Empowering Elasticsearch with Exact and Fast \( r \)-Neighbor Search in Hamming Space

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ABSTRACT

A growing interest has been witnessed recently in building nearest neighbor search solutions within Elasticsearch—one of the most popular full-text search engines. In this paper, we focus specifically on Hamming space nearest neighbor search using Elasticsearch. By combining three techniques: bit operation, substring filtering and data preprocessing with permutation, we develop a novel approach called FENSHSES (Fast Exact Neighbor Search in Hamming Space on Elasticsearch), which achieves dramatic speed-ups over the existing term match baseline. This will empower Elasticsearch with the capability of fast information retrieval even when documents (e.g., texts, images and sounds) are represented with binary codes—a common practice in nowadays semantic representation learning.

KEYWORDS

Elasticsearch, nearest neighbor search, Hamming space

1 INTRODUCTION

Elasticsearch (ES) [19], built upon Apache Lucene [7, 15, 26], is a real-time, distributed and multi-tenant full-text search engine. Since its first release in Feb. 2010, it has become the most popular enterprise search engine and widely adopted by a variety of companies (e.g., Ebay, Facebook, GitHub, Lyft, Shopify) for either internal or external uses to discover relevant documents.

Recently, efforts from both academia and industry [1, 27, 29, 30] have been actively made to empower Elasticsearch with the capability of (approximate) nearest neighbor search (NNS). This is largely driven by the great success, made by the field of deep learning [6, 18], in representing documents—including texts, images and sounds—as numeric vectors in a semantic manner (where similar images are located nearby). These efforts towards Elasticsearch have led to novel solutions to NNS with a number of favorable properties. First, by leveraging cutting-edge engineering designs from ES, such systems are extremely easy to be deployed, distributed and monitored. Moreover, due to Elasticsearch’s disk-based inverted index mechanism, NNS systems built upon Elasticsearch mainly consume secondary memory instead of RAM and thus quite cost-effective compared with conventional RAM-consuming approaches. Furthermore, as particularly pointed out by Mu et al. [27], enabling Elasticsearch with NNS paves a coherent solution to multimodal searches, allowing users to express their interests in both visual and textual queries (see Fig. 1), at which most of other NNS systems fall short.

In this paper, we focus on empowering Elasticsearch with fast and exact NNS in Hamming space (namely the set of binary codes). Specifically, given the binary dataset

\[ B = \{ b_1, b_2, \ldots, b_n \} \subset \{0, 1\}^m, \]  

we develop an efficient solution for Elasticsearch to find all \( r \)-neighbors of \( q \) in \( B \), namely

\[ B_H(q, r) := \{ b \in B \mid d_H(b, q) \leq r \}, \]
where \( d_H(b, q) := \sum_{i=1}^{m} d_i \cdot (b_i \neq q_i) \) denotes the Hamming distance between binary code \( b \) and \( q \). Finding nearest neighbors in Hamming space is an extremely important subclass of NNS, as learning and representing textual or visual data with compact and semantic binary vectors is a pretty mature technology and common practice in nowadays information retrieval. Using well-trained binary vectors instead of floating ones enables dramatic reductions in storage and communication costs without too much sacrifice in search accuracy [2, 17, 21, 24, 33, 34, 37]. However, most of the aforementioned scalable NNS solutions implemented on ES conduct approximate NNS by generating and indexing surrogate textual tokens merely based on information collected from several top entries of each floating vector in terms of magnitude, which would clearly fail for this Hamming case. Currently, the widely used approach on ES for exact Hamming space NNS is the term match one from LIRE, which we will review in Sec. 2. Its core idea is to calculate Hamming distance between two binary codes by matching their bits at each position. This is a natural way to leverage ES as a full-text search engine. However, this term approach treats binary digits in a textual way and heavily overlooks the intrinsic and special properties within binary codes. Motivated by this, in Sec. 3, we develop a novel approach called Fast Exact Neighbor Search in Hamming Space on Elasticsearch (FENSHSES) by combining three techniques: bit operation, which enables Elasticsearch to compute Hamming distance with just a few bit operations; sub-code filtering, which instructs Elasticsearch to conduct a simple but effective screening process before any Hamming distance calculation and therefore empower FENSHSES with sub-linear search times; data preprocessing with permutation, which preprocesses binary codes with appropriate permutation to maximize the effect of sub-code filtering. In Sec. 4, we show that FENSHSES outperforms the term match baseline dramatically in terms of search latency.

2 BASELINE APPROACH: TERM MATCH

Based on its definition, Hamming distance is nothing but the number of positions at which two binary codes vary. Elasticsearch, as a full-text search engine, can naturally compute this through term match [9]. In specific, for each binary code \( b \), we can index its positions corresponding to ones and zeros, respectively, i.e.,

\[
O_b = \{ i \in [m] \mid b_i = 0 \} \quad \text{and} \quad I_b = \{ i \in [m] \mid b_i = 1 \},
\]

with \([m] := \{1, 2, \ldots, m\}\). When the query binary code \( q \) arrives, Elasticsearch can simply calculate its Hamming distance to each binary code \( b \in B \) by matching its zero and one positions with \( b \)'s:

\[
d_H(b, q) = m - \left( \sum_{i \in I_q} \mathbb{1}_{\{i \in I_b\}} + \sum_{j \in O_q} \mathbb{1}_{\{j \in O_b\}} \right). \tag{2.1}
\]

It is worth noting that the \( r \)-neighbor search problem solved by the paper can also be easily adapted to conduct \( k \)-NN search by progressively increasing the Hamming search radius \( r \) until \( k \) neighbors are found.

The JSON-encoded request body to find \( B_H(q, r) \) by computing (2.1) is illustrated in JSON 1,\(^2\) where we denote \( u := [I_q] \) and \( v := [O_q] \). This term match approach together with its variants (e.g., using fuzzy query based on Levenshtein edit distance) is currently one of the most common approaches for full-text search engines to find nearest neighbors within binary codes. For example, the Java library LIRE [25] essentially applies the same methodology directly on Lucene to find visually similar images (based on their binary visual features), and LIRE’s ES implementation is also available [35] and widely used.

| JSON 1 Request body of the term match approach to the exact \( r \)-neighbor search in Hamming space |
|-----------------------------------------------|
| ```json |
|   "min_score": n-r, |
|   "query": { |
|     "function_score": { |
|       "functions": [ |
|         { "filter": { |
|           "term": { "Ib": Iq[1] } |
|         }, |
|         "weight": 1 |
|       }, |
|       "filter": { |
|         "term": { "Ob": Oq[1] } |
|       }, |
|       "weight": 1 |
|     ], |
|     "score_mode": "sum", |
|     "boost_mode": "replace" |
|   } |
| ``` |

\(^2\)All ES-related implementations are based on Elasticsearch 6.1.0.
3 PROPOSED APPROACH: FENSHSES
The term match approach treats each binary digit (i.e., bit) in a textual way, which heavily overlooks the intrinsic and special properties of binary codes. By making a better use of these properties, we introduce a novel approach called FENSHSES (Fast Exact Neighbor Search in Hamming Space on Elasticsearch), whose complete JSON-encoded ES request body can be found in JSON 4. In essence, FENSHSES integrates three techniques: bit operation, sub-code filtering and data preprocessing with permutation, which we will elaborate respectively in the following.

3.1 Bit Operation
Motivated by the fact that hamming distances between binary codes can be computed extremely fast using bit operations [36], in this part, we will explore how we can natively empower Elasticsearch to calculate hamming distances through bit operations.

For an m-bit binary code b, we will first segment it into s sub-codes:\n\[
\begin{bmatrix}
[b_1, \ldots, b_{m-2}, b_{m-1}], & \ldots, & b_m, & \ldots, & b_m, \ldots, b_{m-2}, b_{m-1}]
\end{bmatrix}
\]

(3.1)

Since \( d_H(q, b) = \sum_{i=1}^{s} d_H(q^i, b^i) \), the Hamming distance calculation is reduced into s ones with binary codes of much shorter length. The Hamming distance between two short binary codes of length 64 or less can be efficiently computed through just a few bit operations [5, Item 169], which we implement as an Elasticsearch script called hmd64bit (see JSON 2) in the language of Painless—a simple and secure scripting language designed specifically for use with ES [13]. When the query binary code q is issued, we will invoke hmd64bit s times to calculate \( \{d_H(q^i, b^i)\}_{i=1}^{s} \) by specifying \( q^i \) and \( b^i \) as parameters accordingly and then sum them up. The whole process can be efficiently implemented in ES using the function score query [8], where several functions are combined to calculate the score of each document (see lines 15-31 in JSON 4).

JSON 2 Create the script called hmd64bit into Elasticsearch cluster through the _scripts:end-point.

POST _scripts/hmd64bit
{
  "script": "painless",
  "source": "long u = params.subcode"doc[params.field].value;
  long uCount = u;((u>>>1)&-5276498386774157605L)
  -((u>>>2)&-7905747460161236407L);
  return ((uCount + (uCount >>> 3))
    & 819855292164869807L) % 63;
}

3.2 Sub-Code Filtering
So far, regardless of the term match approach or the bit operation one, we have to exhaustively compute the Hamming distance between q and each binary code in \( \mathcal{B} \). This expensive linear scan is not desirable for many applications where the number of codes in \( \mathcal{B} \) is in the order of millions or even billions [38]. As a remedy, in this part, we will leverage a simple counting argument to conduct a screening process before any Hamming distance calculation, which successfully empowers our FENSHSES approach with sub-linear search times.

Suppose binary codes are segmented into s sub-codes as in (3.1). Then for two codes \( b \) and \( q \) within \( \mathcal{R} \) Hamming distance, among all their \( s \) sub-code pairs \( \{b^i, q^i\}_{i=1}^{s} \), there must be at least one pair with Hamming distance no larger than \( \lfloor \frac{r}{s} \rfloor \), which mathematically implies

\[
B_H(q, r) \subseteq \bigcup_{i=1}^{s} \left\{ b \in \mathcal{B} \middle| b^i \in B_H\left(q^i, \lfloor \frac{r}{s} \rfloor \right) \right\}.
\]

(3.2)

This simple counting argument yields great potentials in reducing the number of Hamming distance calculations needed to find all \( r \)-neighbors \( q \) in \( \mathcal{B} \). Specifically, according to relationship (3.2), it is safe to just consider binary codes belonging to the set on the right side of (3.2), whose size could be substantially smaller than \( n \) for \( r \ll m \). It is worth noting that similar ideas have been frequently revisited in many different contexts—e.g., to build multi-index hashing tables [20, 28].

This screening process can be easily conducted on Elasticsearch using the filter context [11] (see lines 8-14 in JSON 4), within which each sub-code Hamming ball \( B_H(q_i, \lfloor \frac{r}{s} \rfloor) \) is obtained by the terms query [14] (e.g., line 11 in JSON 4), and the union is achieved through a boolean combination of should clauses [10].

3.3 Data Preprocessing with Permutation
The effectiveness of sub-code filtering will be maximized if the bits within the same sub-code group are statistically independent. Since hamming distance is invariant to permutation transformation, it is tempting to transform binary codes in \( \mathcal{B} \) with appropriate permutation towards this desired group independence property.

For two Bernoulli random variables \( x \) and \( y \), they are independent if and only if their correlation coefficient \( \rho(x, y) = 0 \). Therefore, it is natural to find a permutation \( \pi \) to minimize correlation effects among each sub-code segment. This immediately leads to the following mathematical optimization known as balanced graph partitioning [3, 4, 22, 23, 32]:

\[
\min_{\pi : [m]\rightarrow [m]} \langle D, \pi^* M \pi^T \rangle
\]

s.t. \( \pi \) is a permutation.

(3.3)

Here \( D = \text{diag}(I_{d\times d}, \ldots, I_{d\times d}) \in \mathbb{R}^{m\times m} \) is a block diagonal matrix with \( I_{d\times d} \) as a matrix of ones and \( d = m/s \). \( P_{\pi} \) is the permutation matrix induced by \( \pi \):

\[
P_{\pi} = [\mathbf{e}_{\pi(1)}, \mathbf{e}_{\pi(2)}, \ldots, \mathbf{e}_{\pi(m)}]^T
\]

and \( M \) is a matrix in \( \mathbb{R}^{m\times m} \) whose \( (i,j) \)-entry is obtained from \( \mathcal{B} \) as the absolute value of the correlation between the \( i \)-th and the \( j \)-th bits. We solve problem (3.3) by the well-known
and scalable Kernighan-Lin algorithm [22], the gist of which is to find appropriate pairs \(i, j \in [m]\) and swap their mappings in \(\pi\) with \((\pi(i), \pi(j)) \leftrightarrow (\pi(j), \pi(i))\). We leave it as a future work to solve (3.3) by more recently developed approximation algorithms with better theoretical guarantees: e.g., the one based on semidefinite relaxation [23].

### 3.4 Elasticsearch index for FENSHSES

For the proposed FENSHSES approach, the data to be indexed into Elasticsearch cluster is pretty minimal. For each binary code \(b \in B\), we only need to index its sub-codes \(\{b^1, b^2, \ldots, b^s\}\) (see JSON 3). For the scenario that bit operation and sub-code filtering segment binary codes differently, we would index two sets of sub-codes into the same Elasticsearch index by treating each set as a nested datatype [12].

| JSON 3 Request body to create the Elasticsearch index and define its mapping to support the FENSHSES approach. |
|-------------------------------|
| PUT /fenshes/ subcodes/_mapping |
| {                               |
|   "properties": {              |
|     "b1": {"type": "long"},   |
|     ...,                       |
|     "bs": {"type": "long"}    |
| }                               |
| }                                |
|                                 |

### 4 EXPERIMENT

We will compare search latencies between the term match approach and FENSHSES for the application of content-based image retrieval on Elasticsearch.

**Settings.** Our dataset \(B\) consists of binary codes generated from half a million images selected from Jet.com’s furniture catalog. Specifically, each image is first embedded into a vector in \(\mathbb{R}^{1536}\) by taking the output from the penultimate layer (i.e., the last average pooling layer) of the pretrained INCEPTION-ResNet-V2 model [31], and then hashed into compact binary codes in \(\{0, 1\}^m\) using iterative quantization (ITQ) [16], where \(m \in \{128, 256\}\). Each Elasticsearch index is created with five shards and zero replica on a single-node Elasticsearch cluster deployed on a Microsoft Azure virtual machine with 12 cores and 112 GiB of RAM.

Evaluation. To better understand the contribution of each technique involved in FENSHSES, we experiment systematically with four methods: the term match baseline, FENSHSES with just bit operation, FENSHSES without data preprocessing and FENSHSES, where we always choose the sub-code length as 64 for bit operation and 16 for sub-code filtering. We randomly select 1,000 binary codes from \(B\) to act as query codes \(q\). For each \(q\), we compare the average search latencies among all four methods with Hamming distance \(r \in \{5, 10, 15, 20\}\).

4 More accurately speaking, what being indexed are the integers represented by the binary sub-codes.

### Results

As shown in Fig. 2 and 3, FENSHSES is dramatically faster than the term match baseline, and all of the three techniques involved in FENSHSES contribute substantially to this performance improvement. Specifically, the speed-ups achieved range from one hundred times (for \(r = 20\)) to six hundred times (for \(r = 5\)). This difference in speedup is much expected, as the sub-code filtering technique will be most effective when \(r\) is small.

#### Figure 2: Experimental results for 128-bit binary codes.

#### Figure 3: Experimental results for 256-bit binary codes.

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