NEXT: A System for Real-World Development, Evaluation, and Application of Active Learning

Kevin Jamieson
University of California, Berkeley
Berkeley, CA 94720
kjamieson@eecs.berkeley.edu

Lalit Jain
University of Wisconsin
Madison, WI 53706
jain@math.wisc.edu

Chris Fernandez
University of Wisconsin
Madison, WI 53706
crfernandez@wisc.edu

Nick Glattard
University of Wisconsin
Madison, WI 53706
glattard@wisc.edu

Robert Nowak
University of Wisconsin
Madison, WI 53706, USA
nowak@engr.wisc.edu

Abstract

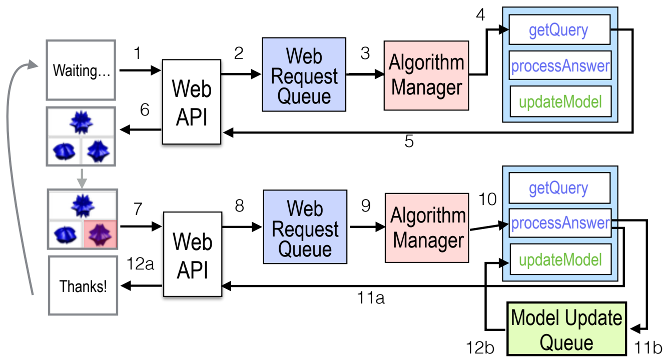
Active learning methods automatically adapt data collection by selecting the most informative samples in order to accelerate machine learning. Because of this, real-world testing and comparing active learning algorithms requires collecting new datasets (adaptively), rather than simply applying algorithms to benchmark datasets, as is the norm in (passive) machine learning research. To facilitate the development, testing and deployment of active learning for real applications, we have built an open-source software system for large-scale active learning research and experimentation. The system, called NEXT, provides a unique platform for real-world, reproducible active learning research. This paper details the challenges of building the system and demonstrates its capabilities with several experiments. The results show how experimentation can help expose strengths and weaknesses of active learning algorithms, in sometimes unexpected and enlightening ways.

1 Introduction

We use the term "active learning" to refer to algorithms that employ adaptive data collection in order to accelerate machine learning. By adaptive data collection we mean processes that automatically adjust, based on previously collected data, to collect the most useful data as quickly as possible. This broad notion of active learning includes multi-armed bandits, adaptive data collection in unsupervised learning (e.g. clustering, embedding, etc.), classification, regression, and sequential experimental design. Perhaps the most familiar example of active learning arises in the context of classification. There active learning algorithms select examples for labeling in a sequential, data-adaptive fashion, as opposed to passive learning algorithms based on preselected training data.

The key to active learning is adaptive data collection. Because of this, real-world testing and comparing active learning algorithms requires collecting new datasets (adaptively), rather than simply applying algorithms to benchmark datasets, as is the norm in (passive) machine learning research. In this adaptive paradigm, algorithm and network response time, human fatigue, the differing label quality of humans, and the lack of i.i.d. responses are all real-world concerns of implementing active learning algorithms. Due to many of these conditions being impossible to faithfully simulate active learning algorithms must be evaluated on real human participants.

Adaptively collecting large-scale datasets can be difficult and time-consuming. As a result, active learning has remained a largely theoretical research area, and practical algorithms and experiments are few and far between. Most experimental work in active learning with real-world data is simulated



1. Request query display from web API
2. Submit job to web-request queue
3. Asynchronous worker accepts job
4. Request routed to proper algorithm
5. Query generated, sent back to API
6. Query display returned to client
7. Answer reported to web API
8. Submit job to web-request queue
9. Asynchronous worker accepts job
10. Answer routed to proper algorithm

11a. Answer acknowledged to API

12a. Answer acknowledged to Client

11b. Submit job to model-update queue

12b. Synchronous worker accepts job

Figure 1: NEXT Active Learning Data Flow

```
def getQuery( context ):
    // GET suff. statistics stats from database
    // use stats, context to create query
    return query
def processAnswer( query,answer ):
    // SET (query,answer) in database
    // update model or ENQUEUE job for later
    return "Thanks!"
def updateModel( ):
    // GET all (query,answer) pairs S
    // use S to update model to create stats
    // SET suff. statistics stats in database
```

Figure 2: Example algorithm prototype that active learning researcher implements. Each algorithm has access to the database and the ability to enqueue jobs that are executed in order, one at a time.

by letting the algorithm adaptively select a small number of labeled examples from a large labeled dataset. This requires a large, labeled data set to begin with, which limits the scope and scale of such experimental work. Also, it does not address the practical issue of deploying active learning algorithms and adaptive data collection for real applications.

To address these issues, we have built a software system called NEXT, which provides a unique platform for real-world, large-scale, reproducible active learning research, enabling

1. **machine learning researchers** to easily deploy and test new active learning algorithms;
2. **applied researchers** to employ active learning methods for real-world applications.

Many of today's state-of-the-art machine learning tools, such as kernel methods and deep learning, have developed and witnessed wide-scale adoption in practice because of both theoretical work and extensive experimentation, testing and evaluation on real-world datasets. Arguably, some of the deepest insights and greatest innovations have come through experimentation. The goal of NEXT is to enable the same sort of real-world experimentation for active learning. We anticipate this will lead to new understandings and breakthroughs, just as it has for passive learning.

This paper details the challenges of building active learning systems and our open-source solution, the NEXT system[1]. We also demonstrate the system's capabilities for real active learning experimentation. The results show how experimentation can help expose strengths and weaknesses of well-known active learning algorithms, in sometimes unexpected and enlightening ways.

2 What's NEXT?

At the heart of active learning is a process for sequentially and adaptively gathering data most informative to the learning task at hand as quickly as possible. At each step, an algorithm must decide what data to collect *next*. The data collection itself is often from human helpers who are asked to answer queries, label instances or inspect data. Crowdsourcing platforms such as Amazon's Mechanical Turk or Crowd Flower provide access to potentially thousands of users answering queries on-demand. Parallel data collection at a large scale imposes design and engineering challenges unique to active learning due to the continuous interaction between data collection and learning. Here we describe the main features and contributions of the NEXT system.

System Functionality - A data flow diagram for NEXT is presented in Figure 1. Consider an individual client among the crowd tasked with answering a series of classification questions. The client interacts with NEXT through a website which requests a new query to be presented from the NEXT web api. Tasked with potentially handling thousands of such requests simultaneously, the

[1]The NEXT system is open source and available `https://github.com/nextml/NEXT`.

API will enqueue the query request to be processed by a worker pool (workers can be thought of as processes living on one or many machines pulling from the same queue). Once the job is accepted by a worker, it is routed through the worker's algorithm manager (described in the extensibility section below) and the algorithm then chooses a query based on previously collected data and sufficient statistics. The query is then sent back to the client through the API to be displayed.

After the client answers the query, the same initial process as above is repeated but this time the answer is routed to the 'processAnswer' endpoint of the algorithm. Since multiple users are getting queries and reporting answers at the same time, there is a potential for two different workers to attempt to update the model, or the statistics used to generate new queries, at the same time, and potentially overwrite each other's work. A simple way NEXT avoids this race condition is to provide a locking queue to each algorithm so that when a worker accepts a job from this queue, the queue is locked until that job is finished. Hence, when the answer is reported to the algorithm, the 'processAnswer' code block may either update the model asynchronously itself, or submit a 'modelUpdate' job to this locking model update queue to process the answer later synchronously (see Section 4 for details). After processing the answer, the worker returns an acknowledgement response to the client.

Of this data flow, NEXT handles the API, enqueueing and scheduling of jobs, and algorithm management. The researcher interested in deploying their algorithm is responsible for implementing getQuery, processAnswer and updateModel. Figure 2 shows pseudo-code for the functions that must be implemented for each algorithm in the NEXT system; see the supplementary materials for an explicit example involving an active SVM classifier.

A key challenge here is latency. A getQuery request uses the current learned model to decide what queries to serve next. Humans will notice delays greater than roughly 400 ms. Therefore, it is imperative that the system can receive and process a response, update the model, and select the next query within 400 ms. Accounting for 100-200 ms in communication latency each way, the system must perform all necessary processing within 50-100 ms. While in some applications one can compute good queries offline and serve them as needed without further computation, other applications, such as contextual bandits for personalized content recommendation, require that the query depend on the context provided by the user (e.g. their cookies) and consequently, must be computed in real time.

Realtime Computing - Research in active learning focuses on reducing the *sample complexity* of the learning process (i.e., minimizing number of labeled and unlabeled examples needed to learn an accurate model) and sometimes addresses the issue of *computational complexity*. In the latter case, the focus is usually on polynomial-time algorithms, but not necessarily *realtime* algorithms. Practical active learning systems face a tradeoff between how frequently models are updated and how carefully new queries are selected. If the model is updated less frequently, then time can be spent on carefully selecting a batch of new queries. However, selecting in large batches may potentially reduce some of the gains afforded by active learning, since later queries will be based on old, stale information. Updating the model frequently may be possible, but then the time available for selecting queries may be very short, resulting in suboptimal selections and again potentially defeating the aim of active learning. Managing this tradeoff is the chief responsibility of the algorithm designer, but to make these design choices, the algorithm designer must be able to easily gauge the effects of different algorithmic choices. In the NEXT system, the tradeoff is explicitly managed by modifying when and how often the updateModel command is run and what it does. The system helps with making these decisions by providing extensive dashboards describing both the statistical and computational performance of the algorithms.

Reproducible research - Publishing data and software needed to reproduce experimental results is essential to scientific progress in all fields. Due to the adaptive nature of data collection in active learning experiments, it is not enough to simply publish data gathered in a previous experiment. For other researchers to recreate the experiment, the must be able to also reconstruct the exact adaptive process that was used to collect the data. This means that the complete system, including any web facing crowd sourcing tools, not just algorithm code and data, must be made publicly available and easy to use. By leveraging cloud computing, NEXT abstracts away the difficulties of building a data collection system and lets the researcher focus on active learning algorithm design. Any other researcher can replicate an experiment with just a few keystrokes in under one hour by just using the same experiment initialization parameters.

Expert data collection for the non expert - NEXT puts state-of-the-art active learning algorithms in the hands of non-experts interested in collecting data in more efficient ways. This includes psychologists, social scientists, biologists, security analysts and researchers in any other field in which large amounts of data is collected, sometimes at a large dollar cost and time expense. Choosing an appropriate active learning algorithm is perhaps an easier step for non-experts compared to data collection. While there exist excellent tools to help researchers perform relatively simple experiments on Mechanical Turk (e.g. PsiTurk [1] or AutoMan [2]), implementing active learning to collect data requires building a sophisticated system like the one described in this paper. To determine the needs of potential users, the NEXT system was built in close collaboration with cognitive scientists at our home institution. They helped inform design decisions and provided us with participants to beta-test the system in a real-world environment. Indeed, the examples used in this paper were motivated by related studies developed by our collaborators in psychology.

NEXT is accessible through a REST Web API and can be easily deployed in the cloud with minimal knowledge and expertise using automated scripts. NEXT provides researchers a set of example templates and widgets that can be used as graphical user interfaces to collect data from participants (see supplementary materials for examples).

Multiple Algorithms and Extensibility - NEXT provides a platform for applications and algorithms. Applications are general active learning tasks, such as linear classification, and algorithms are particular implementations of that application (e.g., random sampling or uncertainty sampling with a C-SVM). Experiments involve one application type but they may involve several different algorithms, enabling the evaluation and comparison of different algorithms. The algorithm manager in Figure 1 is responsible for routing each query and reported answer to the algorithms involved in an experiment. For experiments involving multiple algorithms, this routing could be round-robin, randomized, or optimized in a more sophisticated manner. For example, it is possible to implement a multi-armed bandit algorithm inside the algorithm manager in order to select algorithms adaptively to minimize some notion of regret.

Each application defines an algorithm management module and a contract for the three functions of active learning: getQuery, processAnswer, and modelUpdate as described in Figure 2. Each algorithm implemented in NEXT will gain access to a locking synchronous queue for model updates, logging functionality, automated dashboards for performance statistics and timing, load balancing, and graphical user interfaces for participants. To implement a new algorithm, a developer must write the associated getQuery, processAnswer, and updateModel functions in Python (see examples in supplementary materials); the rest is handled automatically by NEXT. We hope this ease of use will encourage researchers to experiment with and compare new active learning algorithms. NEXT is hosted on Github and we urge users to push their local application and algorithm implementations to the repository.

3 Example Applications

NEXT is capable of hosting any active (or passive) learning application. To demonstrate the capabilities of the system, we look at two applications motivated by cognitive science studies. The collected raw data along with instructions to easily reproduce these examples, which can be used as templates to extend, are available on the NEXT project page.

3.1 Pure exploration for dueling bandits

The first experiment type we consider is a pure-exploration problem in the dueling bandits framework [3], based on the New Yorker Caption Contest[2] . Each week New Yorker readers are invited to submit captions for a cartoon, and a winner is picked from among these entries. We used a dataset from the contest for our experiments. Participants in our experiment are shown a cartoon along with two captions. Each participant's task is to pick the caption they think is the funnier of the two. This is repeated with many caption pairs and different participants. The objective of the learning algorithm is to determine which caption participants think is the funniest overall as quickly as possible (i.e., using as few comparative judgments as possible). In our experiments, we chose an arbitrary cartoon and $n = 25$ arbitrary captions from a curated set from the New Yorker dataset (the cartoon and all

[2]www.newyorker.com

25 captions can be found in the supplementary materials). The number of captions was limited to 25 primarily to keep the experimental dollar cost reasonable, but the NEXT system is capable of handling arbitrarily large numbers of captions (arms) and duels.

Dueling Bandit Algorithms - There are several notions of a "best" arm in the dueling bandit framework, including the Condorcet, Copeland, and Borda criteria. We focus on the Borda criterion in this experiment for two reasons. First, algorithms based on the Condorcet or Copeland criterion generally require sampling all $\binom{25}{2} = 300$ possible pairs of arms/captions multiple times [4, 3]. Algorithms based on the Borda criterion do not necessarily require such exhaustive sampling, making them more attractive for large-scale problems [5]. Second, one can reduce dueling bandits with the Borda criterion to the standard multi-armed bandit problem using a scheme known as the Borda Reduction (BR) [5], allowing one to use a number of well-known and tested bandit algorithms.

The algorithms considered in our experiment are: random uniform sampling with BR, Successive Elimination with BR [6], UCB with BR [7], Thompson Sampling with BR [8], and Beat the Mean [9] which was originally designed for identifying the Condorcet winner (see the supplementary materials for more implementation details).

Experimental Setup and Results - We posted 1250 NEXT tasks to Mechanical Turk each of which asked a unique participant to make 25 comparison judgements for $\$0.15$. For each comparative judgment, one of the five algorithms was chosen uniformly at random to select the caption pair and the participant's decision was used to update that algorithm only. Each algorithm ranked the captions in order of the empirical Borda score estimates, except the Beat the Mean algorithm which used its modified Borda score [9].To compare the quality of these results, we collected data in two different ways. First, we took union of the top-5 captions from each algorithm, resulting in 8 "top captions," and asked a different set of 1497 participants to vote for the funniest of these 8 (one vote per participant); we denote this the plurality vote ranking. The number of captions shown to each participant was limited to 8 for practical reasons (e.g., display, voting ease).

The results of the experiment are summarized in Table 1. Each row corresponds to one of the 8 top captions and the columns correspond to different algorithms. Each table entry is the Borda score estimated by the corresponding algorithm, followed by a bound on its standard deviation. The bound is based on a Bernoulli model for the responses and is simply $\sqrt{1/(4k)}$, where k is the number judgments collected for the corresponding caption (which depends on the algorithm). The relative ranking of the scores is what is relevant here, but the uncertainties given an indication of each algorithm's certainty of these scores. In the table, each algorithm's best guess at the "funniest" captions are highlighted in decreasing order with darker to lighter shades.

Overall, the predicted captions of the algorithms, which generally optimize for the Borda criterion, appear to be in agreement with the result of the plurality vote. One thing that should be emphasized is that the uncertainty (standard deviation) of the top arm scores of Thompson Sampling and UCB is about half the uncertainty observed for the top three arms of the other methods, which suggests that these algorithms can provide confident answers with $1/4$ of the samples needed by other algorithms. This is the result of Thompson Sampling and UCB being more aggressive and adaptive early on, compared to the other methods, and therefore we recommend them for applications of this sort. **We conclude that Thompson Sampling and UCB perform best for this application and require significantly fewer samples than non-adaptive random sampling or other bandit algorithms.** The results of a replication of this study can be found in the supplementary materials, from which the same conclusions can be made.

3.2 Active Non-metric Multidimensional Scaling

Finding low-dimensional representations is a fundamental problem in machine learning. Non-metric multidimensional scaling (NMDS) is a classic technique that embeds a set of items into a low-dimensional metric space so that distances in that space predict a given set of (non-metric) human judgments of the form "k is closer to i than j." This learning task is more formidable than the dueling bandits problem in a number of ways, providing an interesting contrast in terms of demands and tradeoffs in the system. First, NMDS involves triples of items, rather than pairs, posing greater challenges to scalability. Second, updating the embedding as new data are collected is much more computationally intensive, which makes managing the tradeoff between updating the embedding and carefully selecting new queries highly non-trivial.

Caption	Plurality vote	Thompson	UCB	Successive Elim.	Random	Beat the Mean
My last of...	0.215 ± 0.013	0.638 ± 0.013	0.645 ± 0.017	0.640 ± 0.033	0.638 ± 0.031	0.663 ± 0.030
The last g...	0.171 ± 0.013	0.632 ± 0.017	0.653 ± 0.016	0.665 ± 0.033	0.678 ± 0.030	0.657 ± 0.031
The women'...	0.151 ± 0.013	0.619 ± 0.026	0.608 ± 0.023	0.532 ± 0.032	0.519 ± 0.030	0.492 ± 0.032
Do you eve...	0.121 ± 0.013	0.587 ± 0.027	0.534 ± 0.036	0.600 ± 0.030	0.578 ± 0.032	0.653 ± 0.033
I'm drowni...	0.118 ± 0.013	0.617 ± 0.018	0.623 ± 0.020	0.588 ± 0.032	0.594 ± 0.032	0.667 ± 0.031
Think of i...	0.087 ± 0.013	0.564 ± 0.031	0.500 ± 0.044	0.595 ± 0.032	0.640 ± 0.034	0.618 ± 0.033
They promi...	0.075 ± 0.013	0.620 ± 0.021	0.623 ± 0.021	0.592 ± 0.032	0.613 ± 0.029	0.632 ± 0.033
Want to ge...	0.061 ± 0.013	0.418 ± 0.061	0.536 ± 0.037	0.566 ± 0.031	0.621 ± 0.031	0.482 ± 0.032

Table 1: Dueling bandit results for identifying the "funniest" caption for a New Yorker cartoon. Darker shading corresponds to an algorithm's rank-order of its predictions for the winner.

Formally, the NMDS problem is defined as follows. Given a set S comparative judgments and an embedding dimension $d \geq 1$, the ideal goal is to identify a set of points $\{x_1, \dots, x_n\} \subset \mathbb{R}^d$ such that $||x_i - x_k||_2 < ||x_j - x_k||_2$ if "k is closer to i than j" is one of the given comparative judgments. In situations where no embedding exists that agrees with all of the judgments in S, the goal is to find an embedding that agrees on as many judgements as possible.

Active learning can be used to accelerate this learning process as follows. Once an embedding is found based on a subset of judgments, the relative locations of the objects, at least at a coarse level, are constrained. Consequently, many other judgments (not yet collected) can be predicted from the coarse embedding, while others are still highly uncertain. The goal of active learning algorithms in this setting is to adaptively select as few triplet queries (e.g., "is k closer to i or j?") as possible in order to identify the structure of the embedding.

Active Sampling Algorithms - NMDS is usually posed as an optimization problem. Note that

$$||x_i - x_k||_2 < ||x_j - x_k||_2 \iff x_i^T x_i - 2x_i^T x_k - x_j^T x_j + 2x_j^T x_k \iff \langle XX^T, H_{i,j,k} \rangle$$

where $X = (x_1, x_2, \dots, x_n)^T \in \mathbb{R}^{n \times d}$ and $H_{i,j,k}$ is an all-zeros matrix except for the sub-matrix $\widetilde{H} = [1, 0, -1; 0, -1, 1; -1, 1, 0]$ defined on the indices $[i, j, k] \times [i, j, k]$. This suggests an optimization: $\min_{X \in \mathbb{R}^{n \times d}} \frac{1}{|S|} \sum_{(i,j,k) \in S} \ell \left(\langle XX^T, H_{i,j,k} \rangle \right)$, where ℓ in the literature has taken the form of hinge-loss, logistic-loss, or a general negative log-likelihood of a probabilistic model [10, 11, 12].

One may also recognize the similarity of this optimization problem with that of learning a linear classifier; here XX^T plays the role of a hyperplane and the $H_{i,j,k}$ matrices are labeled examples. Indeed, we apply active learning approaches developed for linear classifiers, like uncertainty sampling [13], to NMDS. Two active learning algorithms have been proposed in the past for this specific application [11, 14]. Here we consider four data collection methods, inspired by these past works: 1) (passive) uniform random sampling, 2) uncertainty sampling based off an embedding discovered by minimizing a hinge-loss objective 3) approximate maximum information gain sampling using the Crowd Kernel approach in [11], and 4) approximate maximum information gain sampling using the t-STE distribution in [12]. Care was taken in the implementations to make these algorithms perform as well as possible in a realtime environment, and we point the interested reader to the Supplementary Materials and source code for details.

Experimental Setup and Results - We have used NEXT for NMDS in many applications, including embedding faces, words, numbers and images. Here we focus on a particular set of synthetic 3d shape images that can be found in the supplementary materials. Each shape can be represented by a single parameter reflecting it's smoothness, so an accurate embedding should recover a one dimensional manifold. The dataset consists of $n = 30$ shapes selected uniformly from the 1d manifold, and so in total there are $30\binom{29}{2} = 12180$ unique triplet queries that could be asked. For all algorithms we set $d = 2$ for a 2d embedding (although we hope to see the intrinsic 1d manifold in the result). Each participant was asked to answer 50 triplet queries and 400 total participants contributed to the experiment. For each query, an algorithm was chosen uniformly at random from the union of the set of algorithms plus an additional random algorithm whose queries were used for the hold-out set. Consequently, each algorithm makes approximately 4000 queries.

We consider three different algorithms for generating embeddings from triplets, 1) embedding that minimizes hinge loss that we call "Hinge" [10], 2) the Crowd Kernel embedding with $\mu = 0.05$ that

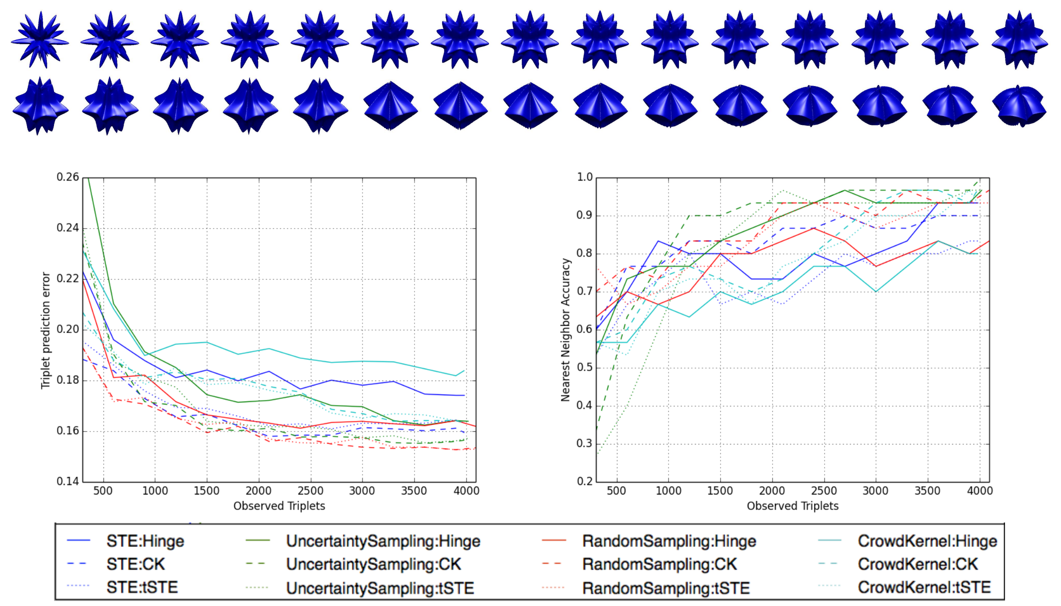


Figure 3: (Top) Stimuli used for the experiment. (Left) Triplet prediction error. (Right) Nearest neighbor prediction accuracy.

we call “CK” [11], and 3) and the t-STE embedding $\alpha = 1$ [12]. We wish to evaluate the sampling strategies, not the embedding strategies, so we apply each embedding strategy to each sampling procedure described above.

To evaluate the algorithms, we sort the collected triplets for each algorithm by timestamp, and then every 300 triplets we compute an embedding using that algorithm’s answers and each strategy for identifying an embedding. In Figure 10, the left panel evaluates the triplet prediction performance of the embeddings on the entire collected hold-out set of triplets while the right panel evaluates the nearest neighbor prediction of the algorithms. For each point in the embedding we look at its true nearest neighbor on the manifold in which the data was generated and we say an embedding accurately predicts the nearest neighbor if the true nearest neighbor is within the top three nearest neighbors of the point in the embedding, we then average over all points. Because this is just a single trial, the evaluation curves are quite rough. The results of a replication of this experiment can be found in the supplementary materials from which the same conclusions are made.

We conclude across both metrics and all sampling algorithms, the embeddings produced by minimizing hinge loss do not perform as well as those from Crowd Kernel or t-STE. In terms of predicting triplets, the experiment provides no evidence that the active selection of triplets provides any improvement over random selection. In terms of nearest neighbor prediction, UncertaintySampling may have a slight edge, but it is very difficult to make any conclusions with certainty. As in all deployed active learning studies, we can not rule out the possibility that it is our implementation that is responsible for the disappointment and not the algorithms themselves. However, we note that when simulating human responses with Bernoulli noise under similar load conditions, uncertainty sampling outperformed all other algorithms by a measurable margin leading us to believe that these active learning algorithms may not be robust to human feedback. **To sum up, in this application there is no evidence for gains from adaptive sampling, but Crowd Kernel and t-STE do appear to provide slightly better embeddings than the hinge loss optimization.** But we caution that this is but a single, possibly unrepresentative datapoint.

4 Implementation details of NEXT

The entire NEXT system was designed with machine learning researchers and practitioners in mind rather than engineers with deep systems background. NEXT is almost completely written in Python, but algorithms can be implemented in any programming language and wrapped in a python wrapper.

We elected to use a variety of startup scripts and Docker[3] for deployment to automate the provisioning process and minimize configuration issues. Details on specific software packages used can be found in the supplementary materials.

Many components of NEXT can be scaled to work in a distributed environment. For example, serving many (near) simultaneous ‘getQuery’ requests is straightforward; one can simply enlarge the pool of workers by launching additional slave machines and point them towards the web request queue, just like typical web-apps are scaled. This approach to scaling active learning has been studied rigorously [15]. Processing tasks such as data fitting and selection can also be accelerated using standard distributed platforms and machine learning packages (see next section).

A more challenging scaling issue arises in the learning process. Active learning algorithms update models sequentially as data are collected and the models guide the selection of new data. Recall that this serial process is handled by a model update queue. When a worker accepts a job from the queue, the queue is locked until that job is finished. The processing times required for model fitting and data selection introduce latencies that may reduce possible speedups afforded by active learning compared to passive learning (since the rate of ‘getQuery’ requests could exceed the processing rate of the learning algorithm).

If the number of algorithms running in parallel outnumber the number of workers dedicated to serving the synchronous locking model update queues, performance can be improved by adding more slave machines, and thus workers, to process the queues. Simulating a load with stress-tests and inspecting the provided dashboards on NEXT of CPU, memory, queue size, model-staleness, etc. makes deciding the number of machines for an expected load a straightforward task. An algorithm in NEXT could also bypass the locking synchronous queue by employing asynchronous schemes like [16] directly in processAnswer. This could speed up processing through parallelization, but could reduce active learning speedups since workers may overwrite the previous work of others.

5 Related Work and Discussion

There have been some examples of deployed active learning with human feedback; for human perception [11, 17], interactive search and citation screening [18, 19], and in particular by research groups from industry, for web content personalization and contextual advertising [20, 21]. However, these remain special purpose implementations, while the proposed NEXT system provides a flexible and general-purpose active learning platform that is versatile enough to develop, test, and field any of these specific applications. Moreover, previous real-world deployments have been difficult to replicate. NEXT could have a profound effect on research reproducibility; it allows anyone to easily replicate past (and future) algorithm implementations, experiments, and applications.

There exist many sophisticated libraries and systems for performing machine learning at scale. Vowpal Wabbit [22], MLlib [23], Oryx [24] and GraphLab [25] are all excellent examples of state-of-the-art software systems designed to perform inference tasks like classification, regression, or clustering at enormous scale. Many of these systems are optimized for operating on a fixed, static dataset, making them incomparable to NEXT. But some, like Vowpal Wabbit have some active learning support. The difference between these systems and NEXT is that their goal was to design and implement the best possible algorithms for very specific tasks that will take the fullest advantage of each system's own capabilities. These systems provide great libraries of machine learning tools, whereas NEXT is an experimental platform to *develop, test, and compare* active learning algorithms and to allow practitioners to easily use active learning methods for *data collection*. NEXT is a system designed to give machine learning researchers and applied data scientists the tools necessary to understand the best ways to adaptively collect data and to actively learn.

In the crowd-sourcing space there exist excellent tools like PsiTurk [1], AutoMan [2], and CrowdFlower [26] that provide functionality to simplify various aspects of crowdsourcing, including automated task management and quality assurance controls. While successful in this aim, these crowd programming libraries do not incorporate the necessary infrastructure for deploying active learning across participants or adaptive data acquisition strategies. NEXT provides a unique platform for developing *active* crowdsourcing capabilities and may play a role in optimizing the use of human-computational resources like those discussed in [27].

[3]`https://www.docker.com/`

Finally, while systems like Oryx [24] and Velox [28] that leverage Apache Spark are made for deployment on the web and model serving, they support very specific types of models because they were optimized for that purpose, limiting their versatility and applicability. They were also built for an audience with a greater familiarity with systems and understandably prioritize computational performance over, for example, the human-time it might take a cognitive scientist or active learning theorist to figure out how to actively crowdsource a large human-subject study using Amazon's Mechanical Turk.

At the time of this submission, NEXT has been used to ask humans hundreds of thousands of actively selected queries in ongoing cognitive science studies. Working closely with cognitive scientists who relied on the system for their research helped us make NEXT predictable, reliable, easy to use and, we believe, ready for everyone.

Acknowledgements

Aritra Biswas at the University of Wisconsin, Madison also contributed to the development of this project. We thank April Murphy, Chris Cox, and Tim Rogers (UW-Madison Psychology) who helped inform design decisions and beta-test NEXT. We thank Bob Mankoff, cartoon editor of *The New Yorker*, for sharing the cartoon and caption data used in our experiments. We would also like to thank Eric Jonas and Evan Sparks in the AMP Lab at UC Berkeley for many helpful conversations. This research is supported in part by the NSF grant IIS-1447449, a Sandia National Labs Fellowship, and gifts from Amazon Web Services.

References

[1] T.M. Gureckis, J. Martin, J. McDonnell, A.S. Rich, D. Markant, A. Coenen, D. Halpern, J.B. Hamrick, and P. Chan. psiTurk: An open-source framework for conducting replicable behavioral experiments online. (in press).

[2] Daniel W Barowy, Charlie Curtsinger, Emery D Berger, and Andrew McGregor. Automan: A platform for integrating human-based and digital computation. *ACM SIGPLAN Notices*, 47(10):639–654, 2012.

[3] Yisong Yue, Josef Broder, Robert Kleinberg, and Thorsten Joachims. The k-armed dueling bandits problem. *Journal of Computer and System Sciences*, 78(5), 2012.

[4] Tanguy Urvoy, Fabrice Clerot, Raphael Féraud, and Sami Naamane. Generic exploration and k-armed voting bandits. In *Proceedings of the 30th International Conference on Machine Learning*, 2013.

[5] Kevin Jamieson, Sumeet Katariya, Atul Deshpande, and Robert Nowak. Sparse dueling bandits. *AISTATS*, 2015.

[6] Eyal Even-Dar, Shie Mannor, and Yishay Mansour. Action elimination and stopping conditions for the multi-armed bandit and reinforcement learning problems. *The Journal of Machine Learning Research*, 7:1079–1105, 2006.

[7] Kevin Jamieson, Matthew Malloy, Robert Nowak, and Sébastien Bubeck. lil'ucb: An optimal exploration algorithm for multi-armed bandits. In *Proceedings of The 27th Conference on Learning Theory*, 2014.

[8] Olivier Chapelle and Lihong Li. An empirical evaluation of thompson sampling. In *Advances in neural information processing systems*, pages 2249–2257, 2011.

[9] Yisong Yue and Thorsten Joachims. Beat the mean bandit. In *Proceedings of the 28th International Conference on Machine Learning (ICML-11)*, pages 241–248, 2011.

[10] Sameer Agarwal, Josh Wills, Lawrence Cayton, Gert Lanckriet, David J Kriegman, and Serge Belongie. Generalized non-metric multidimensional scaling. In *International Conference on Artificial Intelligence and Statistics*, pages 11–18, 2007.

[11] Omer Tamuz, Ce Liu, Ohad Shamir, Adam Kalai, and Serge J Belongie. Adaptively learning the crowd kernel. In *Proceedings of the 28th International Conference on Machine Learning (ICML-11)*, 2011.

[12] Laurens Van Der Maaten and Kilian Weinberger. Stochastic triplet embedding. In *Machine Learning for Signal Processing (MLSP), 2012 IEEE International Workshop on*, pages 1–6. IEEE, 2012.

[13] Burr Settles. Active learning literature survey. *University of Wisconsin, Madison*, 52(55-66):11.

[14] Kevin G Jamieson and Robert D Nowak. Low-dimensional embedding using adaptively selected ordinal data. In *Allerton Conference on Communication, Control, and Computing*, 2011.

[15] Alekh Agarwal, Leon Bottou, Miroslav Dudik, and John Langford. Para-active learning. *arXiv preprint arXiv:1310.8243*, 2013.

[16] Benjamin Recht, Christopher Re, Stephen Wright, and Feng Niu. Hogwild: A lock-free approach to parallelizing stochastic gradient descent. In *Advances in Neural Information Processing Systems*, 2011.

[17] All our ideas. `http://allourideas.org/`. Accessed: 2015-09-15.

[18] Byron C Wallace, Kevin Small, Carla E Brodley, Joseph Lau, and Thomas A Trikalinos. Deploying an interactive machine learning system in an evidence-based practice center: abstrackr. In *Proceedings of the 2nd ACM SIGHIT International Health Informatics Symposium*, pages 819–824. ACM, 2012.

[19] Kyle H Ambert, Aaron M Cohen, Gully APC Burns, Eilis Boudreau, and Kemal Sonmez. Virk: an active learning-based system for bootstrapping knowledge base development in the neurosciences. *Frontiers in neuroinformatics*, 7, 2013.

[20] Lihong Li, Wei Chu, John Langford, and Robert E Schapire. A contextual-bandit approach to personalized news article recommendation. In *International conference on World wide web*. ACM, 2010.

[21] Deepak Agarwal, Bee-Chung Chen, and Pradheep Elango. Explore/exploit schemes for web content optimization. In *Data Mining, 2009. ICDM. Ninth IEEE International Conference on*. IEEE, 2009.

[22] Alekh Agarwal, Olivier Chapelle, Miroslav Dudík, and John Langford. A reliable effective terascale linear learning system. *The Journal of Machine Learning Research*, 15(1):1111–1133, 2014.

[23] Xiangrui Meng et al. MLlib: Machine learning in apache spark. *arXiv:1505.06807*, 2015.

[24] Oryx 2. `https://github.com/OryxProject/oryx`. Accessed: 2015-06-05.

[25] Yucheng Low, Danny Bickson, Joseph Gonzalez, Carlos Guestrin, Aapo Kyrola, and Joseph M Hellerstein. Distributed graphlab: a framework for machine learning and data mining in the cloud. *Proceedings of the VLDB Endowment*, 5(8):716–727, 2012.

[26] CrowdFlower. `http://www.crowdflower.com/`. Accessed: 2015-06-05.

[27] Seungwhan Moon and Jaime G Carbonell. Proactive learning with multiple class-sensitive labelers. In *Data Science and Advanced Analytics (DSAA), 2014 International Conference on*. IEEE, 2014.

[28] Daniel Crankshaw, Peter Bailis, Joseph E Gonzalez, Haoyuan Li, Zhao Zhang, Michael J Franklin, Ali Ghodsi, and Michael I Jordan. The missing piece in complex analytics: Low latency, scalable model management and serving with velox. *CIDR*, 2015.

Supplementary Material

A Example algorithm implementation

Algorithms in NEXT are implemented for a specific application and follow a particular contract. As an example, we consider a `LinearClassification` application and an implementation of a linear support vector machine (SVM) that chooses which examples to label based on uncertainty sampling [13] called `UncertaintySamplingSVM`. Each algorithm is passed in an object `resource` that can be used to access the database (with endpoints `exists`, `get`, `set`, `increment`, `set_list`, `append_list`, `delete`) or submit jobs to the locking synchronous queue (`submit`) that is executed by a different worker/process.

```
class UncertaintySamplingSVM(LinearClassification):
    # Called to initialize algorithm
    # X is examples-by-features matrix to choose examples from to label
    def initExp(self,resource,X):
        n,d = X.shape
        resource.set('X',X)
        resource.set('w',zeros(d))
        resource.set('b',0.)
        resource.set_list( 'example_pairs',[] )

    # return index of example you want labeled by annotator
    def getQuery(self,resource):
        X = resource.get('X')    # X is n-by-d
        return argmin(  abs( self.predict(resource,X) )  )

    # saves index of example and received label to database
    # submits job to synchronous queue to update model
    def processAnswer(self,resource,index,label):
        resource.append_list( 'example_pairs', (index,label) )
        resource.submit(task='modelUpdate',args={})

    # takes m-by-d matrix of examples-by-features as input and returns m-by-1 real vector back.
    # Take sign() to get predicted labels
    def predict(self,resource,M):
        w = resource.get('w')    # w is d-by-1
        b = resource.get('b')    # b is a float
        return dot(M,w) + b

    def updateModel(self,resource,args):
        answer_pairs = resource.get( 'answer_pairs' )
        X = resource.get('X')    # X is n-by-d
        M = [ X[ pair[0] ] for pair in answer_pairs ]     # construct m-by-d matrix of features
        y = [ pair[1] for pair in answer_pairs ]      # construct m-by-1 matrix of labels

        import sklearn.svm     # import sci-kit learn SVM solver
        model = sklearn.svm.LinearSVC().fit(M,y)     # fit an SVM classifier
        w = model.coef_[0]   # d-by-1 weight vector
        b = model.intercept_[0] # float intercept / bias
        resource.set('w',w)
        resource.set('b',b)
```

Figure 4: Simple implementation of an active learning algorithm for learning a linear SVM using uncertainty sampling. `resource` is an object that abstracts access to the database and job enqueuing.

B Dueling Bandit Empirical Results Continued

B.1 Cartoon and captions

All $n = 25$ captions used in the study are shown in Figure 5. Figure 6 shows an example of what the participant saw, with the cartoon used on the top.

I'm drowning in work.
At least your computer is working.
What's your name again?
I won this job at a carnival.
Some guys never make it out of the plastic bag.
It helps that I only have a three second memory span.
Any plans for feeding time?
The last guy got flushed.
If you work hard they give you a rock and plastic seaweed.
I liked the old NSA better.
The fish ate my mouse.
Can you swim?
I'm thinking of getting a goldfish.
They pay us crumbs.
They promised me a bowl of my own.
As a heads-up, the boss is freakishly tall.
My last office had a castle.
Think of it as a cornerless office.
I'd love a glass of water.
There is no Esc.
Your seat cushion can be used as a flotation device.
The women's office is the same, except it has glass on the top, too.
Do you ever get the feeling we're purely decorative?
Want to get some air?
Staring contest?

Figure 5: The captions used in the dueling bandit study.

B.2 The Borda Reduction scheme

The Borda score of the ith caption is defined as $s_i = \frac{1}{n-1}\sum_{j\neq i} p_{i,j}$ where $p_{i,j}$ is the probability that a participant drawn at random from the population prefers caption i to j; i.e., we model participant responses as a Bernoulli random variable with probability $p_{i,j}$. An unbiased estimator for s_i can be constructed by asking participants to compare caption i to another caption chosen uniformly at random from the remaining captions. We call this the Borda Reduction (BR), since it effectively reduces the dueling bandit problem into a standard multi-armed bandit problem (see [5] for a detailed look at this strategy).

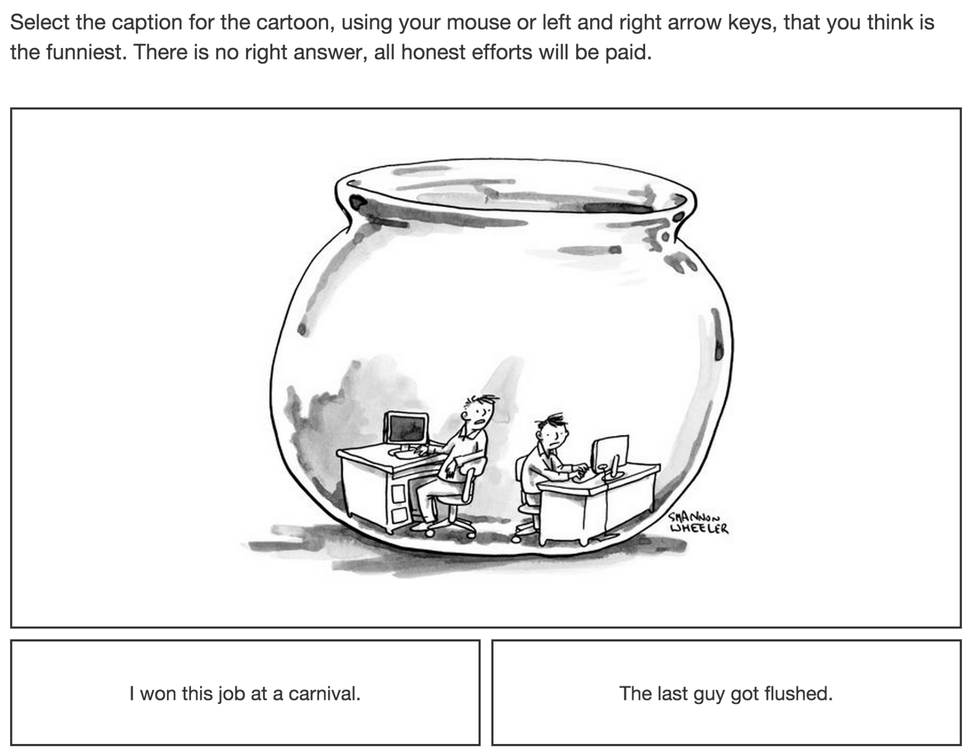
Let $S_{i,k}$ the sum of k independent comparisons for caption i. The sum is a random walk and the average is an unbiased estimator of s_i. Standard concentration bounds show that

$$|S_{i,k} - \mathbb{E}[S_{i,k}]|/k \ \leq \ C(k,\delta) =: \sqrt{\tfrac{\log(4k^2/\delta)}{2k}}$$

for all $k \geq 1$ with probability at least $1-\delta$, and these confidence intervals are used for all our algorithms that require a confidence interval with $\delta = 0.05$. The algorithms considered: (1) random sampling with BR, (2) Successive Elimination with BR with $C(k,\delta/n)$ [6], a version of UCB with BR with confidence interval $C(k,\delta)$ justified by [7], Thompson Sampling with BR as prescribed in [8] with $\alpha = 2$, and Beat the Mean [9] with $C(k,\delta/n)$ and $\gamma = 1$ which was originally designed for identifying the Condorcet winner.

B.3 Replication of original study

We repeated the study on the five algorithms with 1250 new participants and obtained the results presented in Table 2 that essentially support the findings of the first experiment. In this round we added an additional algorithm that showed 1000 participants 8 cartoons chosen uniformly at random from the possible 25 and asked them to pick their favorite. The proportion of times the same top 8 captions of the first study won are listed as "Plurality vote (25,8)" whereas the original plurality vote score is listed as "Plurality vote (8,8)", which was not repeated.


Select the caption for the cartoon, using your mouse or left and right arrow keys, that you think is the funniest. There is no right answer, all honest efforts will be paid.

I won this job at a carnival.

The last guy got flushed.

Figure 6: Example query for the New Yorker cartoon dueling bandits experiment.

Caption	Plurality vote (8,8)	Plurality vote (25,8)	Thompson Sampling	UCB	Successive Elimination	Random Sampling	Beat the Mean
My last of...	0.215 ± 0.013	0.250 ± 0.029	0.680 ± 0.014	0.687 ± 0.014	0.677 ± 0.031	0.679 ± 0.031	0.723 ± 0.032
The last g...	0.171 ± 0.013	0.186 ± 0.029	0.690 ± 0.011	0.697 ± 0.012	0.680 ± 0.030	0.677 ± 0.033	0.663 ± 0.031
The women'...	0.151 ± 0.013	0.246 ± 0.028	0.509 ± 0.046	0.546 ± 0.039	0.521 ± 0.031	0.516 ± 0.030	0.469 ± 0.033
Do you eve...	0.121 ± 0.013	0.175 ± 0.027	0.375 ± 0.088	0.610 ± 0.027	0.617 ± 0.032	0.566 ± 0.033	0.577 ± 0.032
I'm drowni...	0.118 ± 0.013	0.215 ± 0.028	0.623 ± 0.020	0.661 ± 0.018	0.617 ± 0.031	0.664 ± 0.032	0.661 ± 0.030
Think of i...	0.087 ± 0.013	0.208 ± 0.028	0.580 ± 0.035	0.597 ± 0.031	0.515 ± 0.033	0.625 ± 0.032	0.562 ± 0.030
They promi...	0.075 ± 0.013	0.146 ± 0.029	0.632 ± 0.022	0.560 ± 0.039	0.641 ± 0.032	0.632 ± 0.030	0.677 ± 0.033
Want to ge...	0.061 ± 0.013	0.087 ± 0.028	0.459 ± 0.058	0.521 ± 0.045	0.543 ± 0.031	0.561 ± 0.032	0.515 ± 0.030

Table 2: Empirical results of the second study of dueling bandit algorithms for identifying the "funniest" caption for a New Yorker cartoon. Darker shading corresponds to an algorithm's rank-order of its predictions for the winner.

C Active Non-metric Multidimensional Scaling Continued

C.1 Query Example

Figure 7 shows the $n = 30$ stimuli used in the study. Figure 8 shows an example of what the participant saw.

C.2 Query Generation

The uncertainty sampling procedure aims to choose the triplet (i, j, k) that minimizes $\big| ||x_i - x_k||_2 - ||x_j - x_k||_2 \big|$ where $\{x_1, \dots, x_n\}$ are the locations of the most up-to-date embedding at the time of generating the query. The Crowd Kernel and t-STE embedding algorithms generated triplet queries according to the strategy defined in [11]. Ideally, each of these strategies would consider all possible

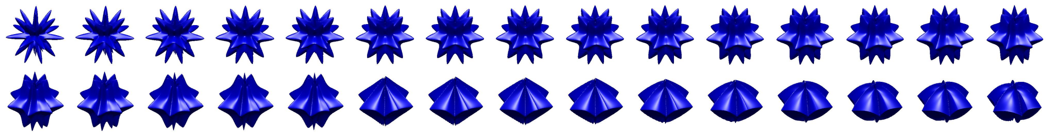


Figure 7: The stimuli generated from a one-dimensional manifold.

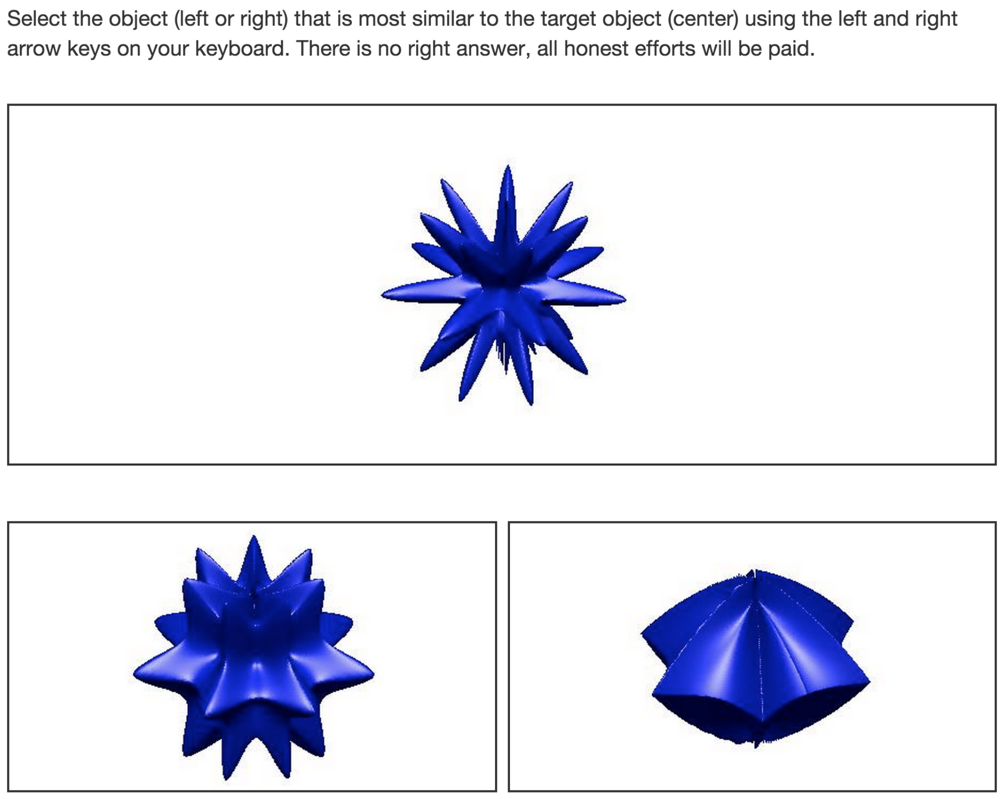

Select the object (left or right) that is most similar to the target object (center) using the left and right arrow keys on your keyboard. There is no right answer, all honest efforts will be paid.

Figure 8: Example query for the strange fruit triplet experiment.

triplets and pick the one that optimizes their respective criterion. However, even for $n = 30$ there are 12,180 possible triplet queries so in practice we had the algorithms consider random triplets for 50 ms and choose the query that was best.

C.3 Model updates

Identifying the embedding that minimizes the loss defined by any of the embedding strategies we consider - hinge, Crowd Kernel, or t-STE - is a non-convex optimization problem in terms of the locations of the n points in d dimensions. It is possible to relax the optimization problem and state it as a semi-definite program [10] (where it is convex) but this relaxation has been observed to perform far worse in practice than attempting to solve the non-convex optimization problem [11, 12].

For all of the embedding strategies we consider, a *full update* consists of running several epochs of stochastic gradient descent followed by many full gradient descent steps with a weak-Wolfe line search. An *incremental update* consists of running as many full gradient descent steps that can be completed in a given amount of time (less than one second was used in our experiments). In our experiments, every time an answer was submitted to the system an incremental update was performed. Every n answers submitted, a full embedding update was performed. The intuition here is that stochastic gradient descent returns a solution that is in a bowl close to a good local minima and gradient descent converges to the local minima. There is no theoretical justification for this approach that we know of, but it appears to be quite effective in practice.

C.4 Embeddings

Figure 9 presents the embeddings of all the algorithms with full data of the experiment presented in the main paper.

C.5 Replication of study

An exact replica of the study was performed to see if we would observe any different behavior. For the most part, the second study provides little more information than the first.

D Implementation details continued

Our front-facing HTTP API uses Flask[4] as a web framework and is served by gunicorn[5], and load-balanced by NGINX[6]. The database uses MongoDB[7] by default. Redis[8], an in-memory database is used as a cache and place for ephemeral data like the results and state of some queues and workers. We also have an optional Redis cache implemented on each worker machine so that hot items are cached on the machine in memory rather than hitting the persistent store that may be on another machine. For a single machine use, which sufficed for the experiments in this work, the difference between a cache hit and hitting MongoDB is negligible as the latter maintains an in-memory cache. To handle the synchronous and asynchronous queues, we used RabbitMQ[9] and Celery[10] with Redis acting as a result backend. Our dashboards are drawn using D3[11].

[4]`http://flask.pocoo.org/`
[5]`http://gunicorn.org/`
[6]`http://nginx.org/`
[7]`https://www.mongodb.org/`
[8]`http://redis.io/`
[9]`https://www.rabbitmq.com/`
[10]`www.celeryproject.org/`
[11]`http://d3js.org/`

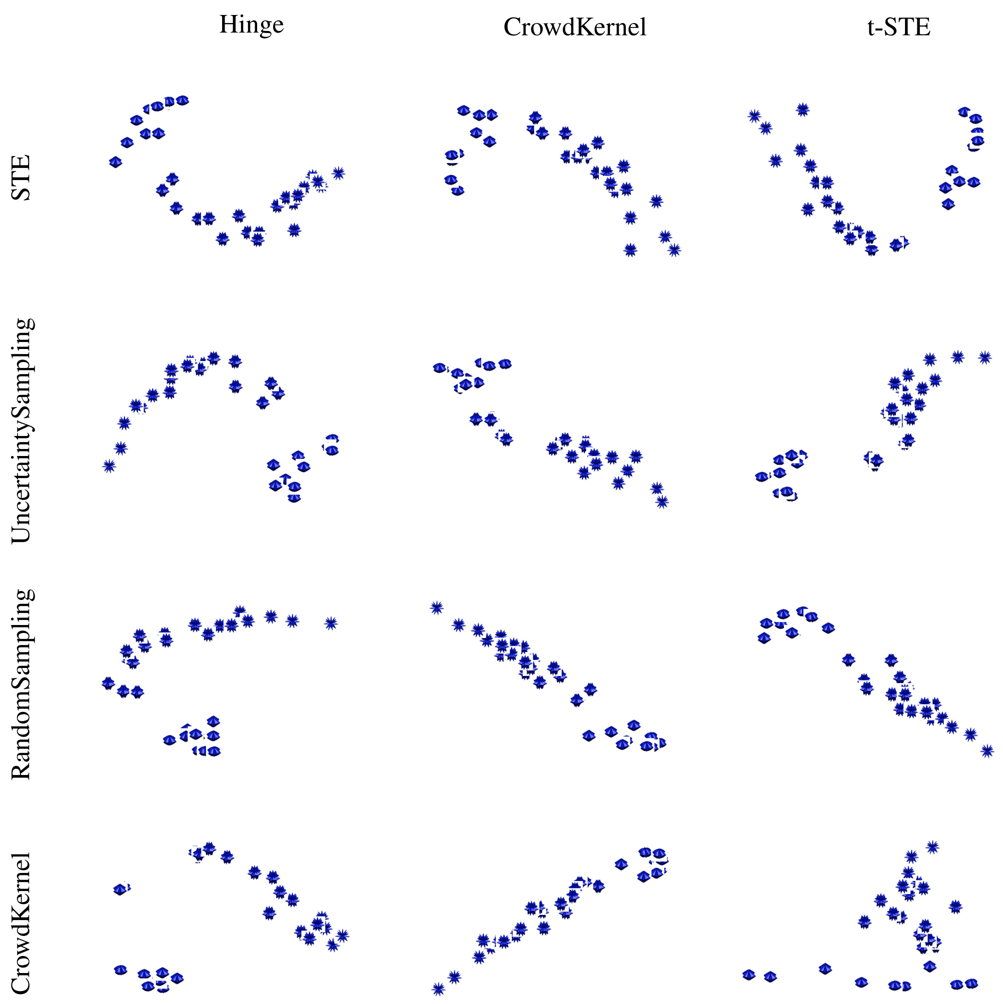


Figure 9: The embeddings of the first experiment. On the vertical is the algorithm that constructed the embedding, on the horizontal is the sampling algorithm.

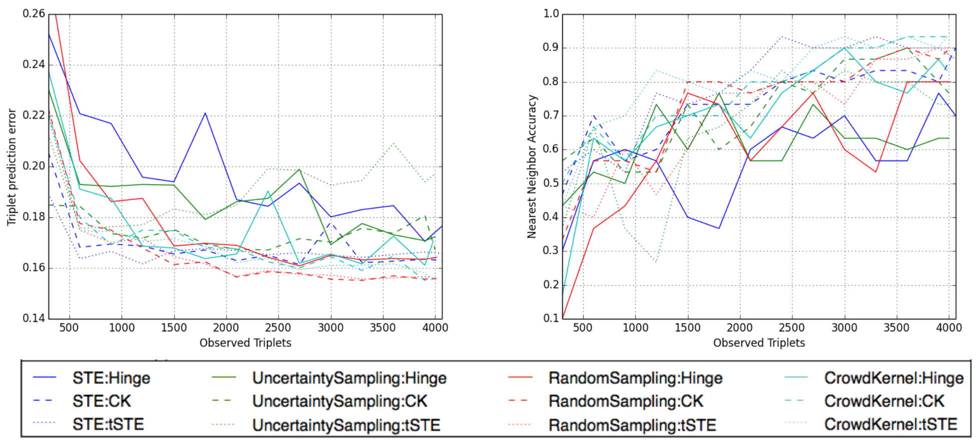


Figure 10: (Left) Triplet prediction error. (Right) Nearest neighbor prediction accuracy.