

# Autonomy and Reliability of Continuous Active Learning for Technology-Assisted Review

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We enhance the autonomy of the continuous active learning method shown by Cormack and Grossman (SIGIR 2014) to be effective for technology-assisted review, in which documents from a collection are retrieved and reviewed, using relevance feedback, until substantially all of the relevant documents have been reviewed. Autonomy is enhanced through the elimination of topic-specific and dataset-specific tuning parameters, so that the sole input required by the user is, at the outset, a short query, topic description, or single relevant document; and, throughout the review, ongoing relevance assessments of the retrieved documents. We show that our enhancements consistently yield superior results to Cormack and Grossman's version of continuous active learning, and other methods, not only on average, but on the vast majority of topics from four separate sets of tasks: the legal datasets examined by Cormack and Grossman, the Reuters RCV1-v2 subject categories, the TREC 6 AdHoc task, and the construction of the TREC 2002 filtering test collection.

## 1. INTRODUCTION

Technology-assisted review (“TAR”) involves the iterative retrieval and review of documents from a collection until a substantial majority (or “all”) of the relevant documents have been reviewed. Applications include electronic discovery (“eDiscovery”) in legal matters [4], systematic review in evidence-based medicine [11], and the creation of test collections for information retrieval (“IR”) evaluation [15]. In contrast to ad hoc search, the information need is satisfied only when virtually all of the relevant documents have been discovered; as a consequence, a substantial number of documents are typically examined for each review task. The reviewer is typically expert in the subject matter, not in IR or data mining. In certain circumstances, it may be undesirable to trust the completeness of the review to the skill of the user, whether expert or not. In eDiscovery, the review is typically conducted in an adversarial context, which may offer the reviewer limited incentive to conduct the best possible search. In systematic review, meta-analysis affords valid statistical conclusions only if the selection of studies for inclusion is reasonably complete and free of researcher bias. The creation of test collections is subject to similar constraints: The assessors are not necessarily search experts, and the resulting relevance assessments must be reasonably complete and free of selection bias.

For the reasons stated above, it may be desirable to limit discretionary choices in the selection of search tools, tuning parameters, and search strategy. Obviating such choices presents a challenge because, typically, both the topic and the collection are novel for each task to which TAR is applied, and may vary substantially in subject matter, content, and richness. Any topic- or collection-specific choices, such as parameter tuning or search queries, must either be fixed in advance, or determined autonomously by the review tool. Our goal is to fully automate these choices, so that the only input required from the reviewer is, at the outset, a short query, topic description, or single relevant document, followed by an assessment of relevance for each document, as it is retrieved.

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At the same time, it is necessary for each TAR task to enjoy a high probability of success. A lawyer engaged in eDiscovery in litigation, or a researcher conducting a meta-analysis or building a test collection, is unlikely to be consoled by the fact that the tool works well on average, if it fails for the particular task at hand. Accordingly, it is necessary to show that such failures are rare, and that such rare failures are readily apparent, so that remedial actions may promptly be taken.

The literature reports a number of search efforts aimed at achieving high recall, particularly within the context of eDiscovery and IR evaluation. Most of these efforts require extensive intervention by search experts, or prior topic- or dataset-specific training, contrary to our objective. Many search and categorization methods are unreliable, in that they fail to achieve reasonable effectiveness for a substantial number of topics, although, perhaps, achieving acceptable effectiveness on average.

Among approaches that meet our criterion of autonomy, the continuous active learning (“CAL”) method, and its implementation in Cormack and Grossman’s TAR Evaluation Toolkit (“Toolkit”) [4], appears to be the standard to beat.<sup>1</sup> Yet uncertainties remain regarding its sensitivity to the choice of “seed query” required at the outset, its applicability to topics and datasets with higher or lower richness, its algorithmic running time for large datasets, its effectiveness relative to non-autonomous approaches, and its generalizability to domains beyond eDiscovery.

We hypothesized the impact of various engineering choices with respect to these considerations and designed an autonomous TAR configuration (“Auto TAR”) that, assuming our hypotheses to be correct, would exhibit greater autonomy, superior effectiveness, increased generalizability, and fewer, more easily detectable failures, relative to existing TAR methods.

This paper offers a historical review of research efforts to achieve high recall, followed by a description of our final design and the results we achieved applying it to the four topics and dataset supplied in Cormack and Grossman’s Toolkit, which we used to pilot the development of Auto TAR. We then describe the hypotheses underlying our choices, along with our rationale. Next, we describe our experiments to evaluate the effectiveness of Auto TAR and competing approaches, relative to strong baselines; specifically:

- (1) The four actual legal matters and datasets studied by Cormack and Grossman, but not included in the Toolkit, relative to the CAL implementation in the Toolkit;
- (2) The 103 subjects of the Reuters RCV1-v2 dataset, relative to the CAL implementation in the Toolkit;
- (3) The 103 subjects of the Reuters RCV1-v2 dataset, relative to the best text categorization method reported by its authors;
- (4) The 50 topics of the TREC 6 AdHoc task, relative to the best-performing manual efforts reported at TREC; and,
- (5) The 50 topics of the TREC 2002 Filtering Track, relative to the labeling effort conducted by the Track coordinators.

With few exceptions, Auto TAR yields comparable or superior results to the chosen baselines, when evaluated for all combinations of topic and representative recall values from 0.1 through 0.9.

We conclude with a brief discussion of the strengths and limitations of our results, and open questions for further study.

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<sup>1</sup>With honorable mention to the interactive relevance feedback (“IRF”) technique pioneered by Soboroff and Robertson [20], which is quite similar.

## 2. RELATED WORK

The TAR problem, along with methods to address it and to evaluate the effectiveness of those methods, resembles but may be distinguished from well-studied problems in ad hoc retrieval, relevance feedback, routing and filtering, text categorization, and active learning.

Blair and Maron [1] evaluated an iterative search effort in which skilled paralegals and lawyers collaborated in an interactive search effort aimed at finding “all and only the relevant items.” Realizing that perfection was an impossible standard to meet, the lawyers “stipulated that they must be able to retrieve at least 75 percent of all the documents relevant to a given request for information.” For each of 51 information requests, the reviewers composed Boolean search queries and assessed the results until they believed they had seen at least 75% of the relevant documents ( $recall \geq 0.75$ ). In fact, according to Blair and Maron’s evaluation effort, the reviewers had found, on average, 20% ( $recall \approx 0.20$ ). On the other hand, it can be deduced from the raw data presented by Blair and Maron, that about 80% of the retrieved documents were relevant ( $precision \approx 0.80$ ).

Blair and Maron themselves conducted a high-recall search for the purpose of evaluating the recall of the reviewers’ efforts [2]. Using complete conjunctive normal form (“CCNF”) of semantically expanded Boolean queries, Blair and Maron identified and sampled subsets of the collection that were rich in relevant documents. While we do not know precisely the recall or precision of the sets of documents identified by these systematic searches, we do know that recall was five times greater than that of the paralegal and lawyer searches, while precision was, presumably, many times lower.

To our knowledge, Blair and Maron’s method has not been widely used to construct labeled datasets for IR evaluation. The most common approach is perhaps the pooling method, used extensively at TREC [21]. The pooling method shares with TAR the objective of identifying substantially all relevant documents in a collection. To this end, the top-ranked documents from a large set of independent ranked-retrieval efforts are combined to form a judging pool, and assessed for relevance. These relevance assessments (“qrels”) are used to evaluate the retrieval efforts used to form the pool, and as part of an archival test collection, to evaluate future efforts. It is well known that the set of relevance assessments is incomplete, as some relevant documents are excluded from the pool [22]. However, the literature suggests that, notwithstanding this incompleteness, the pooling method affords stable evaluation of IR effectiveness [21].

Although the objective of ad hoc retrieval is typically to produce, after limited interaction with a search engine, a set or ranked list of documents for off-line review, a team from the University of Waterloo, as participants in the TREC 6 AdHoc Task [6], conducted a TAR process in which “the aim of the searchers was to find and judge as many relevant documents as possible.” The Waterloo team spent an average of 2.1 hours per topic composing search queries, examining the top-ranked results, labeling each document as “relevant,” “not relevant,” or “iffy.” After examining 13,064 documents (an average of 261 documents per topic), the team achieved per-topic (macro-averaged) recall of 0.8. Because the submissions were padded to 1,000 documents, it is not possible to deduce per-topic precision from the archived TREC 6 results; however, we note that the Waterloo team found 3,058 of 4,611 relevant documents overall, for a micro-averaged recall of 0.66 and a precision of 0.23.

Independent studies by Voorhees [21] and the Waterloo team [6] indicate that Waterloo’s technique – interactive search and judging (“ISJ”) – yields a judging pool about as effective for IR evaluation as the five-times-larger pool derived using the pooling method that was employed for the official TREC 6 evaluation. The ISJ pool, labeled using the official TREC assessors’ judgments, achieved the Kendal rank correlation with respect to the official mean average precision (“MAP”) results of  $\tau \approx 0.98$ . Labeled using the Waterloo assessor’s judgments, ISJ achieved  $\tau \approx 0.90$ , characterized by Voorhees as “essentially the same comparative evaluation results.” Sanderson and Joho [15] simulated ISJ using input

from a wide variety of manual search efforts and concluded that, “ISJ is broadly applicable regardless of retrieval system used or people employed to conduct the searching process.” At the same time, they note that a few ISJ efforts did not fare well, observing that the TREC runs on which these efforts were based had very low MAP scores, concluding that, “it would be unlikely that someone using the Cormack et al. ISJ method would create such runs, as consistent poor performance would be noticed by the experimenter.”

Soboroff and Robertson [20], in constructing qrels for the TREC 2002 Filtering Track, were unable to use the pooling method, because the qrels were required in advance for the purpose of evaluating on-line filtering systems. They eschewed ISJ – on the grounds that the TREC assessors were subject-matter experts, but not search experts – in favor of a relevance feedback approach. For each of 100 candidate topics, ad hoc search was used to retrieve and label 100 potentially relevant documents. These labeled documents were given as relevance feedback to variants of four retrieval systems, and the top-ranked documents (according to the CombMNZ fusion method) were selected for labeling by TREC assessors. These labeled documents were again provided as relevance feedback to the retrieval systems, and a new batch of top-ranked documents were selected for review. The process continued for each topic until relatively few relevant documents were returned, or the assessment budget was exhausted. Based on these results, the “best” 50 topics were selected for use in the TREC 2002 Filtering Track. Once participants submitted their search results, the pooling method was used to augment the qrels for these topics. Robertson and Soboroff report a Kendall rank correlation of  $\tau = 0.91$  between MAP results for the Routing Task derived from the initial and augmented qrels. Sanderson and Joho’s subsequent simulations indicate that relevance feedback, while effective for this purpose, is not as effective as ISJ.

While ad hoc search involves finding documents relevant to a new topic in an existing collection, routing (along with text categorization and batch filtering) involves finding documents relevant to a standing information need in a new collection [20; 18]. The objective of routing is to rank the collection for subsequent review, while the objective of text categorization and batch filtering is to identify the set of responsive documents in the collection without further review. An existing set of labeled data – the training set – is available for tuning and model construction, while a separate set of labeled data – the test set – is used for evaluation. Machine-learning methods, such as support vector machines (“SVM”), logistic regression, and boosting, can, given a large enough training set, generally achieve both high precision and high recall on the test set. The premier test collection for such tasks is perhaps the Reuters RCV1-v2 dataset, for which Lewis [13] reports that SVM-light, applied to the tf-idf representation and training/test sets supplied with the dataset, achieves a macro-averaged score of  $F_1 = 0.619$ , indicating that, on average, this method achieves reasonably high recall as well as reasonably high precision. Nonetheless, there are two topics<sup>2</sup> for which there are no relevant examples in the training set, and the method fails entirely, achieving  $F_1 \approx 0.00$ .

In active learning [19], the learning method interactively chooses only a subset of the documents from the training set to be labeled, thereby reducing labeling effort. Lewis and Gale [12] compare uncertainty sampling, in which the hardest-to-classify documents are selected for labeling, with relevance sampling, in which the most-likely relevant examples are selected, concluding that uncertainty sampling generally works better when the proportion of relevant documents in the collection is high, while relevance sampling works well when the proportion is low. Active learning methods are the subject of much current research interest; derivatives of uncertainty sampling and query-by-committee are generally considered to be the most effective [19].

Drucker [7] shows that machine-learning methods are also useful for relevance feedback in ad hoc retrieval. In contrast to uncertainty sampling and query-by-committee, relevance

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<sup>2</sup>For a third topic, there are no relevant documents in the test set; for this topic,  $F_1$  is indeterminate.

Topic	Cormack and Mojdeh		CAL	
	Recall	Effort	Recall	Effort
201	0.78	6,145	0.75	6,000
202	0.67	12,624	0.75	11,000
203	0.87	4,369	0.75	6,000
207	0.76	34,446	0.75	11,000

Table I: Recall effort of Cormack and Mojdeh vs. CAL.

feedback focuses on retrieving and labeling documents that are most likely to be relevant. Assuming that a preliminary query has retrieved ten documents, of which at least one is relevant and at least one is non-relevant, Drucker shows that iteratively using an SVM to retrieve and review several batches of ten documents can achieve very high relative precision.<sup>3</sup> The ability to achieve high recall is not considered.

Within the context of the TREC Legal Track Interactive Task [14; 9; 5; 8], a number of participating teams achieved high recall using different techniques. In 2008 and 2009, Hogan et al. [10] achieved superior results ( $F_1 = \{0.71, 0.80\}$ ) on two topics using a rule-based approach: composing myriad Boolean queries, sampling the results, and, with the aid of a professional linguist, augmenting the queries, until a high level of recall and precision were achieved. In 2009, Cormack and Mojdeh [3] used a combination of ISJ and relevance feedback via logistic regression to achieve superior results on four topics ( $F_1 = \{0.84, 0.76, 0.77, 0.83\}$ ). In 2010, a team from an eDiscovery provider achieved superior results ( $F_1 = 0.67$ ) on one topic, using a proprietary multi-stage approach – referred to as “predictive coding” in the legal industry – that involved isolating from the dataset a hold-out “control set” for tuning and validation, and a set used to train an SVM using uncertainty sampling. In 2011, a team from a different eDiscovery provider achieved superior results ( $F_1 = \{0.54, 0.53, 0.43\}$ ), using a different proprietary implementation of predictive coding.

Cormack and Grossman [4] provide a taxonomy of TAR systems with three major categories: “continuous active learning” (“CAL”); “simple active learning” (“SAL”); and “simple passive learning” (“SPL”). Each starts with an initial training set (“seed set”) which may be selected randomly or by searching. CAL abstracts the technique of Cormack and Mojdeh [3], using search only to identify the seed set, and using exclusively relevance feedback thereafter. SAL abstracts the predictive coding method outlined above, in which a classifier is trained using supervised active learning, and then applied to the entire collection. SPL abstracts a more primitive version of predictive coding, in which the entire training set is selected either randomly or by searching, without the aid of active learning.

Cormack and Grossman also provide a toolkit for evaluating TAR systems, and, using that toolkit, compare the effectiveness of their implementations of CAL, SAL, and SPL. They concluded that CAL (using a simple “seed query” to identify the seed set) yielded generally superior results to SAL and SPL, although SAL – given an oracle to determine the optimal “stabilization” point – could match CAL for a specific target recall level [4]. Table I juxtaposes Cormack and Grossman’s “75% recall effort” values – the number of documents that must be reviewed (counting both those for training and for any subsequent review) to achieve  $recall = 0.75$  – with the effort expended by Cormack and Mojdeh [3]

<sup>3</sup>“Relative precision,” implemented in trec\_eval [[http://trec.nist.gov/trec\\_eval/](http://trec.nist.gov/trec_eval/)], is equal to

$\frac{R_k}{\min(k, R_\infty)}$ , where  $k$  is the number of documents retrieved,  $R_k$  is the number of relevant documents retrieved, and  $R_\infty$  is the number of relevant documents in the collection. Relative precision is equal to precision when the number of retrieved documents is less than the number of relevant documents in the collection, and equal to recall when the number of retrieved documents is greater.

to achieve similar results. While uncontrolled differences between the two studies preclude direct comparison, we note that they are of the same order.

### 3. AUTONOMOUS TAR

#### 3.1. The method

The autonomous TAR (“Auto TAR”) process proceeds as follows:

- (1) Find a relevant “seed” document using ad hoc search, or construct a synthetic relevant document from the topic description.
- (2) The initial training set consists of the seed document identified in step 1, labeled “relevant.”
- (3) Set the initial batch size  $B$  to 1.
- (4) Temporarily augment the training set by adding 100 random documents from the collection, temporarily labeled “not relevant.”
- (5) Train an SVM classifier using the training set.
- (6) Remove the random documents added in step 4.
- (7) Select the highest-scoring  $B$  documents for review.
- (8) Review the documents, coding each as “relevant” or “not relevant.”
- (9) Add the documents to the training set.
- (10) Increase  $B$  by  $\lceil \frac{B}{10} \rceil$ .
- (11) Repeat steps 4 through 10 until a sufficient number of relevant documents have been reviewed.

Our implementation used a feature space consisting of words occurring at least twice in the collection, and, following Lewis et al. [13], Porter stemming, elimination of SMART stop-words, and Cornell *ltc* term weighting. SVMlight was used with default parameters. For comparison, we also modified Cormack and Grossman’s CAL, SAL, and SPL implementations [4] to use the same features.

#### 3.2. Pilot experiments

The results of our efforts on the four TREC 2009 Legal Track development topics are shown in Figure 1. The left panel shows the average over the four topics of the gain curves for three versions of Auto TAR, compared to our modified versions of Cormack and Grossman’s CAL, SAL, and SPL. The three Auto TAR runs differ in how the seed document was selected: The run labeled “Auto-BM25” was seeded with the top-ranked document resulting from Cormack and Grossman’s seed query, using a Wumpus search with BM25 with default parameters; the run labeled “Auto-Rand” was seeded with a random relevant document; the run labeled “Auto-Syn” was seeded using a synthetic document created using the relevant request for production (“RFP”) from the mock complaint given to TREC 2009 Legal Track participants at the outset of the task, with boilerplate language removed. Table III shows the four seed queries and the four synthetic seed documents created from the RFPs.

Generally, all Auto TAR runs achieve moderate levels of recall with less review effort than CAL, but for very high levels of recall are indistinguishable from CAL. The SAL and SPL gain curves are generally inferior, consistent with the results reported by Cormack and Grossman [4]. Averages, such as those presented in the left panel of Figure 1, are generally inadequate to assess the reliability of Auto TAR. For this reason, we recapitulate the same results as a differential plot, shown in the right panel. Each point in this plot compares the recall achieved by one method with the recall achieved by another, on the same topic, for the same review effort. In effect, it stretches the gain curve for each topic so that the baseline system’s results appear on the diagonal. Points above the diagonal represent improvements on the baseline; points below a degradation. Light gray lines connect points representing the same run. The differential plot shows that the Auto TAR runs, represented by solid,

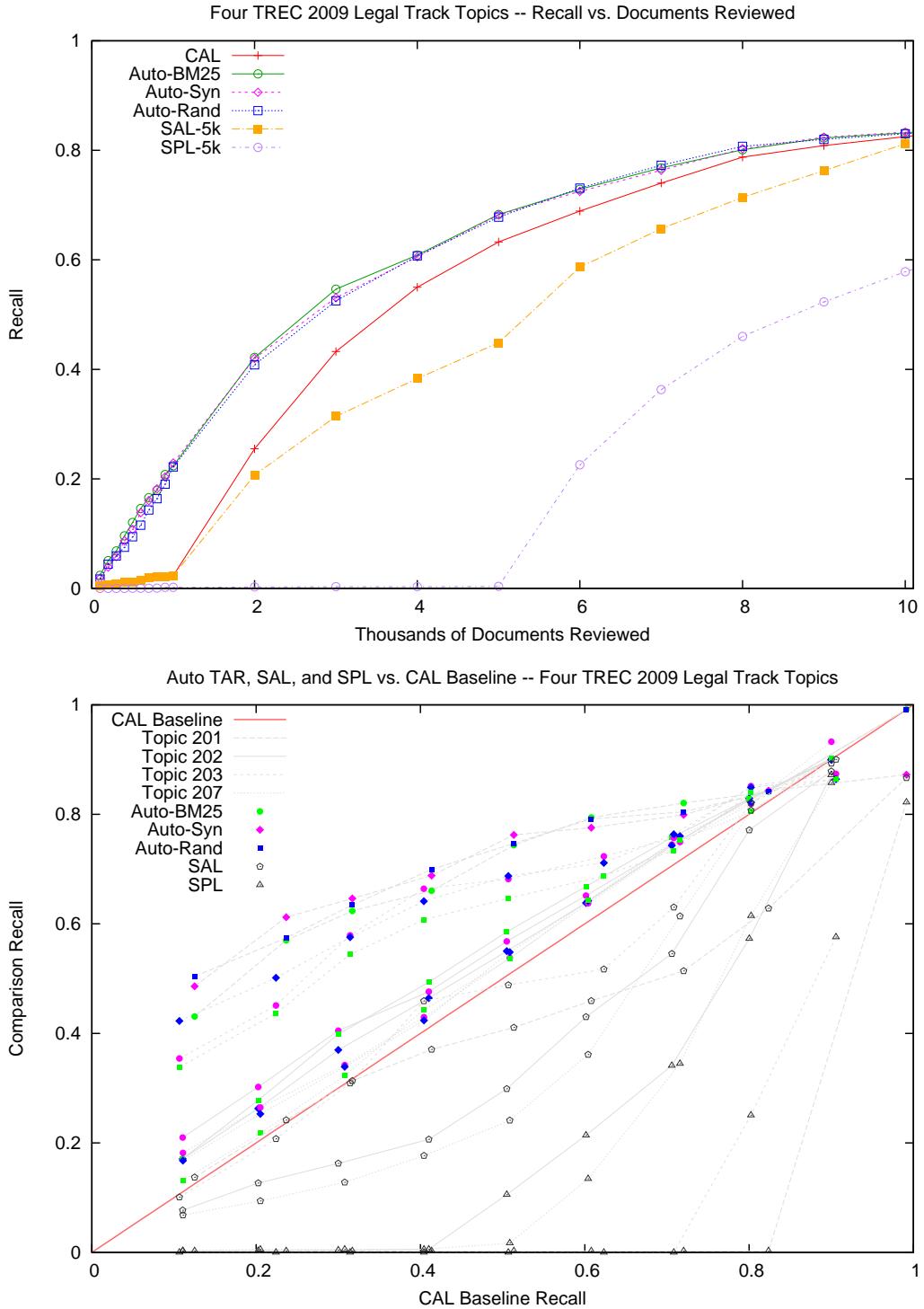


Fig. 1: Recall of Auto TAR, and CAL, SAL, and SPL, using four TREC 2009 Legal Track topics.

Autonomy and Reliability of Continuous Active Learning, Cormack & Grossman, 2015.

Topic	CAL	Auto TAR		
		BM25	Synth.	Rand.
201	3,400	2,400	2,200	2,400
202	9,100	8,300	8,300	8,000
203	4,800	3,800	4,100	4,300
207	9,400	8,200	8,000	8,000

Table II: 75% Recall effort for CAL and Auto TAR.

Topic	Seed Query	Synthetic Seed Document
201	“pre-pay” OR “swap”	engagement in structured commodity transactions known as prepay transactions
202	“FAS” OR “transaction” OR “swap” OR “trust” OR “transferor” OR “transferee”	engagement in transactions that Enron characterized as compliant with FAS 140 (or its predecessor FAS 125)
203	“forecast” OR “earnings” OR “profit” OR “quarter” OR “balance sheet”	had met, or could, would, or might meet its financial forecasts, models, projections, or plans at any time after January 1, 1999
207	“football” or “Eric Bass”	fantasy football, gambling on football, and related activities, including but not limited to, football teams, football players, football games, football statistics, and football performance.

Table III: Seed queries and synthetic seed documents.

colored points, are superior to the CAL baseline for almost all combinations of run, topic, and recall level. The SAL points mostly fall below the baseline, while the SPL points all fall below the baseline.

Table II shows 75% recall effort for our implementation of CAL compared to the three variants of Auto TAR. From the table, it is apparent that the Auto TAR runs all require less effort than CAL to achieve 75% recall, but there is no clear winner among them. We note that our CAL implementation achieves somewhat lower recall effort than the implementation in Cormack and Grossman’s Toolkit, which we attribute to our feature engineering choice (i.e., tf-idf word-based as opposed to binary byte 4-grams).

### 3.3. Hypotheses and design choices

**3.3.1. Single relevant seed document.** One of our principal design choices, which influenced all others, was to use a single relevant seed document, instead of the 1,000-document seed set in Cormack and Grossman’s CAL implementation. This decision was motivated by several factors. Perhaps most important, was our desire to avoid the situation in which the seed set contained no relevant examples, and hence no basis for relevance feedback. We were unwilling to revert to random search because the expected effort to find a relevant document – on the order of  $\frac{1}{\rho}$  where  $\rho$  is the prevalence of relevant documents in the collection – would be unacceptable when prevalence was low. Even in situations where there were one or several relevant documents in the seed set, we were concerned that for such a sparse training set, it would be difficult to set regularization and other parameters for the SVM implementation to converge without overfitting. One of Cormack and Grossman’s examples (Topic 203, CAL and SAL, with random seed [4]) appears to exhibit this abnormality.

Our motivation to use a single relevant seed document also stemmed in part from criticism of the mechanism to determine its content. It has been argued that unless the seed set is “representative of the collection” a TAR effort may fail to yield adequate recall, and that using keywords or other judgmental techniques may “bias” the result [16]. We wished to minimize and isolate the judgmental input needed to initiate the TAR process, so as to analyze its impact. To this end, we chose three methods of selecting the seed document: random, BM25, and synthetic. While we do not believe that random selection is a generally applicable method, due to the low-prevalence issue referenced above, it serves as a proxy for a relevant document already known to the user, or identified by any number of methods. If a random document nearly always fits the bill, such a convenience-sampled document should, as well. We had reason to think that the top-ranked (according to BM25, in our experiments) relevant document from an ad hoc search might be more effective, or more reliable, than a random one, but we could also imagine scenarios in which it might be worse, perhaps resulting in a myopic review. We further posited that a synthetic document consisting of a description of the subject matter would make a good seed for the same reason that such a document would provide a reasonable query for a relevance-ranking algorithm for ad hoc IR. The use of a synthetic seed document offers the simplicity of a turnkey approach. The use of a BM25 seed is predicated on a two-phase approach: an ad hoc search to find a document, followed by Auto TAR. Generally, ad hoc search will yield a relevant document in the first several attempts; if not, the failure will be readily apparent, and the user will reformulate the query rather than reviewing to an absurd depth in the ranking. In our comparisons, we report only the effort required for the Auto TAR phase; we leave it to the reader to account for the effort of finding the seed: For a synthetic seed, there is no search effort; for a BM25 seed, the search effort is usually de minimus; for a truly random seed, the effort is on the order of  $\frac{1}{\rho}$ ; for an arbitrary seed, there is no search effort provided at least one relevant document is known.

**3.3.2. Presumptive non-relevant examples.** When the seed set is restricted to a single relevant seed document, we lack non-relevant documents with which to train the SVM, rendering it unable to find a meaningful decision boundary. Instead of having the reviewer assess random documents for this purpose, we presumptively and temporarily label 100 randomly selected documents “not relevant” for the purpose of training the SVM. We repeat this procedure – augmenting the training set by a different set of 100 randomly selected documents, presumptively labeled “not relevant,” from the documents yet to be reviewed – for each iteration of relevance feedback. Our rationale is as follows: For low prevalence topics ( $\rho \ll 0.01$ ), there will likely be no relevant documents among those presumptively labeled “not relevant”; for high prevalence topics ( $0.01 \ll \rho < 0.5$ ), there will likely be some relevant documents, but even more non-relevant documents, and it is unlikely that the resulting SVM will be so poorly trained as to be unable to find sufficient relevant documents to proceed, given their high prevalence. Moreover, the choice of a different set of non-relevant examples introduces enough nondeterminism that poor training is unlikely to persist through several iterations. The intermediate case of  $\rho \approx 0.01$  falls between the extremes; we see no reason why it should fare worse.

We had reason to believe that the nondeterminism introduced by the use of random presumptively non-relevant examples might aid in the coverage of diverse aspects of the topics, for much the same reason that randomization can help hill-climbing methods avoid local optima. We conducted one auxiliary experiment that supported our impression: Increasing the size of the set of documents to 1,000 appeared to degrade performance. We conjecture that the reason is, in part, because such a large set smooths out the randomness. Another possibility is that the SVM simply overfits with this large an imbalance between relevant and non-relevant examples. Because 100 was our intuitive choice and appeared to work well, we did not investigate other sample sizes.

**3.3.3. Exponential batch sizes.** Instead of using a batch size of 1,000 for relevance feedback as Cormack and Grossman did, we were inclined to explore the boundary case of using a batch size of 1; i.e., retraining the SVM and selecting the single highest-ranked document. This minimal batch size may afford the process the greatest possible opportunity to learn, and hence to achieve high precision. On the other hand, it may deprive the algorithm of sufficient real (as opposed to presumptive) non-relevant examples to clearly mark the decision boundary [17]. An exploration of this issue is met with the formidable problem that the overall running time of such a solution is  $\Omega(n^2)$ , where  $n$  is the size of the collection, by virtue of the fact that it is necessary to re-score the collection (or, at least, those documents not yet reviewed)  $n$  times. Furthermore, if the training time  $T(n)$  is superlinear, the lower bound rises to  $\Omega(n \cdot T(n))$ . Exploration aside, a method with quadratic time complexity is simply not viable for TAR.

We sought to reap the benefits of early precision, while avoiding downside risk and excessive running time, by using exponentially increasing batch sizes. We used an initial batch size of 1, and increased it at each step by the smallest number of documents greater than 10%. We chose a growth rate of 10% because it resulted in about the same number of iterations, and hence similar computation time, as the fixed batch size of 1,000 used in Cormack and Grossman’s Toolkit. It is easy to show that the asymptotic running time of this approach is  $O(n \log n + T(n))$ , assuming that an  $O(n \log n)$  sorting algorithm is used to select the top-ranked documents.

**3.3.4. Feature engineering and learning method.** Our choice of tf-idf word-based feature engineering and SVMlight, in preference to binary byte 4-grams and Sofia-ML, was partly occasioned by our concern over sparse training sets. We were unable to find a feature engineering method and configuration of Sofia-ML (or Vowpal Wabbit, or an implementation of logistic regression) that worked for sparse training sets as well as tf-idf features and SVMlight, with default parameters. A second consideration was the widespread adoption of tf-idf and SVMlight, facilitating better-controlled comparisons with prior work. On the other hand, the use of words and stemming presupposes English documents, and, to our knowledge, the asymptotic training time  $T(n)$  for SVMlight is superlinear, whereas it is linear for Sofia-ML, Vowpal Wabbit, and other stochastic methods. Nevertheless, the running time was adequate for the test collections we used.

## 4. EXPERIMENTS

### 4.1. Actual legal matters

We arranged to run Auto TAR, configured exactly as described in Section 3.1, on the test collections for the four actual legal matters studied by Cormack and Grossman [4]. To this end, it was necessary to create a version of the Toolkit that imported the raw text, constructed the feature representation, and ran Auto TAR. The results were captured using the Toolkit. We compared the three versions of Auto TAR to our reimplementations of CAL, SAL, and SPL. For SAL and SPL, we chose a representative training set size of 5,000 documents. The left panel of Figure 2 shows the average recall over the four topics, while the right panel shows the differential scatterplot with respect to the CAL baseline. These results generally mirror those presented in Section 3.2. We note that for one topic (Matter A), the three AutoTAR runs lag somewhat for precision values between about 0.65 and 0.85, and then catch up. We have no explanation for this behavior and would have examined and reported on the nature of the documents that were retrieved earlier by CAL than by Auto TAR, had we been able to do so. Lacking that information, we note that, for this dataset, the simulated reviewer assessments had a precision of only 0.31, well below that of any other topic. It may be that Auto TAR was simply finding documents that the reviewer thought were relevant, but the ultimate authority did not.

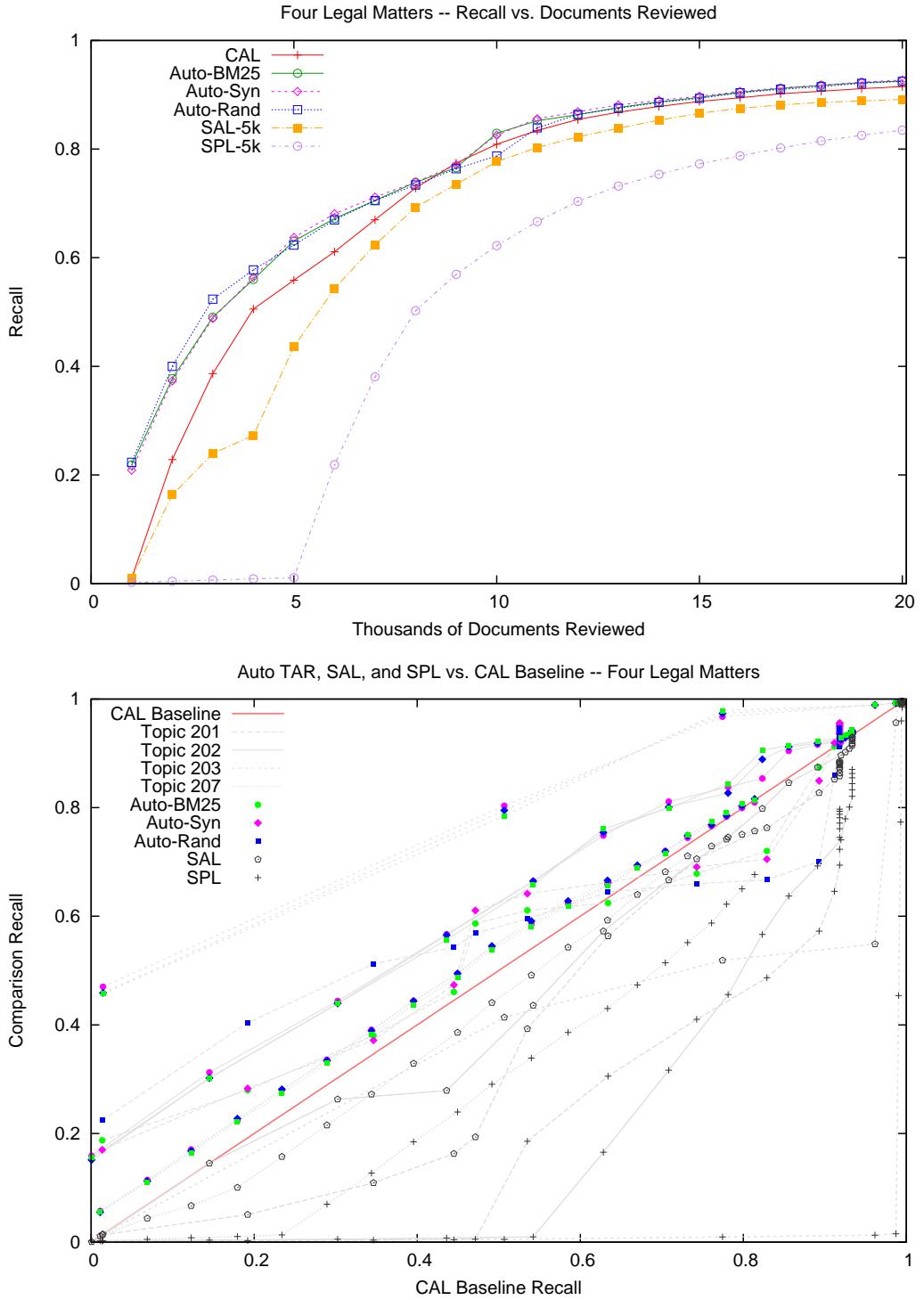


Fig. 2: Recall of Auto TAR, and CAL, SAL, and SPL, using four actual legal matters from Cormack and Grossman.

Autonomy and Reliability of Continuous Active Learning, Cormack & Grossman, 2015.

#### 4.2. Reuters RCV1-v2

The Reuters RCV1-v2 corpus, compiled by Lewis et al. [13], consists of 804,401 documents, 23,149 of which are denoted training documents, and the rest, test documents. Complete labels are available for each of 103 subjects, 364 industries, and 326 geographic locations. We ignored the training/test split and used the entire document set in our experiment. While the subjects form a hierarchy, we treated each as a separate topic. We used the supplied labels for both training and evaluation; that is, the “training standard” and “gold standard” in the Toolkit were identical. For the seed query, we used the subject header in the RCV1-v2 table of contents, e.g., “Consumer Prices.” For the synthetic seed document, we used the subject description, also supplied with the dataset, along with the subject descriptions above it in the hierarchy, e.g., “consumer prices and price indices; inflation, prices and price indices; ALL Economics and Economic Indicators.”

Our feature engineering choices are virtually identical to those used for the feature representation supplied with the collection, but we applied our own, for a number of reasons. First, we did not want to violate our autonomy constraint of doing no dataset-specific configuration. Second, the supplied features excluded documents not appearing in the test set, with the effect that words occurring fewer than 40 times had a high probability of being excluded, potentially affecting Auto TAR’s ability to harness rare but informative terms. Finally, we were not able to replicate the version of the Porter stemmer used to create the supplied features, and were therefore unable to featurize our synthetic seed documents.

To validate our feature engineering, we computed macro-averaged  $F_1$  using SVM-light and the RCV1-v2 splits. Using the supplied feature representation, we achieved  $F_1 = 0.607$ , exactly as reported by Lewis et al. [13] for the same approach. Using our features, we achieved  $F_1 = 0.608$ .

Our first experiment replicates the pilot experiments of Section 3.2, comparing three versions of Auto TAR with CAL, SAL, and SPL. The left panel of Figure 3 show that, on average, the three versions of Auto TAR are indistinguishable, and superior to CAL, while SAL and SPL are inferior. The right panel shows that for virtually all combinations of topic and recall, all versions of Auto TAR are superior or equal to CAL, while SAL and SPL are equal or inferior.

We conducted a supplemental experiment to compare the effectiveness of Auto TAR with the supervised text categorization results we achieved using the RCV1-v2 splits. As noted above, our classification results were virtually indistinguishable from those reported by Lewis et al., which, we understand, still reflect the state of the art. Because TAR and text categorization are different tasks, we must decide how to account for the effort involved in training the classifier. Figure 4 shows the result under two possible interpretations. The left panel shows the recall of the categorization with respect to the baseline of Auto TAR with a random seed document, where the training documents are included in both the recall and effort calculations. This corresponds to an implementation of SPL where the cost (and benefit) of training is attributed to the TAR effort. The right panel shows effort and recall when the training documents are excluded from the calculation. This corresponds to the situation where a labeled training set is available as a sunk cost, but it is still necessary to review documents from the test set. Under the SPL model, all the categorization results are inferior to the baseline. Perhaps surprisingly, the vast majority are also inferior under the sunk-cost model.

#### 4.3. TREC 6 AdHoc Task

Figure 5 compares our three Auto TAR methods to the Waterloo ISJ effort (“UW”) described in Section 2. The left panel shows average recall over 50 topics as a function of review effort per topic. For comparison, two other high-scoring TREC submissions are shown (denoted as “LC” and “ANU”). While Auto TAR achieves higher overall recall than the TREC

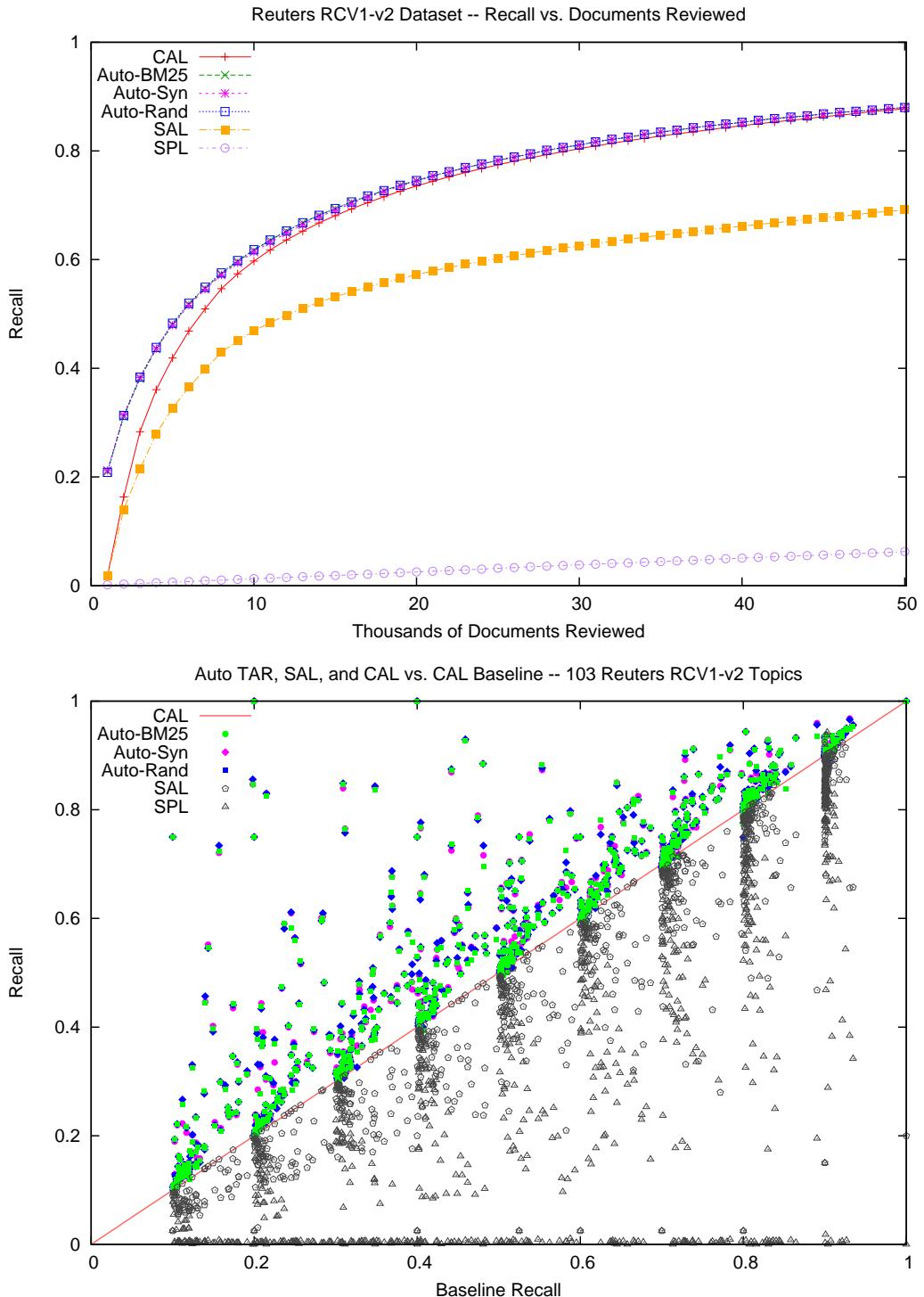
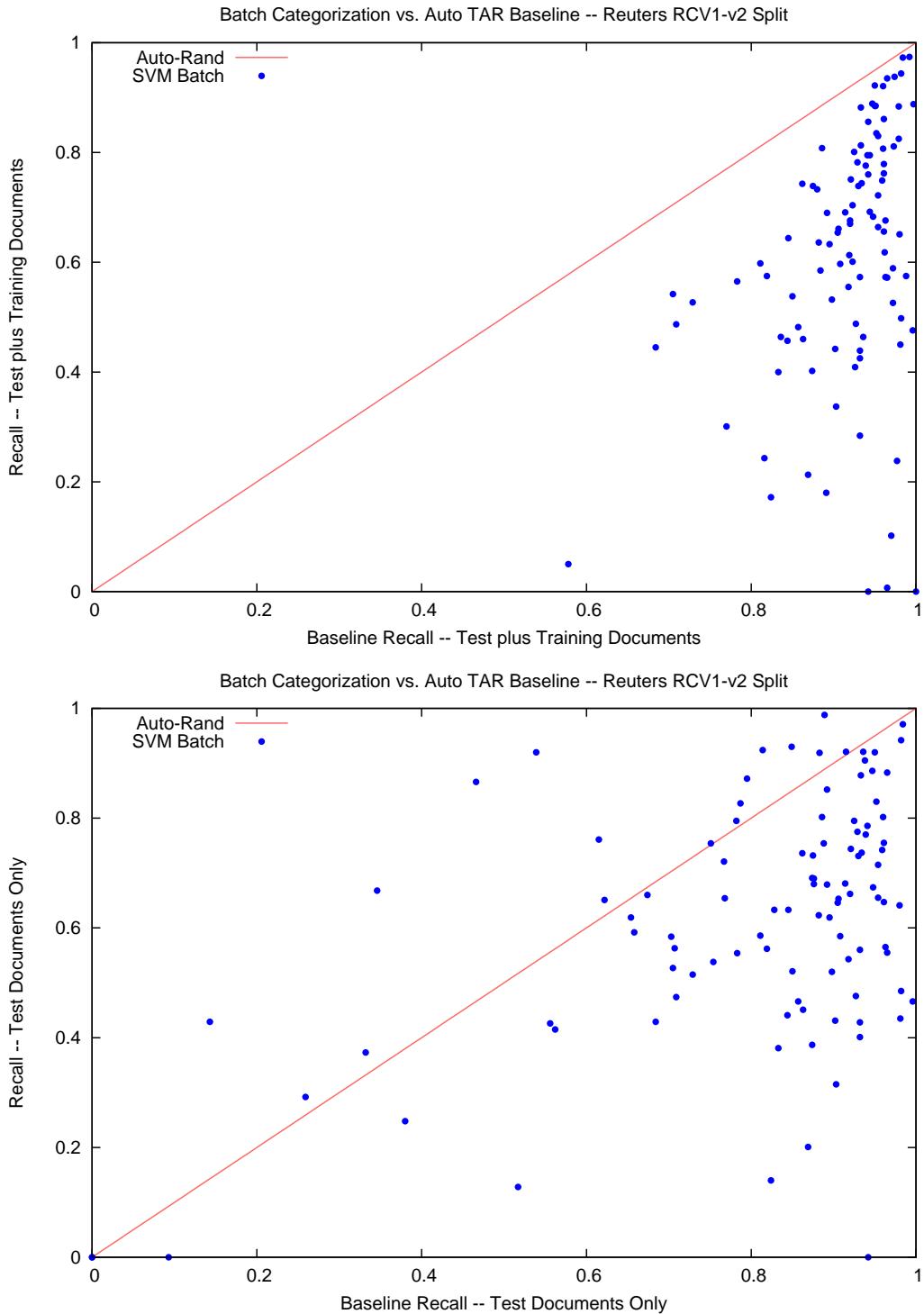


Fig. 3: Recall of Auto TAR, and CAL, SAL, and SPL, using 103 subject-matter topics from Reuters RCV1-v2.

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Fig. 4: Recall of Auto TAR vs. RCV1-v2 Text Categorization ( $F_1$  optimized).

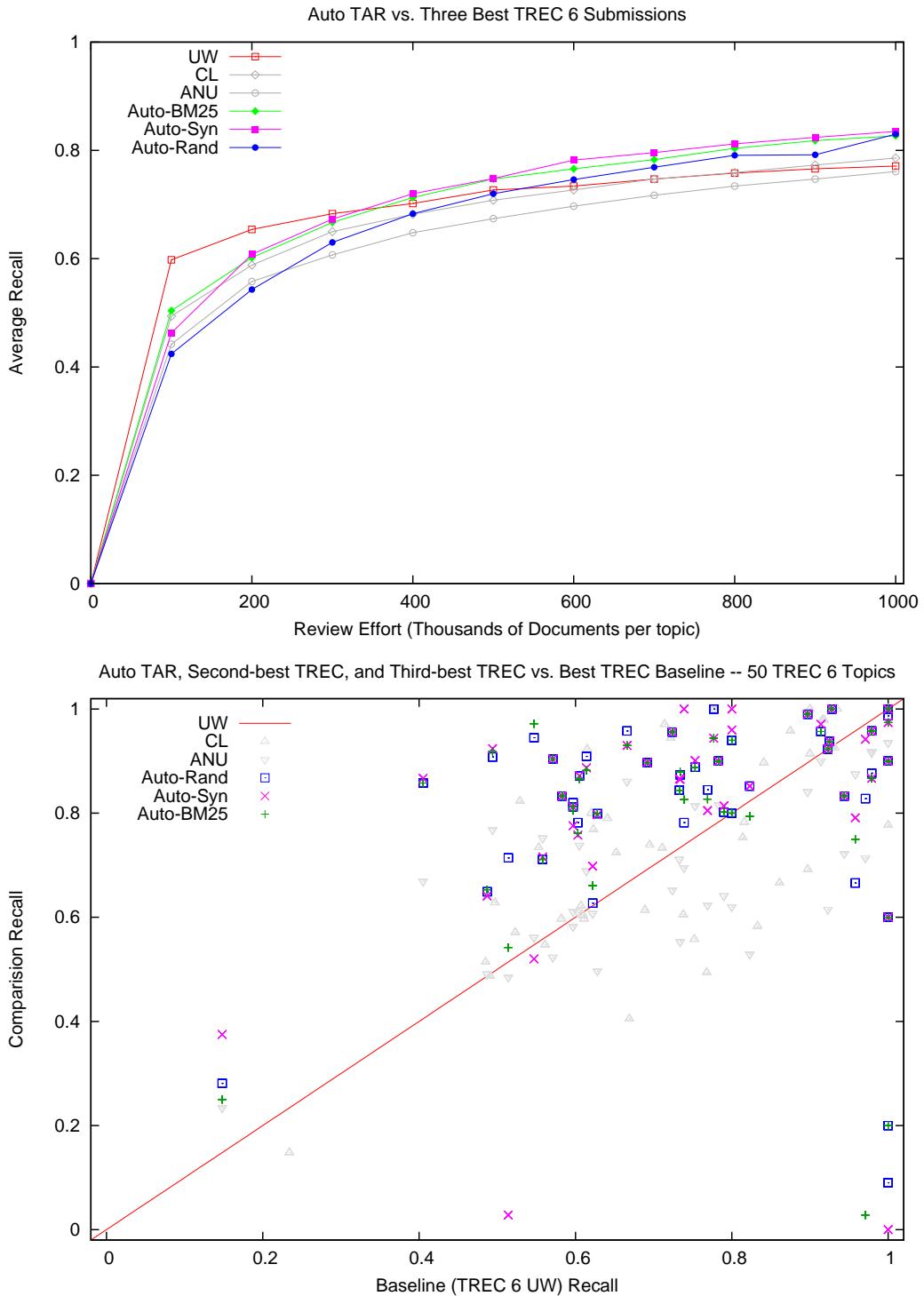


Fig. 5: Recall of Auto TAR and three best submissions to TREC 6 Ad Hoc Task.

submissions, it appears that UW reaches 60% recall more quickly. We note that the Waterloo team re-ranked their submission to put the most-likely relevant documents first, so the order shown is not the order in which the documents were retrieved and reviewed. Therefore, the curve is misleading; one cannot infer from it that Waterloo achieved an average recall of 0.6 while reviewing fewer than 100 documents per topic. The scatterplot further reveals that, for the vast majority of topics, Auto TAR achieves all recall levels (including  $recall = 0.6$ ) with less effort than UW. The average is apparently the result of a few outlier topics with few relevant documents, which Waterloo found, and Auto TAR did not.

#### 4.4. TREC 2002 Filtering Test Collection

Figure 6 shows the average recall of Auto TAR versus Robertson and Sanderson’s work to construct the test collection for the TREC 2002 Filtering Track (“NIST”), described in Section 2. The panels repeat the same story as Subsection 4.3, including the presence of a few cases where Auto TAR failed to get traction. We note that when Auto TAR fails, it seems to do so spectacularly, retrieving a near-vacuous number of documents. Such a situation would be readily apparent, and would, we suggest, signal to the user to abandon the effort and start again with another seed document, or another method.

Figure 7 shows, instead of recall, the Kendall rank correlation versus the official augmented qrels, reflecting the effectiveness of the review efforts for their intended purpose: deriving a good set of qrels.

### 5. CONCLUSION

Our experiments show that the efficacy of CAL extends well beyond the eight legal matters studied by Cormack and Grossman [4]. A handful of principled improvements – tf-idf features, a single relevant seed document, presumptively labeled “not relevant” examples, and exponential batch sizes, in combination – improve recall, especially at lower effort levels, and almost always improve, not only on CAL (which is reaffirmed to be consistently superior to SAL and SPL), but on the best reported efforts for interactive search and judging, as well as interactive relevance feedback. While a sign test shows the win rate to be significantly better than chance, ( $P \approx 0.000$ ), our overarching objective is not to win most of the time, but to win all of the time, or at least not to lose by a substantial margin. To this end, we offer our qualitative observation that the losses incurred by Auto TAR generally involved topics for which it had difficulty finding a non-trivial number of relevant documents beyond the single seed document. It remains an open question how to enhance Auto TAR to detect this eventuality and, perhaps, to request a new seed.

Our results indicate that there is little difference, if any, beyond chance in choosing between a seed selected randomly, a seed selected by chance, and a synthetic seed constructed from the topic description. Auxiliary experiments indicated that chance variation between runs (due to the selection of the seed document, as well as the selection of the presumptively non-relevant training examples) was much larger than any systematic difference between seeding methods.

A commonly expressed sentiment in eDiscovery is that there can be no “one size fits all” TAR solution, suggesting that it is necessary to select tools and strategy with knowledge of the topic and dataset, and that some tools are more appropriate in some situations. Thus far, however, we have been unable to find a situation in which one could choose, without foreknowledge, a tool or strategy to yield better recall, with less effort, than Auto TAR.

Beyond enhancing the effectiveness and reliability of Auto TAR, it remains an open question how best to decide when to terminate the TAR process. The gain curves show clearly diminishing returns at some point, but do not show exactly how many more relevant documents remain to be found. Our results indicate that if a substantial number of relevant documents are found with high precision, and then precision drops, the vast majority

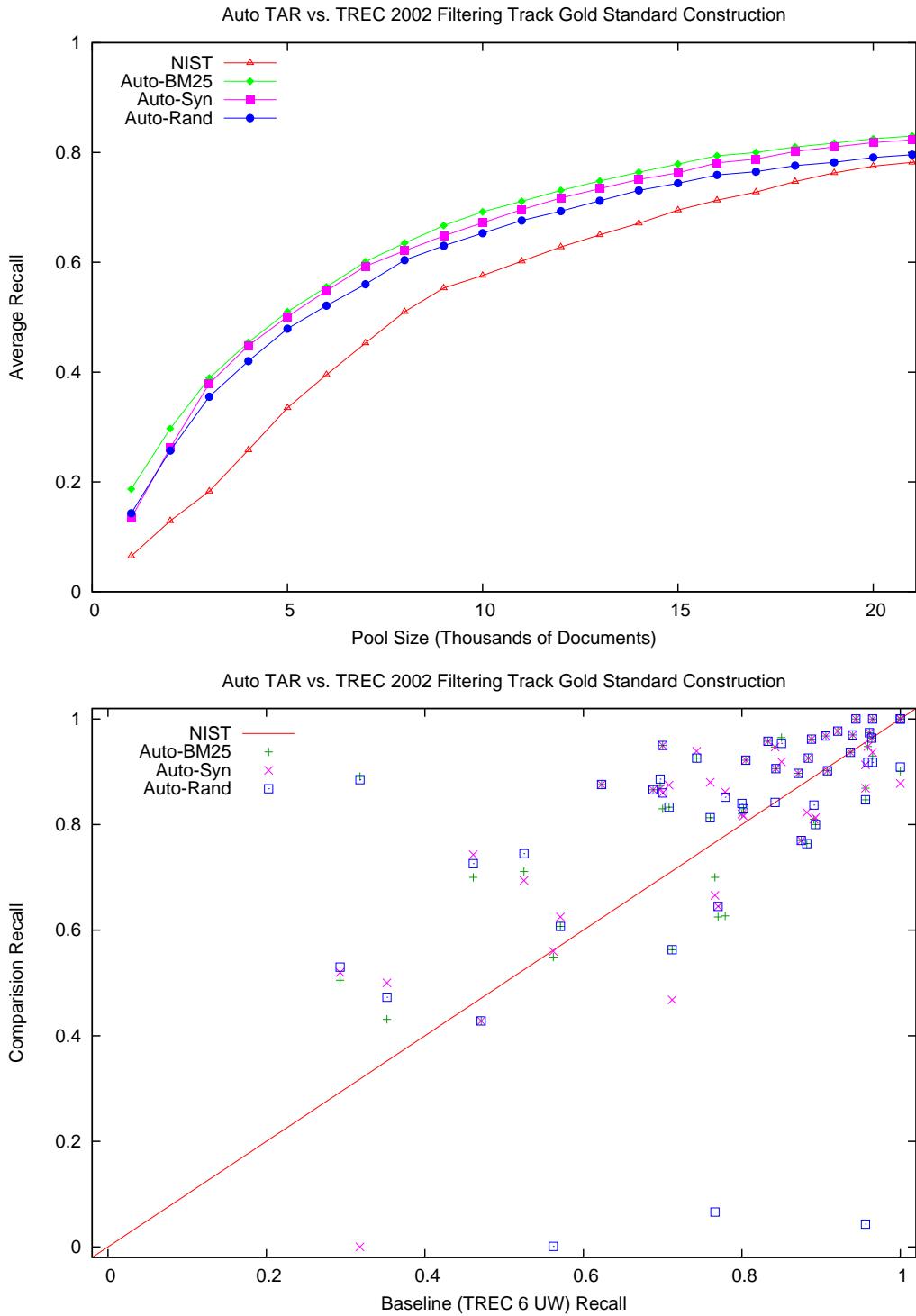


Fig. 6: Recall of Auto TAR and NIST IRF for TREC 2002 Filtering Track qrels.

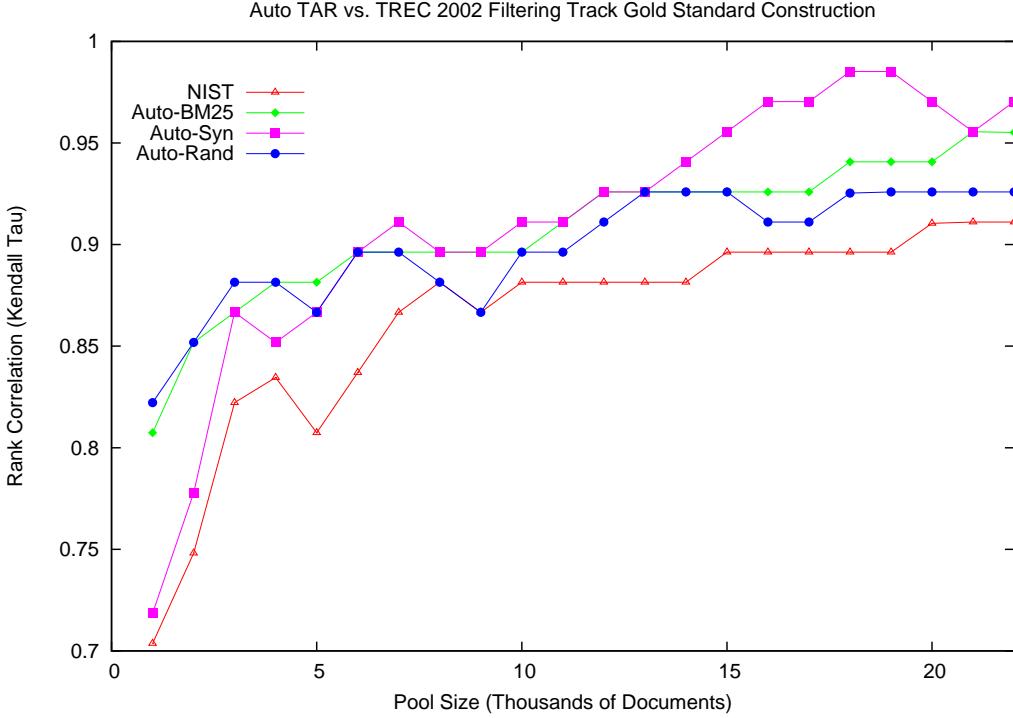


Fig. 7: Rank correlation of Auto TAR and NIST IRF qrels with respect to official TREC 2002 Filtering Track qrels.

of relevant documents have likely been found. Methods for achieving a reliable, efficient, quantitative estimate remain elusive.

Auto TAR demonstrates that reasonable and reliable results can be achieved without discretionary input to the TAR process, thereby avoiding the risk of negative bias. It may be that Auto TAR, by providing a floor level of effectiveness, can still harness discretionary input to advantage, while avoiding the downside risk. For example, the user might provide additional seed documents or queries, either when Auto TAR appears to be stuck in a ditch, or to ensure that all aspects of relevance are covered, if it could be known that Auto TAR would achieve at least its floor level of effectiveness.

Our adaptation of Cormack and Grossman's Toolkit, the feature representation of the TREC and RCV1-v2 collections, as well as gain curves and result tables for the 211 individual topics, are available in the on-line appendix. We believe that Auto TAR sets a new standard to beat.

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