paper explores a possible impact Semantic Web can have on the future of creativity, especially when it deals with AI creativity. Possible uses of Semantic Web and semantic technologies are discussed, regarding three types of creativity: i) exploratory creativity, ii) combinational creativity, and iii) transformational creativity and relevant research questions. For exploratory creativity, how can we explore the limits of what is possible, while remaining bound by a set of existing domain axioms, templates, and rules, expressed with semantic technologies? To achieve a combinational creativity, how can we combine or blend existing concepts, frames, ontology design patterns, and other constructs, and benefit from cross-fertilization? Ultimately, can we use ontologies and knowledge graphs, which describe an existing domain with its constraints and, applying a meta-rule for transformational creativity, start dropping constraints and adding new constraints and see what emerges? Together with these new challenges, the paper also provides pointers to emerging and growing application domains of Semantic Web and knowledge graphs related to computational creativity and design: from food and cooking (recipe generation), fashion and style to program synthesis, software composition and scientific discovery.

Keywords: computational creativity, artificial intelligence, Semantic Web, knowledge graph, ontology

1. Introduction

The seminal paper by Tim Berners-Lee et al. [1] describes a vision of the Semantic Web with its main building blocks and enabling technologies: knowledge representation (KR) and automated reasoning, ontologies, agents. The motivating scenario of this paper, described from its very first sentences, concerns automated, intelligent *services* that are delivered by intelligent (artificial) *agents*. These agents are capable of carrying out sophisticated tasks for users such as making an appointment with a physical therapist, taking constraints on schedules and routes into account. It is possible thanks to adding explicit, machine-readable semantics to the content of the Web.

Exposing semantics for interoperability via the Semantic Web as a set of standards for knowledge representation and exchange with the purpose of Web systems where not only human, but also software agents interact is a recurring major theme of the Semantic Web [2]. From its early days, the Semantic Web has been thus largely related to knowledge representation, but also more broadly to artificial intelligence (AI). Semantic networks [3], as a form of knowledge representation, dating back to early days of AI, gained new attention (kind of 'AI summer' of KR) by adding Web technologies (such as URIs) to them and mechanisms of inference based on formal semantics, leading to nowadays knowledge graphs [4] and the Semantic Web. Not only then it is *linked data* constituting the Semantic Web, but also *linked semantics*, *linked knowledge*, and *linked services*, enabling *reasoning on the Web* and *intelligent applications*.

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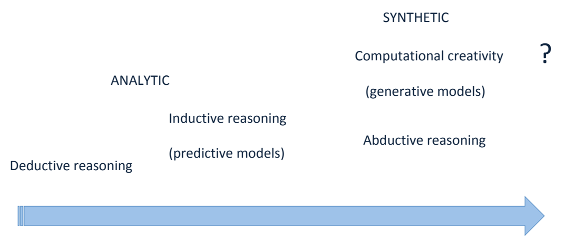

Fig. 1. A possible trend in research interests in Semantic Web reasoning: shift from analytic tasks (deduction, then induction) towards synthetic tasks.

1.1. From analysis to synthesis

It thus comes with no surprise that Semantic Web research evolves influenced by major shift changes in knowledge engineering and AI.

As applications and services are the key to adoption of a given technology by the users, what intelligent applications and services might be then facilitated and enabled with semantic technologies in the age of AI boom? What will be the next Semantic Web services on the Web? Where Semantic Web technologies will have an edge in a broader scope of knowledge representation and AI and their evolution in the next several years?

Early Semantic Web used mainly *deductive* reasoning, employing logic-based reasoning services. With growing amounts of data, this has later shifted to an increased interest in applying statistical approaches, i.e., *inductive* reasoning [5, 6]. Both may be classified as *analytic* tasks, but lately, there is an increasing interest in other types of reasoning. Consider for instance embeddings [7], which enable to perform analogical reasoning. Another example is generating justifications and explanations (for explainable AI), which may serve for debugging purposes, and which are closely related to abductive reasoning. Some of recently popular tasks deal with *synthesis* rather then analysis and aim to *generate* rather than only analyse artefacts (see Figure 1). The domains up to now reserved for humans are starting to be addressed by AI, such as creating art by generative models and making creative designs and scientific discoveries [8].

Can we thus make use of Semantic Web research results, technologies and resources for AI creativity?

1.2. What is Creativity?

Creativity, creative reasoning and creative problem solving have been researched in cognitive [9] and computational sciences [10]. Cognitive psychologists aim to understand the human creative process. In her influencial works, Boden [11, 12] describes creativity as the ability to come up with *ideas* or *artifacts* that are *new*, *surprising*, and *valuable*. Ideas and artefacts are products of creation. The former ones may be concepts, musical compositions, poems but also cooking recipes, or even scientific theories. The latter ones may be paintings, pottery, but also vacuum cleaners, engines, etc. . Moreover, many researchers use the term ’concept’ to refer to a range of things: abstract ideas in arts, science, and in everyday life.

1.3. Computational creativity

Can machines be creative? Some time ago it was hardly believable. Ada Lovelace, referred to as the first computer programmer, was reflecting on the Charles Babbage’s mechanical general-purpose computer, the Analytical Engine that it “has no pretensions whatever to *originate* anything. It can do whatever we *know how to order it* to perform”. However, with the development of machine learning, it is not needed anymore to explicitly program machines that apparently have begun to reveal creative behaviours [8, 13].

The computational creativity research area has emerged which is concerned with “*computational systems which, by taking on particular responsibilities, exhibit behaviours that unbiased observers would deem to be creative*”[14].

Creative systems perform various ’generative acts’ that create exemplars, concepts, or provide an aesthetic evaluation for the generated artefacts. Computationally creative systems have already been built in various fields, not only in ’typical’ creative domains like music, art, poetry, architecture, design, but also for tasks such as inventing recipes [15], software composition [16] or program synthesis [17].

2. Three Types of Creativity: opportunities for Semantic Web

Best known categorization of creativity types is by Boden [11], where three types of creativity are defined: (i) *combinational*, which concerns new combinations of familiar ideas, (ii) *exploratory*, where new ideas are generated by exploration of a space of concepts, and (iii) *transformational*, where the space is transformed what facilitates new kinds of ideas to be generated. Other formulations have also been proposed, including extending the Boden's categorization to also include approaches for extraction and induction of concepts as additional ways of concept creation by Xiao et al. [18]. In particular, Wiggins [19] proposes a unifying formalization of creativity as search, which unifies the categorization of Boden and from [18]. Combinational and exploratory creativity are defined there as search at the concept level, and transformational creativity as search at the meta-level.

2.1. Exploratory: generation of new ideas by exploration of a space of concepts

Exploratory creativity refers to search within a predefined search space (limited by rules, constraints, biases in the search process etc.). It is often modeled as an objective-driven search, using techniques such as constraint satisfaction, evolutionary algorithms, and data mining [20].

Regarding data mining, one may notice that its definition as the nontrivial process of identifying valid, *novel*, potentially useful, and ultimately understandable patterns in data [21] has commonalities with definitions of computational creativity. Indeed, various techniques of data mining have found their applications in computational creativity, for tasks such as concept creation [22].

Potential for Semantic Web Ontologies and knowledge graphs may provide conceptualizations for the given domain, including its constraints. As such, they serve to define the search space for generating novel concepts.

One interesting area of research related to exploratory creativity is scientific discovery. Here ontologies are being used to describe the domain of interest for scientific experiments for automation. A notable example of this kind is Robot Scientist, which originates novel hypotheses in functional genomics and has been shown to make scientific discoveries [23] with use of expressive domain ontologies. *What other semantic resources are needed to fuel computationally creative systems also in the domains of arts and design? Are existing ontologies and knowledge graphs in domains such as fashion [24], food [25] etc. sufficient to effectively support creative computing?*

Evolutionary computation has recently been used to generate recipes and using a graph-representation of the recipes [26].

Concept induction [27, 28] and pattern mining [29] have been an area of active research in data mining in the Semantic Web context [6]. Many of these approaches use so-called *refinement operators*, i.e. functions that 'traverse' the search space and generate specializations or generalizations of concepts. Those refinements are further evaluated regarding their quality. To assess the quality of generated candidate concepts various measures can be used, not only based on frequency or predictive quality but also such that promote diversity [30] or novelty.

What would be then opportunities for further Semantic Web research? *What research is needed to define quality measures and evaluation procedures for concept creation with use of Semantic Web technologies that promote novelty? What properties should have refinement operators to support exploratory creativity on the Semantic Web?*

2.2. Combinational: novel combinations of familiar ideas

Creativity, understood as unfamiliar combinations of familiar ideas, dates back to the notion of *bisociation*, presented by Koestler in 1964 [31], where creativity is described as a result of combining distinct frames of reference. The work of Koestler was followed by a subsequent cognitive theory of conceptual blending [32].

2.2.1. Conceptual blending

Conceptual blending is a process of inventing a *novel concept* (the *blend*) by combining two familiar input concepts.

The framework of *conceptual blending* proposed by Fauconnier and Turner [32] concerns so-called *mental spaces* that connect schematic knowledge and frames representing the organization of elements and relations of the familiar knowledge. In the center of the conceptual blending theory, there is a *conceptual integration network*, which contains such elements as: (i) *input spaces*, (ii) a *generic space* (with a structure being an abstraction of commonalities of all the spaces of the system), (iii) a *blended space*, containing chosen aspects of the structures from the input spaces and its own, created structure, (iv) a *partial mapping*, connecting chosen aspects of the models in the input mental spaces. This basic framework may be also extended to include additional structure in the blend, that is not copied from the input spaces, via composition, completion, and elaboration.

One of the classical examples of conceptual blending concerns the concepts of house and boat (e.g. [32–

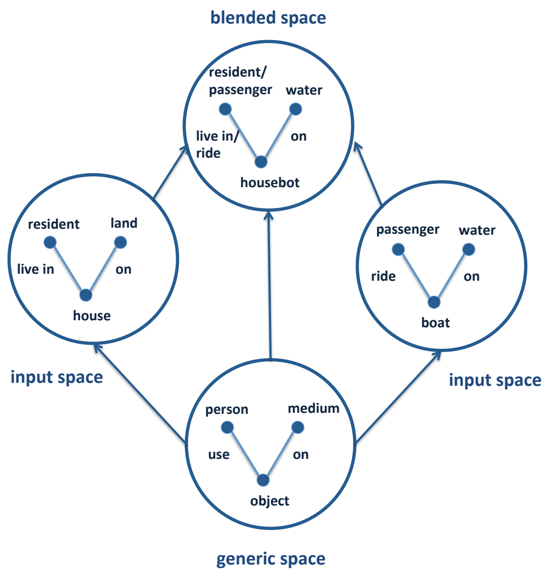

Fig. 2. The housebot blend (adapted from [32–34]).

34]. Figure 2 illustrates one of the possible results, which is a house-boat concept (another example could be a boat-house concept).

Various formalisms have been used to represent input spaces, including concept maps, frames, rules and constraints by Pereira [35], Prolog and micro-theories as in the system Divago [36], semantic networks used by Veale and Donoghue [37], description logics by Confalonieri et al., [38], Distributed Ontology Language by Kutz et al. [39], and algebraic specifications by Eppe et al. [34]. Not only concepts may be blended, but also ontologies, as proposed in [39].

The computational challenges associated with conceptual blending are: (i) to compute a generic space, which can be later specialised to produce meaningful blends with elements from the input concepts and (ii) to ensure that there are no inconsistencies by combining concepts in a too naive and arbitrary way.

Potential for Semantic Web There are multiple options for Semantic Web research in the area of conceptual blending. There have already been proposals to use the Web as a source of background information to generate blends, such as 'conceptual mash-ups' proposed by Veale [40].

Can thus these ideas be taken further, and *can Linked Data and knowledge graphs be sources of vast amounts of (already structured) knowledge for producing blends? How can we combine or blend existing concepts, semantic frames, and other constructs, and benefit from cross-fertilization? Could we exploit (and how) Ontology Design Patterns [41, 42] with their semantics to represent a generic space?*

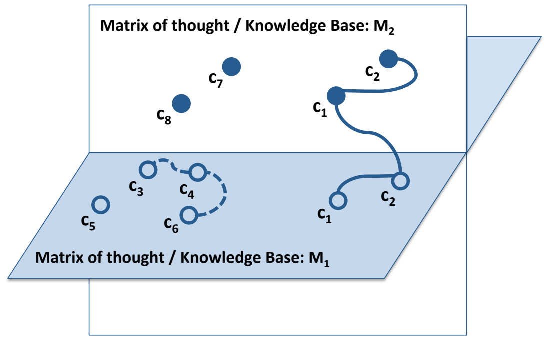

Fig. 3. A concept of bisociation, illustrated with a solid line connecting concepts c_1, c_2 viewed in two different matrices of thought or from two different knowledge bases, versus an association, illustrated with a dashed line, which connects concepts from one matrix of thought or a knowledge base (adapted from [31, 43]).

When two input spaces are being combined, another challenge is to compute a generic space automatically, especially for expressive representation languages, and many of the proposed blending approaches are not capable of it. *Can thus automated approaches be developed for computing a generic space automatically, leveraging of reasoning services developed within the Semantic Web research area and aimed to compute a most generic concept or of generalisation refinement operators?*

Even after the generic space is identified, there still remains a challenge of a large number of possible combinations to generate blends. Some of them need to be pruned, and, besides application of quality measures, *can also consistency checking be applied and how to prune blends?*

2.3. Bisociaton

The term *bisociation* was introduced by Koestler [31] to describe the creative act in humor, science and art. It stands for a blend of *bi-* + *association*. An association represents a relation between concepts within one domain, and bisociation fuses the information from multiple domains. Elements that are blended are taken from two (previously) unrelated 'matrices of thought' (or domains) to form a new matrix of meaning, applying processes such as abstraction, categorisation, analogies and metaphors, and comparisons.

Figure 3 illustrates a concept of bisociation.

Hence, bisociative thinking occurs when a problem, idea etc. are viewed in two (or more) 'matrices of

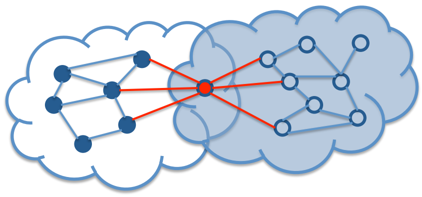

Fig. 4. A BisoNet with a bridging concept.

thought', domains. Therefore, to find bisociations, it is required to integrate data from different domains. Bisociative Networks (BisoNets) [43] have been proposed as a method to compute Koestler's bisociation, and to semantically integrate information. BisoNets are based on a k-partite graph structure, containing nodes that represent units of information or concepts and edges that represent their relations. Each partition of a BisoNet contains a certain type of concepts or relations (terms, documents etc.). Figure 4 illustrates BisoNets, where one of the nodes in the network plays a role of a bridge between the network partitions.

Once a BisoNet is formed, it can be mined for novel, and interesting information, and patterns to support creative discoveries. Such patterns can be bisociations, that in the context of BisoNets are understood as links connecting concepts from two or more domains. This may lead to so-called *creative information exploration*, which aims to explore large volumes of heterogeneous information to discover new, surprising and valuable relationships in data that would not be mined by conventional information retrieval and data mining approaches [43]. Such discovered links represent non-obvious connections and domain-crossing links, where concepts from various domains are not commonly related. Such connections may be discovered by graph mining and analysis techniques. One 'classic' example from literature of such non-obvious link regards connecting magnesium and migraine. There had been a body of articles on how migraine can be treated with calcium blockers, and another body of articles (not connected with previous ones) describing how magnesium works as a calcium blocker, but the potential to treat migraine with magnesium had not been realized [44].

Ultimately, bisociations may be useful in discovering analogies and creating metaphors.

Potential for Semantic Web Semantic Web and Linked Data seem to coincide with the model of BisoNets as k-partite, heterogeneuos information networks, integrating concepts. *How then the modeling choices of Linked Data may impact creative information discovery? Could thus the ideas and methods developed for creative information exploration be used to mine multi-domain Linked Data and vice-versa, i.e. can link discovery approaches developed within Semantic Web research be applied to creative information exploration?* Mining potential novel associations between Linked Data [45] have already been explored within Semantic Web research. Can this be taken further? *Is research on ontology mapping for bridging domains also relevant here? How to compute which nodes in the Semantic Web would bridge domains in creative ways?*

2.4. Transformational: transforming the search space

Transformational creativity may be seen as meta-search, i.e. search not only for concepts, but also for *rules*, that is modifying rules and constraints and the search method. Transformational creativity happens, when the search space itself is also modified. The result are novel concepts in the modified space.

Potential for Semantic Web Semantic Web technologies serve well to describe domain knowledge with making explicit constraints existing in the domain. *Can we use ontologies and knowledge graphs, which describe an existing domain with its axioms and constraints and, applying a meta-rule for transformational creativity, start dropping constraints and adding new constraints and see what emerges?*

One active area of research in Semantic Web concerns (word) *embeddings* [7], which involve mathematical embedding from a multidimensional space to a vector space with a much lower dimension, where words are represented as dense vectors. Most embeddings are inspired by language models, and as such, they assume the input representation as sequences of words or characters, and state-of-the-art methods for learning embeddings do it adequatly in Euclidean vector spaces. However, in the Semantic Web we deal with structured, graph data. Recently, Nickel et al. [46] have considered to drop the common assumption of operating in Euclidean space, and proposed to learn hierarchical representations of symbolic data by embedding them into a non-Euclidean, hyperbolic space – an n-dimensional Poincaré ball. Leveraging the hyperbolic geometry has been shown to improve learning representations of symbolic data by simultaneously capturing hierarchy and similarity. *Are there other possibilities to use non-Euclidean geometries for learning ef-*

fective embeddings regarding Semantic Web representations?

One transformatory assumption regarding reasoning on the Web was to assume 'open world' rather then 'closed world', which started new research lines. *Can we also change some other assumptions underlying reasoning on the Web to obtain novel problem settings and surprising and useful results?*

3. Conclusions

In this position paper, we have made several claims. We claim that to achieve its full potential the Semantic Web must be accompanied with valuable applications, and that those applications could be based in many cases on AI. We have pointed, that the seminal vision paper motivated the Semantic Web with use of examples of such intelligent applications and services delivered by intelligent agents. Therefore, we explored under-explored and rising opportunities for Semantic Web research in the growing area of AI, namely in computational creativity.

We have briefly surveyed the domain of computational creativity, with focus on aspects relevant to the Semantic Web research: knowledge representation and reasoning, ontologies and knowledge bases, linked data, and intelligent applications built over networked, heterogeneous knowledge bases. We conclude that there is a lot of potential for future research in Semantic Web for AI creativity in developing resources, languages, reasoning services, mapping techniques.

These include: (i) knowledge representation languages to represent concepts in a broader sense (e.g., procedural knowledge to represent ideas such as culinary recipes), (ii) data mining approaches, including their building blocks such as refinement operators, (iii) cross-domain mappings, (iv) reasoning services beyond deduction and predictive inductive models (e.g., analogical reasoning, generative models), (v) knowledge resources in domains such as art and design, scientific discovery and others.

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