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Interactive Multimodal Learning on 100 Million Images

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ABSTRACT
This paper presents Blackthorn, an efficient interactive multimodal learning approach facilitating analysis of multimedia collections of 100 million items on a single high-end workstation. This is achieved by efficient data compression and optimizations to the interactive learning process. The compressed I64 data representation costs tens of bytes per item yet preserves most of the visual and textual semantic information. The optimized interactive learning model scores the I64-compressed data directly, greatly reducing the computational requirements. The experiments show that Blackthorn is up to 105x faster than the conventional relevance feedback baseline. Blackthorn is shown to vastly outperform the baseline with respect to recall over time. Blackthorn reaches up to 92% of the precision achieved by the baseline, validating the efficacy of the I64 representation. On the YFCC100M dataset, Blackthorn performs one complete interaction round in 0.7 seconds. Blackthorn thus opens multimedia collections comprising 100 million items to learning-based analysis in fully interactive time.

Keywords
Interactive multimodal learning; multimedia analytics; data compression; YFCC100M

1. INTRODUCTION
Multimedia collections are becoming the central information resource for a growing number of domains, such as physics, forensics, and marketing. This increases the need for methods for fast and insightful analysis of the data. Often, the analysts need to progress from the dataset to insight in hours or few days at most. For example, a journalist discovering stories about the Brussels terrorist attacks in the ensuing flood of social media content cannot wait weeks before publishing the story; she needs at least preliminary insights right away. An essential ingredient of insight gained in multimedia analytics in any knowledge domain is interaction [17, 28]. Currently, multimedia collections can easily reach millions of items, and even larger datasets are common. Behemoths such as the Yahoo Flickr Creative Commons 100M (YFCC100M) dataset [21] were not so long ago considered inconceivable challenges, yet to truly advance large-scale multimedia analytics, techniques for analyzing such large datasets are needed. How can interactivity in multimedia analytics be assured facing the rapid growth of collection size?

Interactive learning techniques, such as relevance feedback or active learning, are a good fit for multimedia analytics, as they elicit training data labels from the user directly and train the model based on them [9]. This paradigm aligns well with insight, the goal of multimedia analytics. Insight is iteratively built by the analyst through interaction with all or most of the data in the collection and application of the analyst’s domain knowledge [17, 28]. Since interactive learning trains its model online based on the user’s interactions, the analysis is timely. How to enable interactive and multimodal learning to support large-scale multimedia analytics using modest computational resources (standard high-end workstation with 64 GB RAM and 16-core CPU) is the research question addressed in this work.

In this paper we introduce Blackthorn, an efficient interactive multimodal learning approach for collections of 100 million multimedia items.∗ The architecture of Blackthorn is depicted in Figure 1. Blackthorn brings three main contributions: a multimedia content compression method allowing to fit billions of items into 64 GB of RAM; optimizations to the interactive learning process; and opening up the possibility of analytics on a collection of 100M multimedia items in interactive time (under 1 second per interaction round). To the best of our knowledge, no work has yet addressed fully interactive-learning-based exploration of an image dataset with 100 million items on a single workstation.

2. RELATED WORK
In response to the rapid growth of digital collections, a number of approaches facilitating more efficient search and exploration have been proposed. Interactive learning (e.g., relevance feedback) has been proven invaluable for improving multimedia information retrieval [9], and benchmarks such as the Video Browser Showdown were introduced [19]. However, the collections considered in these benchmarks are much smaller than the one considered in this work. In addition, most of current approaches employ entire computa-

*As this paper focuses on efficiency of interactive learning, the name is inspired by the efficiency of the blackthorn shrub: as fire wood, it yields much heat with little smoke.
Figure 1: Interactive learning with Blackthorn. The components of interactive learning innovated by Blackthorn are marked orange.

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The SVM scoring function $\sigma$ performs a vector multiplication of the model’s weight vector $w$ with the feature vector $x$, adding bias $b$ to the result. This costs $2n_f + 1$ mathematical operations (multiplications and additions) per item and modality. In the $\ell$-164 representation, only the $6\ell$ encoded features carry any value. Hence, we can obtain the SVM score by multiplying only the decompressed feature values by the corresponding values of the model’s weight vector $w$:

$$\sigma_c(I) = \sum_{j=0}^{i-1} \sum_{k=0}^{\ell_j-1} (w_{3(i\ell_j+k)} \cdot \delta(S, b_j + k)) + b$$ \hspace{1cm} (6)

This computation costs $42\ell + 1$ mathematical operations per item and modality. Since $\ell \ll n_f$, this amounts to a considerable speedup: for example, in a setting with $\ell = 1$ and $n_f = 1000$ (for instance, 1000 visual concepts), the number of mathematical operations is reduced 46.5x.

Late modality fusion is another aspect requiring attention with respect to algorithmic complexity. With a straightforward implementation, this requires $O(N \log N)$ time, which is higher than the $O(N)$ complexity of scoring. To reduce fusion complexity to $O(N)$, we follow the protocol of top-$d$ rank aggregation [7] in order to obtain the top $r$ relevant results. For each modality, the top-scoring $\nu$ ($r \leq \nu < n$) results in that modality are nominated to the final rank.
5 minutes is depicted in Figure 2. For all three evaluation measures, we compare svm_rf with the best-scoring \( \nu, \iota \) configuration of blackthorn. We have tested blackthorn with \( \nu \in \{100, 200, \ldots, 1000\} \) and \( \iota \in \{1, 2, 3\} \). Varying \( \nu \) has some impact on precision, with \( \nu = 100 \) reaching roughly 75% of the precision of \( \nu = 1000 \). Increasing \( \nu \) impacts the time per interaction round: \( \nu = 1000 \) costs roughly twice the time of the \( \nu = 100 \). Regarding recall over time, low \( \nu \) tends to outperform the higher values due to the lower time per interaction round. Regarding \( \iota \), we observe that increasing its value brings very minimal precision and recall gain, but has a negative impact on the time per interaction round. We believe that the low precision and recall gain is caused by insufficient decimal precision of the compressed values. We aim to investigate this further. Overall, we recommend choosing \( \iota = 1 \) in all cases, higher \( \nu \) for maximum precision, and lower \( \nu \) for maximum recall over time and speed.

The experiments clearly show that computational speed and efficiency are blackthorn’s forte. One interaction round of blackthorn on YFCC100M-California takes 0.05 ± 0.01 seconds on average across all evaluated \( \nu \) values, and the fastest configuration is 105x faster than svm_rf. The information loss incurred by the \( \nu \)-I64 representation turns out to be affordable. The highest-precision configuration of blackthorn keeps 92% of the average precision with a speed-up of 45. The recall over time plot (Figure 2) clearly shows that blackthorn dramatically surpasses svm_rf.

7. RESULTS ON YFCC100M

Our approach succeeded in the test of interactivity on the large dataset: on average across all \( \nu \) values, blackthorn takes 0.69 ± 0.01 seconds per interaction round. Figure 3 shows the development of recall over time on YFCC100M. Given the dataset’s prohibitive size, svm_rf is infeasible. In order to compare the approaches, we extrapolate svm_rf’s results on YFCC100M-California. Since svm_rf’s computational cost is \( O(N) \), the 3.16 second performance on 1.2M becomes roughly 4.3 minutes. Hence, only the first interaction round needs to be considered. The base extrapolation is twice the recall value of blackthorn’s recall in the first interaction round, following the trend observed on YFCC100M-California. In addition, we report two \( \lambda \)-extrapolated svm_rf baselines, where \( \lambda \in \{10, 100\} \) further multiplies the base extrapolation. We believe this more than compensates for any potential unverifiable factors influencing the true recall scalability. The results clearly show blackthorn’s efficiency with respect to recall gain over time: it is able to surpass all three interpolations in the first 5 minutes of the analysis.

The precision per interaction round on the YFCC100M dataset, averaged over all \( \nu \) values, is 0.003 ± 0.0001. Note that the low values are influenced by two important factors. Firstly, the size of the dataset brings an increase in noise and lower discriminative power of feature vectors. Secondly, the evaluation task is extremely difficult. Indeed, there are cases where the algorithm’s suggestions are evaluated as irrelevant, despite their semantic similarity to the provided positives. This is demonstrated in Figure 4. In a less strict setting, these suggestions could be easily deemed relevant. Despite the low values of precision, blackthorn does provide relevant suggestions even on the large dataset.

8. CONCLUSION

In this paper, we have presented Blackthorn, an efficient interactive multimodal learning framework which enables full interactive-learning-based analysis of a collection with 100M multimedia items. The data compression method of Blackthorn, \( \nu \)-I64, is shown to reduce the size of multimodal features by a factor of 220 and preserve most of the information contained in the original features. Blackthorn yields a massive 105x speed-up in comparison to the classic relevance feedback paradigm. The experiments further show that Blackthorn is suitable for the analysis of the entire YFCC100M dataset. It is able to learn on the fly from the user-provided training samples, and one interaction round on the entire 100M collection takes less than a second. Its high efficiency and low resource cost would also support multi-category exploration with proactive suggestions by the system. The analysis can be performed on a single standard high-end workstation with 64 GB RAM and 16 CPU cores. In order to foster further research on YFCC100M, the Blackthorn software package has been made available as an open-source tool [27]. In conclusion, Blackthorn is a step forward towards fully harnessing the wealth of information contained in large-scale multimedia collections.
9. REFERENCES


