Torchhd: An Open-Source Python Library to Support Hyperdimensional Computing Research

Mike Heddes, Igor Nunes, Pere Vergés, Dheyay Desai, Tony Givargis and Alexandru Nicolau
Department of Computer Science, University of California, Irvine
Irvine, California, United States of America
{mheddes,igord,pvergesb,desaidn,givargis,nicolau}@uci.edu

Abstract
Hyperdimensional Computing (HDC) is a neuro-inspired computing framework that exploits high-dimensional random vector spaces. HDC uses extremely parallelizable arithmetic to provide computational solutions that balance accuracy, efficiency and robustness. This has proven especially useful in resource-limited scenarios such as embedded systems. The commitment of the scientific community to aggregate and disseminate research in this particularly multidisciplinary field has been fundamental for its advancement. Adding to this effort, we propose Torchhd, a high-performance open-source Python library for HDC. Torchhd seeks to make HDC more accessible and serves as an efficient foundation for research and application development. The easy-to-use library builds on top of PyTorch and features state-of-the-art HDC functionality, clear documentation and implementation examples from notable publications. Comparing publicly available code with their Torchhd implementation shows that experiments can run up to 104× faster. Torchhd is available at: https://github.com/hyperdimensional-computing/torchhd

CCS Concepts: • Computing methodologies → Parallel computing methodologies; Machine learning; Bio-inspired approaches.

Keywords: hyperdimensional computing, vector symbolic architectures, machine learning

1 Introduction
Recent changes in computing technologies and applications have presented obstacles to the established, von Neumann-based, computational frameworks. This scenario, predominantly driven by Machine Learning (ML) workloads, has encouraged research in neuromorphic computing paradigms (also known as: brain-like, unconventional and natural computing) [14]. While the conventional architecture was designed with the assumption of precise components that provide exact answers, the “hardware of the future” is expected to operate with massive parallelism, in the nanoscale, with ultra-low voltage and unreliable components. This stochastic execution environment would in turn, better serve some important computational demands [19]. Among these emerging platforms, one that has attracted increasing attention is Hyperdimensional Computing (HDC) [17], also known as Vector Symbolic Architecture (VSA) [8]. HDC is a Turing complete computing framework that serves as an abstraction layer between the emerging hardware architectures and applications [20]. The framework is grounded in the mathematical properties of high-dimensional random vector spaces [16]. In these spaces, all information is represented using random points of very high—but fixed—dimension, called hypervectors. Applications built on HDC consist of manipulating, combining and comparing these hypervectors. Important examples of such applications range from natural language processing [34], graph learning [27] and gesture/voice recognition [13, 33], to dynamic hashing techniques [11]. See Section 3.4 for more details.

HDC’s initial ideas date back more than three decades and since then its motivations and theoretical framework have strengthened [7, 23, 32, 39]. Despite this, it was only recently that HDC started gaining momentum and attracting attention from the wider ML community [21]. In face of this growing interest, there has been great effort to disseminate HDC by its research community. One of the main challenges in this initiative has been the fact that HDC involves many disciplines, including computer science, neuroscience, machine learning, electrical engineering and mathematics. Keeping up with the latest advances is not trivial as publications are spread across different venues and fields. This context makes it challenging, but extremely important, to create mechanisms to facilitate and integrate research endeavors. Despite the important and commendable effort to carry out detailed surveys of the area [10, 21, 22], much less attention has been paid towards facilitating the translation of concepts and methodologies into implementations.

Given this context, we present Torchhd—an open-source Python library for HDC. Up to date with the latest advances in the field, Torchhd aims to make HDC more approachable for novices in the area and to provide a high-performance execution platform for experienced researchers. Our design philosophy focuses first on ease-of-use, aiming to be accessible without limiting expressiveness, and secondly on performance, facilitating much faster evaluation of new algorithms. We believe that Torchhd will benefit the HDC/VSA community based on its following aspects:

• State-of-the-art HDC components for hypervector encoding and data structures;
• Modular design, supporting both learning and non-learning related workflows;
• Python idiomatic interface design for a flexible, developer-first experience;
• High-performance execution, which means that applications can run up to 104× faster;
• Support for automatic differentiation solutions for learning-based HDC applications;
• Greater community collaboration potential due to its open-source nature;
• Complete, clear and concise documentation;
• Interfaces for several datasets commonly used in the literature to evaluate HDC methods;
• A direct mapping from theory to implementation, as didactically described in this manuscript;
• Implementations of several notable publications to be used as examples and to facilitate follow-up studies.

The remainder of the manuscript is organized as follows: it starts with a thorough, yet accessible, introduction to HDC in Section 2. Then, Section 3 discusses the design of Torchhd and its features. In Section 4 we describe the experiments and their results using the library. Finally, in Section 5 we present our conclusions.

2 Hyperdimensional Computing

Hyperdimensional Computing (HDC) [17], also known as Vector Symbolic Architecture (VSA) [8], is a computing framework whose theory emerged from attempts to understand the animal nervous system [19]. HDC can represent a "concept space" by exploiting the geometry and algebra of high-dimensional random vector spaces. Intuitively, it enables metaphorical and by analogy reasoning like the animal brain [18]. The central idea is to represent information \( x \in X \) by projecting it onto a hyperspace \( \mathcal{H} \) with \( d \) dimensions.

Many variations of the hyperspace have been proposed, ranging from binary till complex numbers [37], however, they are all largely similar at a conceptual level. Typically, the space is binary \( \mathcal{H} = \{0, 1\}^d \) or bipolar \( \mathcal{H} = \{-1, 1\}^d \) with \( d \approx 10,000 \) dimensions. For the remainder of this manuscript we assume bipolar hypervectors. At the core of HDC is the mapping \( \phi : X \rightarrow \mathcal{H} \), called encoding, which will be extensively discussed throughout this section. The encoding has an important property: the resulting representations in \( \mathcal{H} \), called hypervectors, are holographic, i.e., each dimension is independently and identically distributed (i.i.d.). This property makes hypervectors inherently robust, since each dimension carries exactly the same amount of information.

To perform cognitive tasks, the encoding function must map similar objects in the input space \( X \) to similar hypervectors in \( \mathcal{H} \). Hypervector similarity is commonly measured using the cosine similarity, denoted by \( \delta : \mathcal{H} \times \mathcal{H} \rightarrow \{\sigma \in \mathbb{R} \mid -1 \leq \sigma \leq 1\} \). Every application in HDC is ultimately based on this similarity. Classification tasks, for example, are based on the similarity of an encoded sample with the class prototypes (see Section 2.4). Both the information encoding and the creation of prototypes (models) are done using HDC arithmetic. The arithmetic manipulates and combines hypervectors in a structured way.

Next, we present a detailed and didactic description of the elements and concepts that constitute HDC. The definitions will be exemplified using the fictitious data records in Table 1. In Section 3, we describe the proposed Python library based on the notation and ideas presented here.

### 2.1 Basis-hypervectors

**Basis-hypervectors**, also called seed or atomic hypervectors, are sets of hypervectors that represent, i.e., encode, the smallest units of meaningful information in the hyperspace. In Table 1, the atomic information is the possible fruit types, fruit weights, and seasons of the year. Since the nature of these information sets is different, so are the basis-hypervisor sets used to encode them. The different sets of basis-hypervectors are illustrated in Figure 1 and described below.

#### Random-hypervectors

In this set, each hypervector is sampled uniformly at random from the hyperspace. Because of the high dimensionality of \( \mathcal{H} \), each pair of symbols \( R_i \) and \( R_j \) in \( R = \{R_1, \ldots, R_m\} \) (with \( i \neq j \)) is quasi-orthogonal with high probability [16]. For this reason, it is used to map (one-to-one) categorical/symbolic data, such as the **Fruit types** in Table 1, to the hyperspace. We denote by \( \phi_R(x) \) the hypervector in \( \mathcal{H} \) used to encode the atomic information \( x \) using random-hypervectors.

#### Level-hypervectors

The set \( L = \{L_1, \ldots, L_m\} \) is used to encode linearly correlated information, usually representing

<table>
<thead>
<tr>
<th>Record</th>
<th>Fruit (F)</th>
<th>Weight (W)</th>
<th>Season (S)</th>
</tr>
</thead>
<tbody>
<tr>
<td>r₁</td>
<td>mango</td>
<td>173.2</td>
<td>summer</td>
</tr>
<tr>
<td>r₂</td>
<td>lemon</td>
<td>70.5</td>
<td>winter</td>
</tr>
<tr>
<td>r₃</td>
<td>apple</td>
<td>149.0</td>
<td>fall</td>
</tr>
</tbody>
</table>

**Figure 1.** Pairwise similarity of each \( i \)-th and \( j \)-th hypervector within a basis-hypervisor set of size 10. Comparing between random, level and circular basis-hypervectors.
a subinterval of the real number line $\mathbb{R}$. Examples include: distance, time, energy and, in our Table 1 case, the Weight of a fruit. Unlike random-hypervectors, these vectors are generated from an interpolation of vectors $L_1$ and $L_m$ which are the only two that are sampled uniformly at random from the hyperspace. Each hypervector in $L$ is associated with a value, such that the distance of the values in $\mathbb{R}$ is proportional to the distance of their respective hypervectors. We represent by $\phi_L(x)$ the encoding of $x$ using level-hypervectors.

**Circular-hypervectors.** Another important type of information, whose correlation profile is not captured by the sets above, is circular data [31]. This kind of data is derived from the measurement of directions, usually expressed as an angle in $\Theta = [0, 2\pi]$. It is also common to handle time measurements, like the Seasons of the year in our example, as circular data. The set, denoted by $C = \{C_1, \ldots, C_m\}$, is built on the construction of level-hypervectors, but is divided into forward and backwards transformations, making the distance between the hypervectors proportional to the distance of the angles in $\Theta$ that they represent. We denote by $\phi_C(x)$ the hypervector in $C$ used to encode the atomic information $x$ using circular-hypervectors.

For an in-depth study on the characteristics of each basis-hypervector set and a detailed description of the algorithms for their creation, we recommend Nunes et al. [26].

### 2.2 Operations

Arithmetic in HDC is based on three operations: binding, bundling, and permuting, outlined below. These functions are dimension-independent and yield hypervectors in the same space as the operands, allowing recursive compositions.

**Binding.** The binding function $\otimes : \mathcal{H} \times \mathcal{H} \rightarrow \mathcal{H}$ performs element-wise multiplication on two input hypervectors to produce a third vector dissimilar to both operands. This operation is commonly used to “associate” information, for instance, to assign values to variables. The hypervector $\phi_R(F) \otimes \phi_R(\text{apple})$ can be used to represent the variable-value pair Fruit-apple of record $r_1$ in Table 1, where the variable name, i.e., its symbol, is encoded using random-hypervectors. Binding is commutative, serves as its own inverse, i.e., $A \otimes (A \otimes B) = B$, and is distributive over bundling.

**Bundling.** The bundling operation is used to aggregate information into a single hypervector. The function $\oplus : \mathcal{H} \times \mathcal{H} \rightarrow \mathcal{H}$ performs element-wise addition on its inputs to produce a vector that is maximally similar to the operands. In this way, record $r_1$ from our example can be encoded to a single hypervector as the aggregate of variable assignments:

$$\phi(r_1) = [\phi_R(F) \otimes \phi_R(\text{apple})] \oplus [\phi_R(W) \otimes \phi_L(149.0)]$$

$$\oplus [\phi_R(S) \otimes \phi_C(\text{fall})]$$

The encoding uses the appropriate basis-hypervectors based on the concepts presented in Section 2.1.

**Permuting.** The permutation operator is used to assign an order to hypervectors. The function $\Pi : \mathcal{H} \rightarrow \mathcal{H}$ outputs a hypervector that is dissimilar to its input. The exact input can be retrieved with the inverse operation. Cyclic shift is the most commonly used permutation and with $\Pi^i(A)$ we denote a cyclic shift of the elements of $A$ by $i$ coordinates. Suppose that in the example of Table 1, we want to represent not only the fruits and their characteristics, but also someone’s preference order, say mango, apple then lemon. This sequence of records can be encoded as $\phi(r_1) \odot \Pi^1(\phi(r_1)) \odot \Pi^2(\phi(r_2))$. In real applications, permutation has been used to represent time series and n-grams (see Section 3.4).

A significant effort in HDC has been devoted to developing new and better encoding strategies. Encoding functions are generally application specific and are critical in successfully applying HDC to a problem. In the following section we will describe common encoding patterns.

### 2.3 Encodings

Encoding patterns are used to combine multiple atomic pieces of information to encode something more complex. Examples include encoding text from characters [34], graphs from vertices and edges [27], time series from samples [33] and images from pixel values [24], among others. Below we present some of the existing strategies.

**Multisets.** The simplest method to combine information in hyperspace is to create a multiset. A multiset is created by bundling values together, forming a hypervector that is similar to the inputs. The equation below shows the creation of a multiset from the input hypervectors $\{V_1, V_2, \ldots, V_m\}$:

$$\phi_{\text{multiset}}(V_1, V_2, \ldots, V_m) = V_1 \oplus V_2 \oplus \ldots \oplus V_m$$

A multiset can be queried to determine whether it contains a given value by calculating the similarity of the value with the set. If the similarity is close to 1 the element is in the set with high probability. Moreover, the number of occurrences of a value can be determined using the dot product, making it a multiset. For more details on the information retrieval and capacity aspects of multisets refer to Thomas et al. [39].

**Hash tables.** To combine values with different semantic meaning it is common to introduce a key $K_i$ for each value $V_i$. The combined representation, called a hash table, is then encoded as the bundling of all bound key-value pairs [17, 32]:

$$\phi_{\text{hash-table}}(K_1, V_1, K_2, V_2, \ldots, K_m, V_m) = \bigoplus_{i=1}^{m} K_i \otimes V_i$$

This is the method used to illustrate the encoding of the fruits in Table 1. The value associated with a key can be efficiently queried, like a hash table in programming. This is done by unbinding, i.e., binding again (see self-inverse property in Section 2.2), the hash table with the key and comparing the similarity of the resulting hypervector with
the set of basis-hypervectors for the value. The most similar basis-hypervector is the value sought. This similarity search is equivalent to a memory lookup using associative memory.

**Sequences.** A sequence is encoded as a multiset of permuted values, where the number of permutations depends on the index of the value in the sequence [17, 32]:

$$\phi_{\text{sequence}}(V_1, V_2, \ldots, V_m) = \bigoplus_{i=1}^m \Pi^{m-i}(V_i)$$

This bundling-based sequence encoding is used especially when it is important to compare the similarity between sequences. Alternatively, one can use binding-based sequences, where the permuted values are bound together instead of bundled. In this strategy, which has already proved useful in some applications [15, 34], even sequences that differ in only one element are completely dissimilar in hyperspace.

The bundling-based sequences can also be used to implement other common data structures such as stacks and queues [20, 32, 41]. To implement both methods for pushing and popping values from the beginning and end of the sequence need to be defined:

$$\text{lookup}(S, i) = \text{cleanup}(\Pi^{-m+i}(S))$$
$$\text{pushend}(S, V) = \Pi(S) \cup V$$
$$\text{pushstart}(S, V) = \Pi^m(V) \cup S$$
$$\text{popend}(S) = \Pi^-(V \cup \text{lookup}(S, m))$$
$$\text{popstart}(S) = S \cap \Pi^{m-1}(\text{lookup}(S, 1))$$

where $S$ is a sequence of length $m$. The cleanup function performs an associative memory lookup of the given value, returning the original hypervector and thus removing noise introduced by the bundling of multiple values. The $\oplus$ symbol represents the inverse operation to bundling.

**N-grams.** Statistics of $n$-grams from textual data are often used in natural language processing [56]. In HDC, an $n$-gram is encoded by binding $n$ consecutive tokens. A token $V_i$ can be a word or a character, typically encoded using random-hypervectors. The entire text is then encoded as a multiset of all the $n$-grams [15, 34]:

$$\phi_{n\text{-gram}}(V_1, V_2, \ldots, V_m) = \bigoplus_{i=1}^{m-n+i} \Pi^{n-1-j}(V_{i+j})$$

**Graphs.** A graph $G = (V, E)$ is usually represented in the hyperspace as a multiset of its edges $E$. Each edge in turn is encoded by binding its connecting vertices $V$ [9, 27]:

$$\phi_{\text{graph}}(G = (V, E)) = \bigoplus_{(V_i, V_j) \in E} V_i \otimes V_j$$

where the hypervector $V_i$ is the encoded vertex at index $i$. In the case of directed graphs, a permutation operator is applied to the destination vertex to differentiate edges $(V_i, V_j)$ and $(V_j, V_i)$. A graph can be queried to find the neighbors of a node by binding the graph with the node hypervector (followed by an inverse permutation, for directed graphs). All the nodes that are similar to the resulting hypervector are connected to the given node with high probability.

**Random projections.** Alternatively, an information vector $x \in \mathbb{R}^m$ can be mapped to the hyperspace directly using a random projection $\phi_{\text{project}}(x) = \text{sign}(\Phi x)$, where $\Phi \in \mathbb{R}^{d \times m}$ is a matrix whose rows are uniformly sampled at random from the surface of an $m$-dimensional unit sphere. This encoding ensures that similarities in the input space are preserved in the hyperspace [39]. Variations of the projection encoding have been proposed with different nonlinearities and weights sampled from other distributions [4, 12, 43].

### 2.4 Classification

In a learning setting, the encoding methods described above are used to map the data samples to the hyperspace. These samples then need to be combined to form a model. As an illustration, consider a large dataset with fruit records like those in Table 1, where each record has a class label, e.g., the fruit taste: sweet, sour, salty, bitter, etc. If we denote the label of each record $r$ by $l(r) \in \{1, \ldots, k\}$, we can use the hypervectors of each record to create a prototype hypervector $M_i$ for each class $i \in \{1, \ldots, k\}$ as follows:

$$M_i = \bigoplus_{j: l(r_j) = i} \phi(r_j)$$

Each of these hypervectors is referred to as a class-vector.

By building a class-vector for each class, we can combine them as a classification model $M = \{M_1, \ldots, M_k\}$ and use it to predict the class of new records. Given an unlabeled input $\hat{r} \in X$ and $M$, we simply compare $\phi(\hat{r})$, called the query-vector, with each class-vector and infer that the label of $\hat{r}$ is the one that corresponds to the most similar class-vector:

$$\ell^*(\hat{r}) = \arg \max_{i \in \{1, \ldots, k\}} \delta(\phi(\hat{r}), M_i)$$

where $\ell^*(\hat{r}) \in \{1, \ldots, k\}$ is the predicted class for $\hat{r}$.

This concludes the overview of HDC concepts, which will now be used in the description of Torchhd.

### 3 Torchhd

The proposed Torchhd library aims to support a wide variety of HDC/VSA applications and research directions. The provided functions and classes are therefore designed to be modular, enabling users to adopt the aspects that support their workflow. A typical ML workflow, for instance, differs greatly from that of a dynamic hash table, yet both are easily implemented with Torchhd because of its modularity. These examples, among others, will be discussed in Section 3.4.

Our second goal is to provide a simple programming experience, easy enough for those new to HDC to understand, while not limiting its expressiveness. As will be demonstrated...
in Section 3.3, Torchhd provides direct abstractions between the HDC concepts presented in Section 2 and their implementation. This means that application-driven research can focus on the conceptual and methodological aspects of the project. At the same time, for theoretical studies, Torchhd enables the study of atomic elements of HDC, *ceteris paribus*.

The third goal of the library is to provide high-performance execution without hurting the Python idiomatic development experience. Section 3.1 explains how Torchhd is designed to leverage the performance and features of *PyTorch*, renowned by the greater ML community. The results in Section 4.3 show the performance that this design achieves.

Torchhd is developed for Python because the high-level language aligns with our design principles and is the de facto standard for computation-driven research [25]. In addition, the many active research directions in emerging hardware [20] make it difficult to target a specific architecture.

### 3.1 Design

Torchhd consists of four modules, shown in Figure 2. The functional module contains the core functionality, such as functions to create basis-hypervectors, the HDC operations and common encodings. The embeddings module provides embedding classes for basis-hypervectors, and random projections. The structures module contains classes for HDC data structures such as multisets, hash tables, sequences and graphs. The datasets module provides convenient access to datasets commonly used in the HDC literature.

![Figure 2. Overview of the Torchhd library modules.](image)

All the modules are built on PyTorch [30], an open-source library from Facebook AI Research for high-performance Deep Learning. It performs computations based on tensors and provides many of the functions that can be found in scientific computing libraries such as Numpy [28]. In addition, PyTorch and its ecosystem provide many ML utilities, support for hardware accelerators such as GPUs, and built-in automatic differentiation [29]. Our design makes the renowned features of PyTorch available for HDC research as well. Moreover, this architecture enables the exchange of knowledge between HDC and the wider ML community.

The design philosophy of Torchhd follows the same principles of PyTorch. We provide abstractions that work in combination with the PyTorch ecosystem and deliver pragmatic performance by building on the highly-optimized C++ PyTorch core. The library’s implementation is verified with extensive automatic unit testing. We also place an emphasis on clear and concise documentation, which is available at: https://torchhd.readthedocs.io

### 3.2 Hypervector representation

Torchhd computes according to the bipolar variant of the Multiply-Add-Permute (MAP-B) operation set [9, 37]. The properties of this architecture are described in Section 2.2.

The hypervectors are represented as 32-bit floating-point tensors by default. The high precision makes them simple to work with and enables numerous applications. For instance, in combination with PyTorch’s automatic differentiation, this enables Torchhd to support active research into learning-based HDC methods as will be discussed in Section 3.3. Lower precision can still be achieved by composing the bundle operation with quantization.

Despite being less efficient than Boolean values, the use of floating-points is more fitting for Torchhd because it prioritizes ease-of-use over performance. Nonetheless, Torchhd outperforms publicly available implementations of notable publications, as will be shown in Section 4.3. Performance-first approaches, such as FPGA implementations [13, 34], are considered orthogonal to Torchhd because their performance comes at the usability cost of hardware programming.

### 3.3 Features

This section will highlight the features of the library and their simplicity using the same example of the fruit records in Table 1. This connects the concepts mathematically described in Section 2 with the library implementation.

**Creating hypervectors.** The functional module provides functions for each basis-hypervector set described in Section 2.1. These functions return a tensor with randomly generated hypervectors that have the desired correlation. The hypervectors for the atomic information from Table 1 can be generated as follows:

```python
from torchhd import functional
d = 10000  # dimensions
F = functional.random_hv(3, d)  # fruits
W = functional.level_hv(10, d)  # weights
S = functional.circular_hv(4, d)  # seasons
V = functional.random_hv(3, d)  # variables
```

which creates hypervectors for the 3 fruit types, 10 weight levels, 4 seasons and the 3 variables (columns of Table 1).

Similar behavior can be achieved using the classes in the embeddings module. The classes add convenience methods for mapping values to hypervectors. For example, to map
the interval $[0, 200]$ to the ten weight hypervectors the functional version above requires an explicit mapping to an index:

```python
import torch
weight = torch.tensor([149.0])
# explicit mapping of the fruit weight to an index
w_i = functional.value_to_index(weight, 0, 200, 10)
W[w_i]  # select representation of 149
```

whereas the classes in the embeddings module have this common behavior built-in, simplifying development:

```python
from torchhd import embeddings
W_emb = embeddings.Level(10, d, low=0, high=200)
# select representation of 149
W_emb(weight)  # same result as W[w_i]
```

**Operations.** Once the basis-hypervectors are defined, we can use the MAP operations described in Section 2.2 to represent more complex objects. A separate operation for quantization is provided to simulate lower precision if needed. The hypervector for record $r_1$ can then be created as follows:

```python
f = functional.bind(V[0], F[0])  # fruit = apple
w = functional.bind(V[1], W[w_i])  # weight = 149
s = functional.bind(V[2], S[3])  # season = fall
r1 = functional.bundle(functional.bundle(f, w), s)
# equivalent short-hand encoding of record $r_1$:
```

**Data structures.** The common encoding patterns described in Section 2.3 are provided in the functional module. Using these, record $r_1$ can be encoded as follows:

```python
# combine values in one tensor of shape (3, d)
values = torch.stack([F[0], W[w_i], S[3]])
r1 = functional.hash_table(V, values)
```

The structures module contains the same encoding patterns in addition to binary trees and finite state automata, but provides them as data structures. To the best of our knowledge we are the first to provide extensive class-based implementations of these HDC data structures. Using the hash table class, record $r_1$ can be implemented as follows:

```python
from torchhd import structures
r1 = structures.HashTable(d)  # r1 = Ø
r1.add(V[0], F[0])  # r1 = V[0] + F[0]
r1.add(V[1], W[w_i])  # r1 = V[1] + W[w_i]
```

The query results are noisy versions of the value hypervectors. In Figure 3 we compare their similarity to the basis-hypervectors. The season, for example, is most similar to the Fall hypervector, but it also shares similarity with the neighboring seasons because of the circular correlation.

![Figure 3. Similarities between the basis-hypervectors and the query result of the respective key on record $r_1$.](image)

**Automatic differentiation.** As the backbone of modern deep learning, automatic differentiation allows researchers to focus on the model architecture while the library controls gradient descent. Connections between gradient descent and HDC training have been explored in a number of publications [5, 12, 13]. Torchhd facilitates this research direction by exploiting the vast gradient descent infrastructure developed for PyTorch. Torchhd can therefore connect HDC to the broader ML community, enabling the development of hybrid architectures. To highlight this feature, in Section 4.2 we experiment with a novel hybrid architecture that switches between efficient HDC learning and gradient descent.

**Datasets.** The datasets module provides interfaces to eight commonly used datasets in HDC. Shown in Table 2, these datasets include several classification and regression tasks. The interface of each dataset inherits from PyTorch’s dataset class, ensuring interoperability with other datasets in the PyTorch ecosystem, such as those in Torchvision, Torchaudio, Torchtext, and Torch Geometric [6]. The following is an example of using the ISOLET dataset:

```python
from torchhd import datasets
# download dataset into data directory
data = datasets.ISOLET("data", download=True)
# direct indexing, i.e., map-style access
sample, target = data[24]
```
Table 2. Datasets

<table>
<thead>
<tr>
<th>Name</th>
<th># Features</th>
<th># Targets</th>
<th>Train size</th>
<th>Test size</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ISOLET [3]</td>
<td>617</td>
<td>26</td>
<td>6,238</td>
<td>1,559</td>
<td>Classify letters from speech</td>
</tr>
<tr>
<td>UCIHAR [1]</td>
<td>561</td>
<td>12</td>
<td>6,213</td>
<td>1,554</td>
<td>Classify activities from mobile data</td>
</tr>
<tr>
<td>European languages [34]</td>
<td>2 - 1,133</td>
<td>21</td>
<td>210,032</td>
<td>21,000</td>
<td>Classify European languages from text</td>
</tr>
<tr>
<td>Beijing air quality [42]</td>
<td>17</td>
<td>NA</td>
<td>420,768</td>
<td>NA</td>
<td>Various air quality measurements</td>
</tr>
<tr>
<td>EMG hand gestures [33]</td>
<td>4</td>
<td>5</td>
<td>658,004</td>
<td>NA</td>
<td>Classify hand gestures from EMG signal</td>
</tr>
<tr>
<td>PAMAP [35]</td>
<td>53</td>
<td>18</td>
<td>1,921,389</td>
<td>NA</td>
<td>Classify physical activity from IMU data</td>
</tr>
<tr>
<td>Airfoil self-noise [2]</td>
<td>5</td>
<td>1</td>
<td>1,503</td>
<td>NA</td>
<td>Predict the noise level in a wind tunnel</td>
</tr>
<tr>
<td>Cycle power plant [40]</td>
<td>4</td>
<td>1</td>
<td>9,568</td>
<td>NA</td>
<td>Predict electrical output of a power plant</td>
</tr>
</tbody>
</table>

3.4 Examples

Torchhd contains implementations of six HDC applications, described below. These examples serve three uses: 1) to highlight the versatility of the library; 2) to exemplify practical aspects of HDC; and 3) to facilitate follow-up studies.

*Language recognition.* The first example uses a dataset of sentences from 21 European languages. Rahimi et al. [34] present a method to classify the language of a given sentence.

*EMG gesture recognition.* Rahimi et al. [33] propose a method for classifying hand gestures using Electromyography (EMG) signals in the setting of a smart prosthetic.

*VoiceHD.* Imani et al. [13] present an HDC classifier for voice signals to guess the spoken letter from an audio stream. They also show that a hybrid model in combination with a neural network improves the accuracy.

*RegHD.* Hernández-Cano et al. [12] propose a method for regression. They use random projection to map the input vectors to the hyperspace and train with gradient descent.

*GraphHD.* Nunes et al. [27] presented the first approach for graph learning using HDC. This method achieves an accuracy comparable to graph neural networks, but with significantly reduced training and inference times.

*Hyberdimensional Hashing.* The last example implements an HDC-based dynamic hash table with minimal key remapping by Heddes et al. [11]. This problem is very important in many cloud services and distributed applications.

4 Experiments

In this section we present experiments to substantiate our design decisions and to show the value of Torchhd. We begin by discussing the bundling implementation and the use for automatic differentiation. Then, we compare the performance and lines of code of Torchhd to other implementations.

4.1 Bundling implementation

Bundling, described in Section 2.2, is frequently implemented as the element-wise majority function on the operands in a Boolean setting. However, this approach has known problems [38]: 1) existence of ties: when the number of operands is even, a tie-breaking policy is required; 2) unfairness: it does not produce the mean, but tends strongly to the majority of hypervectors; 3) non-associativity: the execution order matters, i.e., \((A \oplus B) \oplus C \neq A \oplus (B \oplus C)\).

To illustrate the problem, we experimented with three tie-breaking strategies: always favoring +1 (Bias), choosing randomly between -1 and +1 (Random), or using a fixed random vector (Auxiliary). The results presented in Figure 5 compare the hypervectors generated by each strategy with the exact mean vector (Baseline). The bundling is applied iteratively using a two-argument majority function. The strategies all rapidly diverge from the baseline, therefore, we decided to take advantage of the floating-point representation (see Section 3.2) to avoid these problems. Instead of the majority function, the bundling operation in Torchhd is implemented as simple element-wise addition. However, if desired, the majority function behavior can be achieved by composing bundling with binary quantization.

4.2 Gradient-based learning

In this experiment we explore the trade-off between compute and accuracy for a hybrid HDC-learning architecture. We observe the accuracy of the trained model while varying the fraction, denoted by \(\alpha\), of HDC versus gradient descent training steps. Early experiments showed that mixing the steps directly results in unstable training. Instead, we only perform gradient steps on the model and write the HDC updates to a buffer hypervector which represents the mean sample. The buffer is then used as the sample during the next gradient update, before being erased. For all settings, the samples are first encoded to the hyperspace.

The results in Figure 4 show that the hybrid architecture outperforms a pure HDC model at the cost of increased computation. Note that the performance of HDC doesn’t change after the first epoch because the model is the mean of the encoded samples, i.e., a multiset of the samples. These
results underline the utility of automatic differentiation in HDC as provided by Torchhd.

4.3 Performance
To assess the performance of Torchhd, we implemented three applications and compared the execution time with the original publicly available code. All the experiments ran on a machine with 20 Intel Xeon Silver 4114 CPUs, 93 GB of RAM and 4 Nvidia TITAN Xp GPUs, running Ubuntu 20.04.4. The experiments, however, only used a single CPU or GPU. To increase utilization, the GPU uses a batch size of 128.

The results in Table 3 show that Torchhd is faster for all applications. The library running on the CPU is on average 24× faster than the original code. With GPU execution, the library is on average 54× faster. In one instance, the GPU is marginally slower than the CPU due to the small scale of the problem and the overhead of data preparation.

4.4 Lines of code saved
In Table 4, we compare the number of lines of code, excluding commented and empty lines, of the original implementations against their Torchhd version. The implementation using the library is considerably more concise, indicating effectively designed abstractions. Torchhd aims to provide direct mapping from theory to implementation, removing the technical overhead during application development.

5 Conclusion
We introduce Torchhd, an open-source Python library for Hyperdimensional Computing (HDC). The library is on average 24× and 54× faster than publicly available code when executed on CPU and GPU, respectively. Hypervectors are represented as bipolar floating-point tensors and manipulated using the Multiply-Add-Permute instruction set. Torchhd includes state-of-the-art methods for hypervector creation and HDC data structures. The library is built on top of PyTorch, enabling the exchange of knowledge between the HDC and the wider ML communities, and making PyTorch’s vast ecosystem of machine learning tools available for HDC as well. Torchhd aims to be simple, versatile and highly performant. Our work joins the community’s important effort to disseminate and aggregate HDC research.
References


[18] Pentti Kanerva. 2010. What we mean when we say “What’s the dollar of Mexico?”: Prototypes and mapping in concept space. In AAAI fall symposium series.


