As redundant as this phrase may sound, new technology has a way of causing things to become more technical. That's what's happening in the world of ESI (electronically stored information). Considering various estimates that from 90 percent1 to 97 percent2 of today's business and personal records are created and maintained electronically, and that as little as 3 percent of information is printed on paper,3 new technology is needed to search huge databases for electronic records relevant to litigation discovery requests. Thus the need becomes apparent for new, speedy, and efficient ways to search and review ESI.

When a lawsuit is commenced in today's technology-driven world, the litigation discovery process requires a search for records that are located on computer hard drives, servers, thumb drives, smart phones, and backup tapes and in the cloud. The discovery protocol of today has gone from searching for relevant papers in banker's boxes and file cabinets in musty warehouses to searching electronic storage media; from searching through several thousand pieces of paper to searching electronic devices having storage capacities of gigabytes and terabytes (millions of pages), and in some extreme cases petabytes (billions of pages). That's enough to make lawyers dizzy—and judges too!

Instead of paralegals, contract lawyers, big firm associates, and general partners looking page by page for documents that are relevant to a discovery request, we can now use computers to perform the task of searching through a database for relevant documents. This process involves the use of sophisticated programs and algorithms by which a computer is trained during several staged interactions with a human reviewer to determine relevance. The process is known by several different acronyms, namely, content-based advanced analytics (CBAA), computer-aided review (CAR), technology-aided review (TAR), machine-aided review (MAR), and, finally, the new kid on the block, predictive coding. And, yes, training the computer is appropriate terminology. This is a form of artificial intelligence.

Why not use technology to search through a huge database of electronic documents? What's so amazing about the concept of training a computer to look for relevant documents? If we can use computers to prepare students to take college and law school entrance tests, the SAT and LSAT, and to teach and grade college-level math courses,4 and if IBM can build and program a computer named "Watson" to compete with and outscore two Jeopardy champions—Jeopardy's all-time money winner and Jeopardy's record holder for the longest championship streak—certainly a computer can be trained to search for relevant electronic documents with at least the same accuracy as a human reviewer.

The Efficiency of Computer-Assisted Electronic Discovery

A research study this year by the RAND Corporation entitled “Where the Money Goes: Understanding Litigant Expenditures for Producing Electronic Discovery”5 noted that the cost of electronic discovery has been ever-increasing, indeed, skyrocketing and spiraling out of control. After reviewing data from various case studies, the RAND report estimates that human review of documents as part of responding to discovery requests consumes about 73 cents of every dollar spent on the production of ESI. The report suggests that the best opportunity to significantly reduce the rising cost of electronic discovery is by reducing the cost of human review.

For another perspective concerning the cost of large-scale discovery, consider ongoing litigation in the case of *Global Aerospace Inc. v. Landow Aviation, L.P. dba Dulles Jet Center*, Consolidated Case No. 61040 (Cir. Ct. Loudoun Cty. Va.,...
Predictive coding . . . takes the very substantial next step of automatically assigning a rating (or proximity score) to each document to reflect how close it is to the concepts and terms found in examples of documents attorneys have already determined to be relevant, responsive, or privileged. This assignment becomes increasingly accurate as the software continues to learn from human reviewers about what is, and what is not, of interest.6

Predictive Coding
The predictive coding process involves a protocol of training a computer by computer-assisted coding to perform the task of the human reviewer to search for relevant documents. As described by U.S. Magistrate Judge Andrew Peck in Da Silva Moore v. Publicis Groupe, quoting from his article Search, Forward:8

Unlike manual review, where the review is done by the most junior staff, computer-assisted coding involves a senior partner (or small team) who review[s] and code[s] a “seed set” of documents. The computer identifies properties of those documents that it uses to code other documents. As the senior reviewer continues to code more sample documents, the computer predicts the reviewer's coding. (Or, the computer codes some documents and asks the senior reviewer for feedback.)

When the system’s predictions and the reviewer's coding sufficiently coincide, the system has learned enough to make confident predictions for the remaining documents. Typically, the senior lawyer (or team) needs to review only a few thousand documents to train the computer.

Some systems produce a simple yes/no as to relevance, while others give a relevance score (say, on a 0 to 100 basis) that counsel can use to prioritize review. For example, a score above 50 may produce 97% of the relevant documents, but constitutes only 20% of the entire document set.

Counsel may decide, after sampling and quality control tests, that documents with a score of below 15 are so highly likely to be irrelevant that no further human review is necessary. Counsel can also decide the cost benefit of manual review of the documents with scores of 15–50.10

According to the RAND report, predictive coding is a generic type of computer-categorized review tool, not a particular methodology or commercial application, that can be trained for the purposes of a document review in several ways:

One approach has attorneys select documents from the review set as “seeds” (or exemplars) that they have judged to be clearly fitting, or not fitting, the desired characteristics of various document categories. One category might be represented by a small group of documents highly relevant to the facts of the case and responsive to the discovery request, and another category by a small group of documents in which there is no obvious connection at all. Another approach has the application initially draw random samples from the review set for the attorneys to examine and make a decision on each selected document. Still another involves keyword or concept searches of the review set to identify small numbers of potentially relevant (or not relevant) documents for the attorneys to examine. No matter how these initial exemplars are chosen, the attorney-reviewed documents are then analyzed by the predictive coding software, which creates a type of template to be used to screen other documents, assigns scores to each document in the review set to reflect the probability that they fit the desired template, and then draws samples of its decisions for human reviewers. Attorneys then review the samples and apply their own judgment as to whether the selected documents are relevant, responsive, or privileged. Those decisions are then used by the software to refine its templates, reassess the review set,
and then draw new samples. This process continues until the results are stabilized or optimized, at which point disagreement between the software's decisions and those of human reviewers should be kept to a minimum.11

Importantly, the report cautions that every predictive-coding effort must draw samples from the final decision set for the attorneys managing the review to audit the results and provide documentation of the process in the event of a challenge. The report continues:

“With the application’s final decisions in hand, those overseeing the review must then decide how to proceed. In the context of a review for relevance and responsiveness, for example, one option might be to assume that all documents with probability scores above a particular percentage threshold can be safely classified as relevant and responsive, all those with scores below a different percentage threshold can be safely classified as not relevant or not responsive, and only those in the middle would require eyes-on review. Another option would be to perform eyes-on review of only those documents exceeding a specific probability score in order to confirm the application’s decisions, while dropping the remainder from all further work. A perhaps unlikely option would be to dispense with human review entirely, selecting a score above which all documents are sent directly to opposing counsel while those below are dropped. Ultimately, it is up to those supervising the review to decide what the appropriate cutoff points might be and to focus on the efforts of human reviewers. Any of these approaches would likely produce significant cost savings for responding litigants.”

Relying on technology to assist in the review of electronic documents does not take humans out of the process. This electronic process requires intensive attorney support throughout in order to advance machine learning. Ironically, for a process that could substantially reduce discovery expenses, the best results are achieved if the attorneys most closely involved in the case select the seed documents and review the sampled extracts.13

Human Review Limitations
A question often asked is how accurate are humans in finding responsive documents in a large-scale review? In analyzing the results by human reviewers searching for relevant documents, the report noted that human reviewers often disagree with one another when they review the same set of documents for relevance and responsiveness, especially in large-scale reviews. In some cases, review teams differed significantly on whether the percentage of certain groups of documents was responsive to a particular document request, ranging from a low of 23.1 percent to a high of 54.2 percent. When asked to compare their agreement on the number of documents that were responsive and the number of documents that were nonresponsive, the level of agreement between certain reviewing teams ranged from 65.5 to 84.9 percent.14

In addition to simple disagreement concerning the responsiveness of a document, the report noted that some of the results were influenced by human error in applying the criteria for whether a document should or should not be included as responsive, as opposed to a lack of clarity in a document’s meaning or an ambiguity in how the scope of the production demand should be interpreted. In other words, according to the report, people make mistakes, and they make them regularly when it comes to judging relevance and responsiveness. It is important to understand that many of these studies were conducted of large-scale reviews that involved thousands and hundreds of thousands of documents. In some of the studies, law students rather than experienced attorneys were involved in the human review test. The report noted, however, that many of the contract attorneys used for high-volume review in many real-life cases are, in fact, relatively recent law school graduates.15

The Benefits of Computer-Assisted Review
The ultimate question is how does the accuracy of computer-assisted review, predictive coding in this case, compare to the accuracy of human reviewers finding responsive documents in a large-scale document review? Unfortunately, the answer is a qualified response. Predictive coding is a new and emerging technology for which there are several computer applications to perform the task, and it would be unusual if new computer applications are not unveiled in the future. Some of the existing computer applications provide better results in certain cases, and there is little research on how the accuracy of predictive coding compares with that of human review, but the report summarizes: “The few studies that exist, however, generally suggest that predictive coding identifies at least as many documents of interest as traditional eyes-on review with about the same level of inconsistency, and there is some evidence to suggest that it can do better than that.”16

Prior research does support the RAND report’s findings. In a 2011 article in the Richmond Journal of Law and Technology, the authors determined that using technology-assisted review identified an average of 76.7 percent of the relevant documents, while approximately 15.3 percent of the documents retrieved were irrelevant, and that human review of every document averaged 59.3 percent of all relevant documents, while an average of 68.3 percent of the documents retrieved were irrelevant.17

Conclusion
Paper is disappearing and document storage is approaching 100 percent electronic. By whatever name predictive coding becomes known in the future, or whatever technology iteration comes next, this author predicts that computer-assisted review will become more adept at the process of search and review of ESI in the litigation discovery process. Considering
that initial studies and review show great promise of accuracy and cost savings as compared with human review of every document, it is time for courts and litigants to embrace the new technology and use it in every appropriate instance.

Endnotes


3. Id.


7. Id.


12. Pace & Zakaras, supra note 5, at 60.

13. Id.

14. Id. at 61.

15. Id. at 57.

16. Id. at 58.