AAAI Technical Report SS-12-06
Wisdom of the Crowd

The Role of AI in Wisdom of the Crowds for the Social Construction of Knowledge on Sustainability

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Abstract

One of the original applications of crowdsourcing the construction of knowledge is Wikipedia, which relies entirely on people to contribute, extend, and modify the representation of knowledge. This paper presents a case for combining AI and wisdom of the crowds for the social construction of knowledge. Our social-computational approach to collective intelligence combines the strengths of human cognitive diversity in producing content and the capabilities of an AI, through methods such as topic modeling, to link and synthesize across these human contributions. In addition to drawing from established domains such as Wikipedia for inspiration and guidance, we present the design of a system that incorporates AI into wisdom of the crowds to develop a knowledge base on sustainability. In this setting the AI plays the role of scholar, as might many of the other participants, drawing connections and synthesizing across contributions. We close with a general discussion, speculating on educational implications and other roles that an AI can play within an otherwise collective human intelligence.

Introduction

Wikipedia is a high-profile and important example of crowdsourcing for the social construction of knowledge. Wikipedia relies entirely on people to contribute, extend, and modify the representation of knowledge, but increasingly AI methods of machine learning, such as conceptual clustering (for example, Fisher 2002) and topic modeling (for example, Blei et al 2003), are proving useful for the construction of knowledge. Different approaches make different assumptions about the representation of the data from which the knowledge is constructed: ranging from highly structured data to unstructured text and/or images.

We present a social-computational approach to collective intelligence that combines the strengths of human cognitive diversity in producing content, with AI methods such as topic modeling, to link and synthesize across these human contributions. In crowd-sourcing contexts we expect an AI to serve important roles of scholar, synthesizer, and evidence-based decision maker, which will benefit the social construction of knowledge and long-term thinking.

The remainder of the paper first highlights some important advantages of cognitive diversity in human problem solving, but with caveats. Informed by this summary, we describe what an AI can bring to crowdsourcing of knowledge construction, using Wikipedia as a motivating example. In this setting, the AI plays the role of scholar, as might many of the other participants, drawing connections and synthesizing across human contributions. We present the design of a system that incorporates both AI and wisdom of the crowds to develop a knowledge base on sustainability issues and encourage interaction with that knowledge base. We close with a general discussion, speculating on educational implications and other roles that an AI can play within an otherwise collective human intelligence.

The Benefit of Diversity

Wisdom of the crowds is based on a model in which large numbers of diverse individuals will produce a better solution than any single expert could provide. Page (2007) describes how diverse individuals bring different perspectives and heuristics to problem solving, and shows how that diversity can result in better solutions than those produced by a group of like-minded individuals. He argues that diversity improves problem solving, even though our individual experiences in working with a diverse group may be associated with the difficulty of understanding other viewpoints, reaching consensus, and the like.

Some have argued against Page's theorem that collective "diversity trumps ability" of individual members as overly simplistic. While Page describes diversity according to differences in perspective and heuristics, Harrison and

Klein (2007) identify three kinds of diversity that are important when trying to achieve the benefit of diversity:

- Diversity as variety: individuals vary in their knowledge.
- Diversity as disparity: individuals vary in their status or power.
- Diversity as separation: individuals vary in their attitudes, leading to polarization.

When variety and disparity co-vary, self-interest mechanisms can interfere with the value of diversity. That is, people with more power or higher status may inhibit or discount the contributions of people with lower status. When variety and separation co-vary the values that divide two individuals may influence the ability of one to understand or consider a solution or contribution from the other. These and other factors of identity, social and organizational interactions make Page's model too simplistic, requiring mediation (Bell and Berry, 2007).

Understanding diversity as variety, disparity, separation, and the effects of covariance among them, provides a framework for understanding how to structure the role of AI to mediate diversity in building knowledge stores. Wikipedia can mediate these combinations of diversity by creating a focus on the incremental collaborative editing of individual articles rather than a focus on the identity of the individuals making the contribution, thus mitigating perceived disparities based on cursory status differences.

Separation, presumably caused by biases of different authoring communities, is another aspect of diversity that can be mediated. In particular, Wikipedia has merging and splitting guidelines; when an editor believes that the content of one or more articles is sufficiently similar then the articles in question can be highlighted, and community input will guide subsequent synthesis, or perhaps block it. Similarly, when articles become unwieldy they can be tagged for splitting. In such cases, "cultural" differences across the article authorship communities might block synthesis, but perhaps an AI scholar can operate on the contributions with no bias on the status or attitude of the individual that makes the contribution or suggests the revision.

Page's examples of problems that benefit from diversity have a correct or optimal solution, which isn't a characteristic of the social construction of knowledge (unless perhaps separation and disparity are dominant, which of course violates the premise of a collective approach to begin with). Nonetheless, another distinction seems very relevant – his illustrative tasks are disjunctive as opposed to conjunctive. Page (2007) refers to J. D. Steiner's distinction between "*disjunctive* tasks, those in which only one person needs to succeed for the group to be successful, and *conjunctive* tasks, those in which everyone's contribution is critical." The social construction of knowledge can be viewed in terms of this distinction. At the top level, almost by definition, it is conjunctive, but Wikipedia has been structured in a way that individual articles may emerge semi-independently of other contributions – that is, article creation is largely at the disjunctive end of the spectrum, with later synthesis and other revisions making the overriding effort conjunctive. We characterize this as 'divide and conquer' problem solving, and one that benefits from crowdsourcing, according to Page, when:

- Condition 1: the problem is difficult,
- Condition 2: all problem solvers are smart,
- Condition 3: some problem solver can find an improvement on the existing or a suggested solution,
- Condition 4: the pool of problem solvers is reasonably large.

Wikipedia facilitates individual contribution to interconnected articles comprising an encyclopedia of knowledge. A contribution is the creation of a new article, but more often, is a modification of an existing article that may involve adding to the article or changing existing content in the article. Wikipedia is self-correcting because it crowdsources contributions, edits, and comments. Diversity works in this case because it is self-correcting. The online challenges that have benefited from crowdsourcing, such as Wikipedia, Innocentive, Goldcorp, have presented tasks to the crowd for which the solutions can be checked for correctness and for which direct interaction among participants is not a significant aspect of the problem solving. Tasks that require long term thinking about the future do not necessarily have the benefit of knowing when a fact is right or wrong, yet diversity of perspective is valuable. In the following sections we present a role and model for AI for such tasks so that the benefit of the diversity of perspectives and heuristics can be achieved.

The Role of AI in Wisdom of the Crowds

AI, and computational models in general, have played various successful roles for achieving benefit from large numbers of human problem solvers in recommender systems (for example, those used by Amazon and Netflix), search engines (for example, Google, Yahoo and others), natural language translation (for example, Hu et al, 2011), story telling about the news (for example, Nichols et al 2009), and others.

The concepts of disjunctive and conjunctive problems can help frame the role of AI in the social construction of knowledge. AI can improve on collective activity, such as Wikipedia, by performing tasks that transform the loosely-coupled disjunctive contributions into a solution of a conjunctive task.

In this section we describe an illustrative example, under development, of AI in collective construction of knowledge about sustainability. The example will prove, we hope, to be a compelling demonstration that an AI can play many important roles -- of scholar, editor, biographer of ideas, librarian -- by cataloguing, linking, and synthesizing human contributions.

A Model for AI and Crowdsourcing

As a scholar, an AI can play a role in finding structure or patterns across multiple documents, seeing similarities and differences, and identifying concepts and relationships. We describe a combined machine learning and human contribution approach to the incremental development of a knowledge base that crowdsources contributions and uses a machine learning component to cluster and index complex, unstructured contributions from many individuals to form a concept map.

A contribution in our model is a potentially complex but self-contained document authored by an individual or a specified set of authors. While all contributions in Wikipedia are in the same format (text, images, and links in html), the types of documents that can be contributed in our model include: text-based documents that may or may not have embedded images, image documents, audio files, video files, animated movies. The types of contributions include: student reports submitted as assignments to a sustainability topic, poems on sustainability, diagrams or artistic renderings on sustainability, live-action movies or animations that address sustainability issues. The AI can accept a broad range of documents, but operates on an unstructured text representation of the contribution. The reason for accepting such a broad range of document types is to be able to display the different contributions in a theatre-like showcase of sustainability issues.

We use a concept map as a target representation for the synthesis of individual contributions because it conveys a sense of overview of a topic comprising individual concepts and their relationships, without restricting the nature of the network as hierarchical, cyclic, or directed. A concept map (Novak & Godwin, 1984; Novak & Cañas, 2010) is a graph of concepts as nodes and relationships (propositions) between concepts as links. Concept maps were initially developed for representing, visualizing and tracking student knowledge on a domain, and they are increasingly used in other contexts as well; there is an active community of practitioners and researchers.

Concept maps are typically constructed manually, but there are automated approaches to generate concept maps from document collections (Bieman, 2005; Zouaq & Nkambou, 2009). However, such automated methods produce maps that are limited in their use of links/propositions, to what we would call ISA parent/child links, so that the map is essentially a generalization tree that is not threaded by other kinds of relationships; these other kinds of relationship can be added through manual inspection, resulting in a semi-automated approach. Concept maps are also used to index single or multiple documents, serving as a good basis for search and browsing (Carnot et al, 2001). Concept maps that encode sustainability-related concepts have been constructed; for example, a publicly available concept map for climate change is part of the IDIOM project (www.ecoresearch.net) which is learned and maintained from a stream of news documents (for example, blogs, articles, web sites). This is an impressive index into the popular and scholarly climate change literature, but as with other automated approaches, it is a strict generalization tree structure, unthreaded by other relationships.

Our model is a semi-automatic approach to building and maintaining a concept map using a combination of topic modeling (Blei, et al, 2003) and conceptual clustering techniques (Fisher, 1996; Fisher 2002). Topic modeling is an unsupervised learning paradigm, whereby a document collection is mapped into topics based on co-occurrence of words and phrases in the documents. Topic modeling is a form of generative clustering, where any particular document may reflect multiple topics to varying ‘degrees’, which may have Bayesian and/or fuzzy interpretations. This measure of ‘degree’ is an important aspect of topic modeling approaches, and some clustering approaches more generally, so that topics don’t reflect hard boundaries, but there is overlap between conceptual categories. Our approach is a semi-automatic model with the following features: incremental and hierarchical, enabling concept evolution; and interactive, because human editors vet the evolving conceptual map.

Building an initial concept map on sustainability

Motivating “cultures of participation” as described in Fischer (2011) often requires creating initial content that encourages and inspires contributions and counter-arguments. This idea of creating an initial concept map has the benefit of encouraging thinking and contributing to the deliberation on sustainability because the topic has many and possibly conflicting views. In our approach we use a semi-automated approach for developing an initial concept map, emphasizing the role of AI as a scholar among human scholars. This process of generating the initial concept map involves human analysts, designers and coders, interacting with topic modeling and concept mapping software applied to a pre-selected set of contributions on sustainability topics. A tree-structured topic model is obtained by applying a hierarchical clustering method to the topic descriptions, which amounts to a clustering of clusters (Fisher, 1996; Fisher 2002); a hierarchical topic model also can be learned directly from data (Blei, et al, 2003; Chang & Blei, 2010), though the richness of hierarchies learned by these means (thus far) appears limited.

The knowledge base representation includes a graphical representation based on concept maps, with associated subgraph statistics (for example, cohesion and coupling), but also a similarity matrix, representing similarity values between all pairs of topics, and other global information, to include that which is relevant to the 3D rendering of the concept. From analysis in inter-topic similarities we expect to find 'markers' for various kinds of relational threads that may exist between topics.

In addition to obtaining richer concept map structures by threading semi-automatically, this model is a novel approach to automatically building overlapping clusters (or topics). In the rare cases where a clustering approach does allow contributions to be classified in multiple clusters, it is done by setting a similarity threshold, and if a contribution exceeds the threshold in multiple places, then it is placed in each. An alternate approach that is both novel and we believe more elegant is to ask, for each path in a hierarchical clustering, where is a contribution's placement 'optimized'? If, for a given path, placement is optimized at the root of the entire structure, then essentially/operationally it will NOT be categorized down that path. If on the other hand, placement below the root is optimal, say at node M, then we can ask recursively where along the sub-paths going through M the contribution should be placed. It may seem extreme to look at all paths, but if certain natural monotone properties on similarity hold, there is radical pruning that can occur. This approach is inspired by Fisher's (1996) work on identifying optimal frontiers for inference within a hierarchical clustering, and on the psychological phenomenon on basic level effects that inspired this family of clustering algorithms.

Extending and maintaining a concept map

Once an initial concept map is developed, and an interactive visualization of the map and its associated contributions goes live in a public environment, AI plays a role in incorporating new contributions by extending, modifying and maintaining the concept map so that it captures the diversity of all contributions relevant to sustainability issues. To support the stream of inputs from public participants, the model supports incremental (aka online) concept map revision, so that an existing knowledge structure can be refined with additional inputs, and we want a hierarchical form of topic modeling to better facilitate rich visualizations and explorations of the underlying data. Incremental (or online) topic modeling is only recently explored (Hoffman, et al, 2010), where the documents arrive in a stream and are incorporated into the evolving models one by one, but the very related activity of incremental clustering has been studied for some time (Fisher, 1987; Anderson and Matessa, 1991; Fisher, 1996), and this longer-established work has been intimately concerned with incremental refinement of hierarchical clusterings, though most of this earlier work focused of hard-boundary clustering. Our model is based on adapting incremental, hierarchical clustering to a soft clustering paradigm, and topic modeling in particular, resulting in incremental hierarchical topic modeling. The approach taken by Anderson and Matessa (1991) on soft hierarchical clustering, together with Hoffman, et al (2010) and Chang and Blei (2010), will serve as a starting points, with iterative optimization methods involving (re)clustering clusters (Fisher, 1996) adapted to the task of reorganizing topic (sub)hierarchies in response to new inputs; (re)clustering clusters can lead to substantial reorganizations, which may yield interesting changes to the concept map, but it may also be desirable to mediate changes for continuity in the visualization.

Interaction Design

Figure 1, adapted from Fisher and Maher (2011), illustrates our design for an interactive public display that encourages people to contribute to the concept map. Such a system may have a web presence, but more importantly, will have a physical presence to encourage communication and collaboration in local, public places (see Russell et al 2002). The interaction design has three components:

1. *Human contributions* via incoming messages to a large, interactive public display: these contributions can be short text messages, URLs, documents, images, videos.
2. *AI generated concept map* that is incremental and adaptive that characterizes and categorizes contributions and identifies links among the contributions using a combination of topic modeling and conceptual clustering.
3. *An interactive virtual world* visualization of the concept map that allows individuals to explore the concepts by touching and expanding nodes of concepts and moving an avatar around galleries of contributions within a node of the concept map.

As part of the interaction design, the AI will be integrated with and informed by contributions from the crowd. When people interact with the 3D visualization of the concept map and the contributions, they can suggest modifications to the concepts map representation and the clustering of contributions. These suggestions will be mediated by the AI and verified by a human team, and if accepted, will be the basis for future machine learning. Extensions to the current role of AI in finding patterns, links, and clusters of contributions include telling a story about a concept, and maintaining information about attribution to specific authors of contributions.

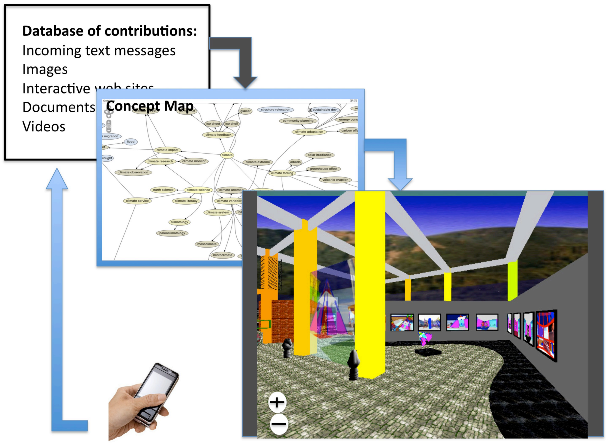

Figure 1: A framework for engaging the public in the social construction of knowledge of social issues. Middle layer concept map screen shot of www.ecoresearch.net.

General Discussion

Our case-study of social knowledge construction on societal and environmental sustainability is motivated by the need for increased and contemplative dialogue on these vitally important issues, particularly among the generation that will soon be stepping into power. Despite the long-time warnings on many fronts, such as environmental poisoning (Carson, 1962) and climate change (Weart, 2008), the reaction to these and other urgent matters has been tepid and ad hoc. We do not view our project as 'emergency response', though such action is needed, as an environmental emergency exists. Rather, we employ AI to improve human intelligence, which is often best when it's slowed down – we view our project as contributing to intelligent and considered reasoning and discourse that must dominate more of human activities, in addition to and beyond current emergencies.

We are currently implementing the prototype eco-village in Second Life to explore the idea of mapping from a concept map to an interactive 3D representation of contributions, thus, we hope encouraging contributions from students in an academic environment where many courses are including sustainability content. We plan to implement the AI component of the system though an initial semi-automated approach to clustering and topic modeling across a pre-selected set of student projects on sustainability. We expect to seed the contributions with a significant number of projects from students at Vanderbilt and provide incentive structures for participation that include requirements in existing courses and recognition from relevant sustainability organizations, teachers, and peers.

With respect to diversity, the resulting combination of concept map and database of contributions will provide a rich dataset for studying the diversity of individuals that contribute. Information about the authors as well as the content of the contributions can lead to characterizing the range of the three kinds of diversity presented in Harrison and Klein (2007): variety (perspectives), disparity (status), and separation (attitude). Having a common experience of interacting with the concept map in a virtual world environment may mediate the differences in these aspects of diversity. Having an AI as scholar may also mediate the differences.

Educational implications

We also expect that our project will have important educational benefits. An experience that we would hope students would have, related to their communication with "authentic audiences," (Light, 2001; Bruff, 2011) is a recognition that they are members of a community of scholars – not only are they citing others, as they would in any traditional education setting, but they are opening themselves to be cited by others. There is no reason that students need wait until graduate school for such an experience, and it is germane to sustainability that the importance of community be highlighted early. Importantly, the AI will be a vital participant, one that works hard at identifying scholarly connections, helping to cement a scholarly community; the AI, we hope, will be perceived as encoding the value of scholarship, and moreover representing a value that scholarship and synthesis are interesting, perhaps even fun

Roles for AI in Collective Knowledge Construction

In addition to AI as scholarly synthesizer, we have alluded to other roles that an AI can play within community-driven knowledge construction, be it our eco-village project, a large-scale effort like Wikipedia, or otherwise.

A central functionality on an AI, say as a historian or biographer of ideas (commonly enough used terms that we don't quote it, but nonetheless a compelling characterization of what an AI might do), would be to examine knowledge construction activities, such as article creation, deletion, revision, merges, and small edits, over large time scales, and to identify the emergence of ideas, from predecessor ideas of various forms, to first explication(s), through mature applications and contributions to other ideas. The AI capable of tracking ideas over long intervals and telling the story later might motivate contributions by some who would not otherwise do so, back propagate credit from the distant future to otherwise nameless authors of the past, and generally contribute to a sensibility that ideas and actions have a long life, focusing attention on long-term thinking and collective discourse. Indeed, Wikipedia edit histories may even now offer data for exploration and evaluation of the AI for such roles.

Beyond credit assignment, a back propagation capability of an attentive AI might also be the basis for counsel on the expected reactions to a contributor's editing actions, based on reactions, temporally distant, from similar editing actions of the past. This AI editing advisor might suggest conservatism, for example, where an individual is being hasty in a revision. In this role too, the AI highlights for human participants the importance of thinking about the future. We see many such possibilities for an AI to play an active role, in community, to advance ideals of scholarship and reflection on the long-term.

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