Publishing against the Machine: A New Format of Academic Expression for the New Scientist

Adam Sofronijevic

University of Belgrade, University library "Svetozar Markovic"

This paper presents possibilities for profound transformation of academic communication. The changing role of humans in scientific communication is analyzed on the basis of ongoing technological developments. Machine analysis and production of scientific texts are discussed, and increasing efficiency in scientific communication is advocated.

Introduction

Communication is crucial for scientific work in two aspects: First, it allows for dissemination of new ideas and findings, thus making progress in science possible. Second, the resulting products of this communication in written form (e.g., journal articles) are the main evaluation tool for judging the entire scientific process behind them. This makes communication important to the scientific work, because only excellence in both fields leads to continuous scientific progress. It seems that in science, too, it is not only about who we are, but also about the clothes we are wearing.

One must remember that good clothing alone may not get one far in the scientific world, but also that one will not be allowed to walk naked. The tremendous importance of scientific communication today seems not to be matched with the same amount of interest, funding, and dynamics as the research area of scientific work is. While the corpus of world knowledge doubles with amazing dynamics, we see no such dramatic changes in scien-

Tokar, A., Beurskens, M., Keuneke, S., Mahrt, M., Peters, I., Puschmann, C., van Treeck, T., & Weller, K. (Eds.). (2012). *Science and the Internet* (pp. 251-262). Düsseldorf: Düsseldorf University Press

tific communication. One can only imagine how it would be if every five or eight years we would have new forms of scientific communication that would allow for twice as efficient dissemination of knowledge and twice as good evaluation tools and methods. All kinds of amazing discoveries and breakthroughs, made on almost a daily basis, are communicated nearly in the same ways as 40, 50, or 100 years ago. While we have computers and the Internet, we are still stuck with humans writing essays word by word, explaining what they have discovered and thought. Machine-enabled help in text production is negligible when compared with machine-enabled help in research.

This may come as no surprise when one contemplates the complex nature of human communication. The strength of computing machines is in computing and thereby solving structured problems. Now, we are on the verge of a revolution that will enable machines to take over the burden of solving more sophisticated problems, also in the area of communication. The possibilities for pattern matching and pattern recognition of contemporary machines will continue to increase. This will make jobs deemed creative in the past available for machines. In order to benefit, scientists need to look into processes in other fields to make the transition as smooth as possible. Competing with machines in performing work in areas where machines excel humans, such as some fields of production and analysis of structured communications, will be inefficient.

Machines Are Taking Over: Other Industries

Changes in technologies play a somewhat surprising role in our lives and in our business environment. To explain it, we need new perspectives and ideas. To master it for everyday purposes, we need new approaches, skills, and competences. Changes that may be dramatic in some industries are unnoticed in other fields due to the dynamics of the environment. The rush to cope with change occupies many available resources. Brynjolfsson and McAfee (2011) discussed the role of human labor in light of ongoing technological developments. More and more human jobs will be replaced by emerging technologies. They are capable of performing work tasks previously considered accomplishable only by human creativity. How will we manage new machines? Will entrepreneurs use machines to provide new work opportunities, replacing those destroyed? So far they have been successful in this task, and every new technological breakthrough brought not only the destruction of old ways, but also gave rise to new workplaces. A new dimension of technology improvement was discussed as early as 1963:

> We are being afflicted with a new disease […] technological unemployment. This means unemployment due to our discovery of means of economizing the use of labor outrunning the pace at which we can find new uses for labor. (Keynes, 1963)

Brynjolfsson and McAfee (2011) claim that these questions are more than ever central for the societies and economies of today. The pace at which technology change destroys workplaces is increasing. One must wonder whether new work opportunities will arise at an appropriate pace or whether high unemployment is inevitable. Certainly, people had to acquire new skills and competences after machines took over their old jobs. Some examples follow to illustrate the previous discussion.

Until a few years ago, vehicle driving was considered impossible to even be considered as a job suitable for machines. The complexity of traffic situations and the need for what was considered intuitive decision-making were deemed beyond the processing power of any machine (Levy & Murane, 2004). Nowadays, computers can drive vehicles autonomously. This puts millions of jobs, including five million truck drivers in the U.S. alone, in jeopardy (see Brynjolfsson & McAfee, 2011). Academic courses on programming autonomous driving vehicles are offered online (e.g., Artificial Intelligence (cs373) Programming a Robotic Car).

One has to wonder how many jobs in higher education will be replaced by computers. As of May 2012, grading robots can do a fantastic job providing timely and accurate grades for more than 90,000 students enrolled at Udacity—Introduction to Computer Science Course (CS101): Building a Search Engine. We see attempts at building on economies of scale, when, for example, MIT and Harvard join forces to form edX. With such a dynamic development environment, machines seem certain on winning at least some jobs in higher education with humans remaining important at those places where interaction and intuition are important in the educational process.

With jobs being taken over by machines in a diversity of industries, one may wonder if there is a general type of job in which machines excel. Licklider (1960) predicted these issues more than fifty years ago:

> Man-computer symbiosis is an expected development in cooperative interaction between men and electronic computers. It will involve very close coupling between the human and the electronic members of the partnership. The main aims are 1) to let computers facilitate formulative thinking as they now facilitate the solution of formulated problems, and 2) to enable men and computers to cooperate in making decisions and controlling complex situations without inflexible dependence on predetermined programs. In the anticipated symbiotic partnership, men will set the goals, formulate the hypotheses, determine the criteria, and per-

> form the evaluations. Computing machines will do the routinizable work that must be done to prepare the way for insights and decisions in technical and scientific thinking. Preliminary analyses indicate that the symbiotic partnership will perform intellectual operations much more effectively than man alone can perform them. Prerequisites for the achievement of the effective, cooperative association include developments in computer time sharing, in memory components, in memory organization, in programming languages, and in input and output equipment.

Thus, skills are discussed in the framework of a symbiotic human-machine collaboration. This clearly represents a plea for humans not to compete with machines. They should develop skills in which they excel and use machines for jobs in which they perform better to increase human productivity. A general conclusion can be derived from Licklider's early insight. The division of work among machines and humans is based on the complexity of the tasks involved. As machine resources grow stronger, more jobs will be given to them to perform. As the need for human activity shrinks, the pressure to develop skills in areas that are extremely complex grows. Thus, human intuition becomes more and more important.

The career of Steve Jobs, late CEO of Apple, Inc., provides an example for the importance of human intuition and its successful implementation for business results. Jobs always emphasized the importance of intuition in business decision-making and even refused to do market research for new products. He relied solely on his own intuitive insight into his customers' nature (Isaacson, 2011).

Levy and Murane (2004) provided a detailed list of skills in which humans or machines excel. Their prediction is that only the knowledge sector will provide new jobs for humans, including entrepreneurs, researchers, computer programmers, educators, and consultants. One thing these jobs have in common is that they require problem-solving skills for which there are no rule-based solutions. In spite of all improvements achieved or predicted, machines have not yet reached the necessary level of storage, speed, and processing power needed to cope with such tasks.

Complex communication is one area in need of significant improvements. Levy and Murane (2004) defined it as "interacting with humans to acquire information, to explain it, or to persuade others of its implications for action." They provide examples: a manager motivating the people whose work he / she supervises; a sales person gauging a customer's reaction to a piece of clothing; a biology teacher explaining how cells divide; an engineer describing why a new design for a DVD player is an advance over previous designs. They predict that machines will eventually supersede humans at jobs requiring application of deductive rules, such as arithmetic operations or boarding pass recognizing, and application of inductive rules (i.e., pattern recognition), such as predicting a mortgage default or recognizing a spoken name. Basically, Levy and Murane (2004) claim that tasks requiring well defined structures that can be accomplished by following a set of rules will be taken over by the machines.

Another interesting insight shared by both Levy and Murane (2004) and Brynjolfsson and McAfee (2011) is that non-routine manual tasks will be an area where humans will be better than machines in the foreseeable future. Therefore, a labor market curve described by demand and level of education will not be linear anymore, but U-shaped, because besides demand for high-level experts, a huge demand for a human workforce will appear in the area of unskilled labor demanding execution of non-routine manual tasks.

The game of chess provides a striking example. Bordering science, arts, and sports, chess was long considered a human-only, creative activity. Everything changed at the end of the 20th century, when chess-playing machines managed to gain such dominance that duels between them and humans became boring. Not even the best human players could ever win against a strong, purposely built chess-playing machine. This changed the notion of creativity forever. The definition is changing, as machines take over fields that are considered creative and reserved for humans only. The most important concept for management that originated in chess is “free-style chess.” This is a tournament where players act as teams and use computers. Since the 2005 competition, tournaments have not been won by teams made up of grandmaster players or the most powerful machines. Instead, in 2005 a team of two human players of average ability using three average machines won the tournament (Rasskin-Gutman, 2009). Their competitive advantage over other teams was a highly optimized process, based on their knowledge of humans to organize themselves using machines to work as a seamless team. One could also say that they made best use of their intellectual capital in producing the best results in a competition based on strict rules and having a straightforward goal. Their experience goes a long way in explaining communication between humans and machines and their interfaces.

The reasons for rapid changes in labor profile demand and technology can be explained with the help of Moore’s law (Brynjolfsson & McAfee, 2011). The observation that the number of components on a chip doubles each year has held true for almost 60 years (Moore, 1965). The increase in complexity leads to an exponential rise in efficiency. The real speed and scope of improvements can be noticed only in later stages of their development. Kurzweil (2000) illustrated such improvements by a story about a prize offered by an emperor to the inventor of the chess game. The inventor asked for a grain of rice on the first square of the chess board and twice that amount on the next square. For the first part of the board he received an amount equivalent to that raised at an average rice field, but in the second part of the chess board, the exponential rise showed its strength: The inventor ended up with a pile of rice equal in size to the Himalayas. Brynjolfsson and McAfee (2011) argue that technology development has entered "the second part of its chess board" and that dynamics will increase in the near future. As evidence, everyone can witness the online education revolution at edxonline.org or udacity.com. However, Cowen (2011) proposed a "technology plateau theory." He believes that there are indeed counter-effects to the potentials for growth provided by current technologies.

Scientific Communication: Machine-Assisted Reading and Writing

Scientific communication comprises two basic aspects or processes: reading and writing—or in terms that are more machine-friendly—analysis and production of the text. I will recapitulate the current state of affairs in several areas of machine-related text production and analysis.

Text analysis has recently become a very dynamic and productive field of research. More importantly, this field corresponds to the growing needs of researchers. One of the main problems has been defined in Takeshima and Watanabe (2010) as the difficulty for researchers to read and understand scientific papers effectually and effectively. To deal with this problem, many different ways of employing machine help have been devised. Takeshima and Watanabe (2010) focused on supporting the understanding process. They based their work on the fact that figures and tables reflect important contents of papers. Subsequently, they developed a method to extract sentences specific to figures or tables. Schafer et al. (2008) described methods for extracting interesting factual relations from scientific texts. The extracted relations are simplified, and the resulting "quirples" are stored in a database from where they can be retrieved by a relation-based search. More recently, Schafer and Kiefer (2011) described breakthroughs that have been made in deep parsing of long sentences. Such deep parsers provide the possibility to answer questions and explore definitions in the near future. Integration of annotation tools and natural language analysis tools can provide useful functions in text analysis and in preparing machine text production. Advances made in this area are diverse and significant (see Rupp et al., 2007). Considerable progress has also been made in accurate statistical parsing of realistic texts (Briscoe & Carroll, 2002) and even in finding predominant word senses in untagged text (McCarthy et al., 2004). Recently, sentence fluency has been analyzed, and means to evaluate this important feature, especially when dealing with machine-produced texts, have been presented (Chae & Nenkova, 2009).

Certain fields have witnessed faster growth of machine involvement in text analysis and creation. One such field is medicine, where vast amounts of data make it impossible for human-only activities to be efficient. For instance, Cao et al. (2009) presented the subject of question answering that differs from information retrieval in providing summaries rather than lists of documents, thus saving users additional work. Grau et al. (2009) presented a solution to automatically extract knowledge from papers in a specific corpus of kidney-related scientific papers. Such extraction may be of great help in scientific areas where data are abundant.

Machine translation is a fast-growing field due to the possibilities for profit. Advances in machine analysis and production of text in conjunction to this field are considerable. I will mention just some of the advances. Zhang and Clark (2011) provided a model for the problem of word-ordering, which is one of the biggest obstacles to smoother machine-translated text. The problem of evaluating machine-produced translation is complex because of the need for automated evaluation. Automatic metrics such as BLEU fail to achieve satisfactory levels of correlation with human judgments at the sentence level. Kulesza and Shieber (2004) proposed a new class of metrics based on machine learning.

Advances in machine transliteration have also been made (e.g., Li et al., 2009). This particular area is of great importance for providing accurate synthesis of different affiliations in a large citation database, which is of enormous importance for evaluating scientific results.

Look into the Future: New Scientist and Communication

It is hard to imagine the scientist of tomorrow who will not use all technological advances at hand to be more efficient and effective in scientific communication. Therefore, we must think that in the future, all kinds of machines will be at one's disposal, providing help in different aspects of scientific communication. How can they help? Based on the advances in text production and analysis described above, we may define several most likely possibilities.

In text analysis, machine readability of texts is of the highest importance. Therefore, such forms of text will be highly used. I will describe one of these forms, which is often called a "nano-publication." Such nano-publications may provide for machine readability of the shortest possible scientific statements with possibilities for referencing. A nano-publication is a very short declaration connecting two concepts by means of a third and providing metadata about this relation—i.e., conditions under which the relation is viable, author, timestamp, etc. (Groth et al., 2010). Originating in the life sciences, nano-publications seem to be envisioned and increasingly shaped as a tool for efficient publication of datasets. Nano-publications are depicted in more detail in Mons and Velterop (2009). Beyond the advantages of machine readability and possibilities for referencing, nano-publications may also be important in providing an important field for human employment, especially in transitional and developing countries. Therefore, the use of this scientific communication tool has a twofold importance: On the one hand, nano-publications foster efficiency by using machine readability to their advantage, while, on the other hand, the need for referencing leaves sufficient incentives for the employment of human scientists in their production. In discussing alternative forms of publications, one must also consider incentives for publication (i.e., the potential rewards for publishing). One interesting idea in this area is to shape future scientific communication to make it more suitable for applying a micro-credit system (Casati et al., 2011). That system may involve more finely graded rewards for publishing and communicating advances to a general body of knowledge than the system that is in place today allows.

Machine translation is another area in which scientific communication could be improved if more machines were involved. Some areas are more prone to structured text forms and therefore will benefit more from advances in this area. Huge scientific communities in China, India, and Russia are on the rise. As English is not a native language to them, the enormous size of these communities makes their members more prone to intra-community communication than to dialog with the international community. In contemplating possibilities for machine translation usage in scientific communication, we have to consider the differences between languages used by people and machines. These languages will have to converge if machine translation is to be used on a wider scale. Recent findings (Branigan et al., 2010) suggest that there is already some convergence and that strong evidence for the alignment of human and machine languages are available in interactions recorded between humans and machines. Evidence from different areas of human and machine interaction suggest that there is a strong difference on the part of the humans in evaluating relations with other humans and with machines (Weibel, 2008). My opinion is that humans seek pragmatic results, especially in a down-to-earth area such as science. This may cause humans to adapt to the language style of machines and make use of the advantages this may provide. The structured nature of language in most scientific fields (Ahmad, 2012) will favor this process.

Possibilities for using machines in scientific processes are numerous. Eureqa is a software tool that provides equations based on data fed to it. It identifies the simplest mathematical formulas describing the underlying mechanisms that produced the data. It is free to download and use.

Autonomous scientific discovery has been considered impossible without at least some human intervention. This seems to change too. King et al. (2009) reported on a laboratory robot that was created by the computational biology research group at Aberystwyth University. This machine is the first one in history to discover new scientific knowledge independently of its human creators. It achieves this by using techniques from artificial intelligence to automate all aspects of the scientific discovery process: generating hypotheses, designing experiments to test these hypotheses, running the physical experiments using robotic systems, analyzing and interpreting the resulting data, and repeating the cycle.

Another unexpected area in which machines may take over jobs that so far have been reserved for humans is original text production. Certain more structured types of text, such as sport results news, may already be produced by machines. In the future, more and more genres will be produced by machines or involve machine participation. Scientific communication is one such area. Structured pieces like abstracts, literary reviews, etc. are possible candidates for machine involvement. A series of texts produced by machines are being published by Forbes online. These texts are highly structured financial reports based on data fed to the text-writing machine. They are almost undistinguishable from human-produced text. Narrative Science is the company based in Chicago that developed the text-producing machine. The early reactions to this development can be illustrated with the help of the following titles of some recent newspaper articles and blog posts: “The robot journalist: an apocalypse for the news industry?” (Bell, 2012, May 13), “Stock advice: Hiring software as analyst” (Fernandez, 2012, July 6), and “Can an algorithm write a better news story than a human reporter?” (Levy, 2012, April 24). As one can see, the fear of skills becoming obsolete drives the first reactions. Such attitude may lead to very inefficient results in all areas of future human-machine interactions and especially in the field of communication regarding science.

Conclusion

A scientist destined to work in an environment providing possibilities of machine assistance in text analysis and production will have to be a manager to an extent far beyond the needs of today. Beyond managing his / her own time and perhaps a team of humans, a new scientist will have to manage a team of humans and machines performing work tasks best suited for each of them and avoid doing work better / faster done by others. To make time for these additional tasks, some activities performed today will be left to machines. Structured tasks are natural candidates for this. As many activities related to scientific communication are highly structured, a growing amount of activities related to both text analysis and text production will be left to machines.

References

AHMAD, J. (2012). Stylistic features of scientific English: A study of scientific research articles. *English Language and Literature Studies*, *2*(1), 47-55.

Artificial intelligence (cs373): Programming a robotic car. (2012, April). Udacity. Retrieved November 11, 2012 from http://tinyurl.com/cgblk82

BELL, E. (2012, May 13). The robot journalist: an apocalypse for the news industry? *The Guardian*. Retrieved November 11, 2012 from http://tinyurl.com/cr3f8mv

BRANIGAN, H. P., PICKERING, M. J., PEARSON, J., & MCLEAN, J. F. (2010). Linguistic alignment between people and computers. *Journal of Pragmatics*, *42*(9), 2355-2368.

BRISCOE, T., & CARROLL, J. (2002, May 29-31). Robust accurate statistical annotation of general text. In *Proceedings of the Third International Conference on Language Resources and Evaluation, Las Palmas* (pp. 1499-1504). Retrieved October 3, 2012 from http://www.lrec-conf.org/proceedings/lrec2002/pdf/250.pdf

BRYNJOLFSSON, E., & MCAFEE, A. (2011). *Race against the machine: How the digital revolution is accelerating innovation, driving productivity, and irreversibly transforming employment and the economy* (Kindle ed.). Lexington, MA: Digital Frontier Press.

CAO, Y., ELY, J., ANTIEAUM L., & YU, H. (2009). Evaluation of the clinical question answering presentation. In *Proceedings of the Workshop on Current Trends in Biomedical Natural Language Processing* (pp. 171-178). Stroudsburg: The Association for Computational Linguistics. Retrieved October 3, 2012 from http://aclweb.org/anthology-new/W/W09/W09-1322.pdf

CASATI, R., ORIGGI, G., & SIMON, J. (2011). Micro-credits in scientific publishing. *Journal of Documentation*, *67*(6), 958-974.

CHAE, J., & NENKOVA, A. (2009). Predicting the fluency of text with shallow structural features: Case studies of machine translation and human-written text. In *Proceedings of the 12th Conference of the European Chapter of the Association for Computational Linguistics* (pp. 139-147). Stroudsburg: The Association for Computational Linguistics. Retrieved November 11, 2012 from http://bit.ly/S9Lboa

COWEN, T. (2011). *The great stagnation* (Kindle ed.). Boston: Dutton.

edX. (2012). Retrieved October, 3 2012 from https://www.edx.org/

GRAU, B., LIGOZAT, A., & MINARD, A. (2009). Corpus study of kidney-related experimental data in scientific papers. In *Proceedings of the Workshop on Biomedical Information Extraction* (pp. 21-26). Stroudsburg: The Association for Computational Linguistics. Retrieved November 11, 2012 from http://tinyurl.com/b7ryaf6

GROTH, P., GIBSON, A., & VELTEROP, J. (2010). The anatomy of a nanopublication. *Information Services and Use*, *30*(1), 51-56.

FERNANDEZ, T. (2012, July 6). Stock advice: Hiring software as analyst. *Securities Technology Monitor*. Retrieved November 11, 2012 from http://bit.ly/KYFbuL

Introduction to computer science (cs101): Building a search engine. (2012, April). Udacity. Retrieved November 11, 2012 from http://tinyurl.com/c7h7g47

ISAACSON, W. (2011). *Steve Jobs* (Kindle ed.). New York: Simon and Schuster.

KEYNES, J. M. (1963). *Essays in persuasion*. New York: W. W. Norton & Co.

KING, D., ROWLAND, J., OLIVER, S. G., YOUNG, M., AUBREY, W., & CLARE, A. (2009). The automation of science. *Science*, *324*(5923), 85-89.

KULESZA, A., & SHIEBER, S. M. (2004, October 4-6). A learning approach to improving sentence-level MT evaluation. In *Proceedings of the 10th International Conference on Theoretical and Methodological Issues in Machine Translation, Baltimore*. Retrieved November 11, 2012 from http://tinyurl.com/aub8rad

KURZWEIL, R. (2000). *The age of spiritual machines: When computers exceed human intelligence*. New York: Viking Adult.

LEVY, F., & MURANE, R. J. (2004). *The new division of labour: How computers are creating the next job market*. Princeton: Princeton University Press.

LEVY, S. (2012, April 24). Can an algorithm write a better news story than a human reporter? Retrieved November 11, 2012 from http://tinyurl.com/7txfscv

LI, H., KUMARAN, A., ZHANG, A., & PERVOUCHINEM, V. (2009). Whitepaper of NEWS 2009 machine transliteration shared task. In *Proceedings of the 2009 Named Entities Workshop: Shared Task on Transliteration* (pp. 19-26). Retrieved October 3, 2012 from http://www.mt-archive.info/NEWS-2009-Li-2.pdf

LICKLIDER, J. C. R. (1960). Man-computer symbiosis. *IRE Transactions on Human Factors in Electronics*, HFE-1, 4-11. Retrieved October 3, 2012 from http://groups.csail.mit.edu/medg/people/psz/Licklider.html

McCarthy, D., Koeling, R., Weeds, J., & Carroll, J. (2004). Finding predominant word senses in untagged text. In *Proceedings of the 42nd Annual Meeting of the Association for Computational Linguistics, Barcelona* (pp. 280-287). Stroudsburg: The Association for Computational Linguistics. Retrieved October 3, 2012 from http://acl.ldc.upenn.edu/acl2004/main/pdf/95_pdf_2-col.pdf

Mons, B., & Velterop, J. (2009). Nano-publication in the e-Science era. Retrieved November 11, 2012 from http://tinyurl.com/9wm6p4b

Moore, G. E. (1965). Cramming more components onto integrated circuits. *Electronics*, *38*(8), 114-117.

Rasskin-Gutman, D. (2009). *Chess metaphors: Artificial intelligence and the human mind*. Cambridge, MA: MIT Press.

Rupp, C. J., Copestake, A., Corbett, P., & Waldron, B. (2007). Integrating general-purpose and domain-specific components in the analysis of scientific text. In *Proceedings of the UK e-Science Programme All Hands Meeting, Nottingham*. Retrieved November 2, 2012 from http://tinyurl.com/cnx6jsl

Schafer, U., & Kiefer, B. (2011). Advances in deep parsing of scholarly paper content. In R. Bernardi, S. Chambers, B. Gottfried, F. Segond, & I. Zaihrayeu (Eds.), *Advanced language technologies for digital libraries* (pp. 135-153). Berlin: Springer.

Schafer, U., Uszkoreit, H., Federmann, C., Marek, T., & Zhang, Y. (2008). Extracting and querying relations in scientific papers on language technology. In *Proceedings of the Sixth International Conference on Language Resources and Evaluation* (pp. 3040-3046). Retrieved October 3, 2012 from http://www.lrec-conf.org/proceedings/lrec2008/pdf/773_paper.pdf

Takeshima, R., & Watanabe, T. (2010). Extraction of co-existent sentences for explaining figures toward effective support for scientific papers reading. In R. Setchi, I. Jordanov, R. J. Howlett, & L. C. Jain (Eds.*), Knowledge-based and intelligent information and engineering systems* (pp. 230-239). Berlin: Springer.

Weibel, D., Wissmath, B., Habegger, S., Steiner, Y., & Groner, R. (2008). Playing online games against computer vs. human-controlled opponents: Effects on presence, flow, and enjoyment. *Computers in Human Behavior*, *24*, 2274-2291.

Zhang, Y., & Clark, S. (2011). Syntax based grammaticality improvement using CCG and guided search. In *Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing, Edinburgh* (pp. 1147-1157). Stroudsburg: The Association for Computational Linguistics. Retrieved November 11, 2012 from http://tinyurl.com/agcyp67