SIMCNN: Exploiting Computational Similarity to Accelerate CNN Training in Hardware

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Abstract—Convolution neural networks (CNN) are computation intensive to train. It consists of a substantial number of multidimensional dot products between many kernels and inputs. We observe that there are notable similarities among the vectors extracted from inputs (i.e., input vectors). If one input vector is similar to another one, its computations with the kernels are also similar to those of the other and therefore, can be skipped by reusing the already-computed results. Based on this insight, we propose a novel scheme based on locality sensitive hashing (LSH) to exploit the similarity of computations during CNN training in a hardware accelerator. The proposed scheme, called SimCNN, uses a cache (SimCACHE) to store LSH signatures of recent input vectors along with the computed results. If the LSH signature of a new input vector matches with that of an already existing vector in the SimCACHE, the already-computed result is reused for the new vector. SimCNN is the first work that exploits computational similarity for accelerating CNN training in hardware. The paper presents a detailed design, workflow, and implementation of SimCNN. Our experimental evaluation with four different deep learning models shows that SimCNN saves a significant number of computations and therefore, improves training time up to 43%.

I. INTRODUCTION

Convolution Neural Networks (CNN) are one of the most commonly used deep learning models. They are used for diverse tasks such as image and video recognition, recommendation systems, image classification, image segmentation, medical image analysis or natural language processing [12], [18], [31]. Due to the versatility of CNN models, special hardware accelerators have been proposed [3]–[5], [7], [8], [10], [16], [19], [27]. Despite notable advances, CNN accelerators remain computationally intensive, requiring 30k to 600k operations per pixel [5]. The volume of computation is even more when the accelerator trains a CNN model. Our objective in this paper is to accelerate CNN training by reducing redundant computations.

CNN operations consist of numerous multidimensional dot products between filters and input vectors extracted from the input matrices (e.g., images). Let us consider a filter \( f \) and two input vectors \( v_1 = [v_{1,1}, \ldots, v_{1,n}] \) and \( v_2 = [v_{2,1} + \epsilon_1 v_{1,1}, \ldots, \epsilon_n v_{1,1}] \), where \( \epsilon_i \) (for \( 1 \leq i \leq 3 \)) represents an insignificant difference. The dot product of \( v_2 \) and \( f \) would be \( v_2 \cdot f = v_1 \cdot f + \epsilon \cdot f \). If \( \epsilon \approx 0 \), then \( \epsilon \cdot f \approx 0 \), and therefore, \( v_2 \cdot f \approx v_1 \cdot f \). In other words, if \( v_1 \) and \( v_2 \) are significantly similar, the computation of \( v_2 \) with a filter will be considerably similar to that of \( v_1 \) and therefore, can be skipped by reusing the results computed for \( v_1 \).

Intuitively, since CNN operates on images (or other similar data [18]) and different parts of an image can be similar, there is a significant opportunity for exploiting computational similarity. Moreover, CNN training is far more computation intensive than CNN inference. Therefore, computational similarity can unlock greater performance potential for training as opposed to inference. However, existing accelerators fail to exploit this potential. For example, UCNN [15] skips computations only when two or more weights are exactly the same. Cnvlutin [2] skips computations when one of the operands is zero. Zhang et al. [32] proposes to skip computations with insignificant weights during training. Ning et al. [22] proposed to reuse computation results during training for similar input vectors in machine learning libraries (software). However, the technique cannot be directly implemented in a hardware accelerator without breaking the accelerator’s dataflow and adding significant computational overhead for clustering and reconstructing outputs (more on this in Section III-C).

In order to exploit computational similarity during CNN operations, we propose SimCNN. SimCNN uses Locality Sensitive Hashing (LSH) in hardware to detect similarity among input vectors in a light-weight fashion. Since LSH computations are similar to those of convolution operations, SimCNN essentially treats those computations as part of its convolution operations using the same hardware processing elements (PEs). For a convolution layer, for each channel, SimCNN generates some random vectors and performs LSH operations using the random vectors and input vectors to compute LSH signature. SimCNN calculates one signature for each input vector in a channel. If two input vectors produce the same signature, they are considered similar and thus, have computational similarity. During the convolution operation between a filter and an input vector, the input vector’s signature is used to access a special cache, called SimCACHE. SimCACHE uses the signature as index and tag and convolution results as data. If there is a hit on SimCACHE, the convolution operation is skipped. Instead, the computed result stored in the data-portion of the cache entry is reused. On the other hand, if there is a miss, the convolution operation continues and the result is stored into SimCACHE. Computational similarity introduces irregularity in the original data flow of a CNN accelerator by skipping some computations. SimCNN adds a special bitmap (called Hitmap) and some shared structures to make the data flow continuous and uninterrupted. The signatures produced during the forward propagation are stored in memory so that they can be reused during the backward propagation of the training process. Moreover, SimCNN dynamically decides when and to what extent computational similarity should be exploited based on its impact on performance and accuracy.
In summary, we make the following contributions:

1) We propose a LSH-based clustering technique in hardware to dynamically detect and exploit computational similarity in a light-weight fashion. StMCNN treats LSH computations as part of convolution operations using random filters. Thus, StMCNN can reuse the same PEs for LSH signatures. StMCNN is the first accelerator to exploit computational similarity dynamically among input vectors to enhance its training performance. We propose to adapt StMCNN dynamically based on accuracy and performance impact.

2) We propose an Overlapped dataflow for LSH signature computation by intentionally introducing some delay. In addition, we propose to use a Hitmap to reuse similar computations without altering or introducing irregularity in the dataflow.

3) We propose a complete taxonomy of computation optimization techniques along with examples (Section II).

4) We implemented StMCNN in Virtex 7 FPGA board [30]. We evaluated it using 4 CNN models and achieved up to 43% speedup with little-to-no impact on accuracy.

II. TAXONOMY OF COMPUTATION OPTIMIZATION

Exploiting computational similarity is one way to optimize computations. We propose a taxonomy of computation optimization techniques based on time, data, and granularity of computation optimization. Table I shows the taxonomy. As an example, Cnvlutin [2] tries to detect zero inputs to reduce unnecessary multiplications in the inference process, thus it is put in Inference/Input/Single Element. Deep Compression [13] tries to quantize model weights to reduce the inference computational cost, therefore it is categorized as an Inference/Filter/Multiple Elements technique.

There are techniques that belong to multiple categories. For instance, [24] exploits the sparsity in both weights and activations, therefore it falls into both Input and Filter classes. StMCNN falls under the category Training/Input/Multiple Elements. Although Ning et al. [22] is in the same category, its goal is to optimize software implementations as opposed to a hardware accelerator. Thus, StMCNN is the first work in its category that accelerates hardware.

Each PE has vertical, horizontal and diagonal connections with neighboring PEs using some on-chip networks. There is a global buffer to hold inputs, filters and, partial-sums. The chip is connected to off-chip memory to receive inputs and store outputs. Each PE contains registers to hold inputs, weights and partial sums. Each PE also contains multiplier and adder units. Each PE distributes inputs, weights and generates partial sums based on a specific dataflow.

Different dataflows have been proposed in literature [5], [6], [17] to optimize different aspects of the CNN operations. Examples are Weight-Stationary, Output-Stationary, Input-Stationary, Row-Stationary etc. The name of the dataflow often reflects which data is kept unchanged in the PE unit throughout the computation. In Weight-Stationary, each PE statically holds a weight inside its register file. Those operations that use the same weight are mapped to the same PE unit [6]. Output-Stationary localizes the partial result accumulation inside each PE unit. At every time step, the input and the filter weight are broadcasted across the PE array. The partial results are computed and kept locally in the register file of each PE. For Row-Stationary, each PE processes one row of the input. Filter weights stream horizontally, input rows stream diagonally, and partial sums are accumulated vertically. Row-Stationary has been proposed in Eyeriss [5] and is considered one of the most efficient data flow to maximize data reuse. We used row- stationary dataflow in our proposed accelerator also.

B. Locality Sensitive Hashing (LSH)

The high level idea of LSH is to build a hash table on some points such that points that are nearby get hashed to the same bucket in the hash table, and points that are far apart get hashed to different buckets. Then nearest neighbor queries can be performed by determining which bucket the query point lies in and then scanning the points that were hashed to the same bucket to find the cluster centroid and check if the point is within a maximum distance from the centroid.

Suppose we have an input vector \( X \) with \( m \) elements. First, a set of random vectors \( R \) is generated. Each random vector \( R_i \) in \( R \) has \( m \) elements, for \( 0 < i < n \) where \( n \) is the number of random vectors in \( R \). LSH of \( X \) is a bit string of length \( n \). We refer to this bit string as LSH Signature (or Signature, for short). To calculate the signature \( S \), a dot product between \( X \) and \( R_i \) (i.e., \( X \cdot R_i \)) is calculated. If \( X \cdot R_i \geq 0 \), then the \( i \)-th bit of \( S \) is set to 0 i.e., \( S_i = 0 \). Otherwise, \( S_i = 1 \). Figure 2 shows an example of how a signature is calculated.

C. State-of-the-art Computation Reuse

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**TABLE I**

| Time       | Data       | Granularity          | Examples          |
|------------|------------|----------------------|-------------------|
| Inference  | Input      | Single Element only  | [22] [24],*       |
|            | Multiple Elements | 1] [28], [23], [14],* |
| Filter     | Single Element only  | [24],* [20],*        |
|            | Multiple Elements | [15], [33], [21], [14],* |
| Training   | Input      | Single Element only  | None              |
|            | Multiple Elements | StMCNN, [22]         |
| Filter     | Single Element only  | [32], [20],*         |
|            | Multiple Elements | [9], [11], [13]      |

Categories of computation optimization techniques. Any work with * belongs to multiple categories.
UCNN [15] exploits the fact that current weight quantization techniques produce a lot of weight repetitions in the CNN model. As such, we can reuse the result and reduce the number of computations. At the core of UCNN is the factorized dot product dataflow and activation group reuse. Factorized dot product first detects and groups the inputs that are multiplied with the same weight into activation groups. Each group is then summed and multiplied with the common weight. As a result, the number of multiplications is reduced to one per group. UCNN further exploits the repetition across different filters using activation group reuse. SumMerge extends the idea of UCNN into CPU based implementation [25]

DeepReUse [23] and Adaptive Deep Reuse (ADR) [22] exploit similarity in inputs to improve inference and training performance. Both approaches are proposed in the context of software implemented CNN models. Both approaches use LSH to find the similarity among input vectors. Although the high level idea of ADR is similar to SimCNN, ADR cannot be directly implemented in hardware because of the following issues. First, the LSH use in ADR requires an expensive preprocessing step to build the clusters and cluster centroids. For this purpose, ADR calculates signatures followed by one-to-one comparison with each signature in a cluster to calculate the centroid. Thus, centroid calculation is expensive \(O(N^2)\) comparisons and is not trivial to do in hardware. SimCNN, on the other hand, does not use LSH signatures in the traditional way (i.e., for cluster and centroid calculation). Instead, it uses signatures for SimCACHE accesses. Second, the granularity to check for similarity is variable and is usually less than the input vector length. So, a dot product result is not directly reused instead, some portion of the dot product is reused. The reused results go through additional reduction step to reconstruct the output. Finally, preprocessing for centroid calculation, output reconstruction and computation reuse breaks the usual dataflow of an accelerator which may result in performance degradation. SimCNN’s carefully crafted design to treat signature calculation as a part of the convolution operation and reuse complete dot product results with SimCACHE and bitmap avoid all of these issues while maintaining the same dataflow.

IV. MAIN IDEA: SimCNN

A. Overview

SimCNN works on input vectors extracted from multidimensional inputs. The overview of SimCNN is shown in Figure 3. SimCNN works in two phases. Phase 1 happens in the forward propagation whereas Phase 2 happens in both forward and backward propagation. During Phase 1, SimCNN determines which input vectors are significantly similar. Similarity is detected among input vectors within a channel using LSH algorithm. This is done before the filters of a channel are processed. SimCNN creates a signature for an input vector by performing a dot product between the input vector and a set of random vectors in hardware. In essence, LSH operations become convolution operations between input vectors and a set of random vectors. That is why the same hardware PEs are used for this purpose. SimCNN generates one signature for each input vector in a channel. If two signatures are same, the corresponding input vectors are virtually similar, and therefore, the computed dot product between one of the input vectors and a filter can be reused for that of the other input vector and the same filter. SimCNN uses a special cache, called SimCACHE, to store computed results corresponding to different signatures. A bitmap keeps track of the signatures that cause a hit. Signatures are calculated once for each channel and are used repeatedly during convolution operations with all filters in that channel. During Phase 2, SimCNN performs a convolution operation between an input vector and a filter (or derivatives during the backward propagation). SimCNN checks if this vector is similar to any prior vector in that channel using the bitmap and if so, the result stored in SimCACHE is reused. SimCNN stores the signatures calculated during the forward propagation and reuses them during the backward propagation to skip similar computations. As the training proceeds, SimCNN increases signature length to adjust to the extent of similarity among vectors. In other words, only vectors with a higher degree of similarity are allowed to reuse computed results in the later stages of training. Thus, SimCNN dynamically adjusts computation reuse to minimize accuracy degradation.

In the next sections, we will elaborate on two phases of SimCNN. For this discussion, we will consider an Eyriress-style [5] row stationary data flow accelerator as our baseline. We choose this baseline because row-stationary is considered as one of the most efficient data flow for CNN accelerators.

B. Phase 1: Detecting Similarity Using LSH Technique

SimCNN detects similarity dynamically among input vectors before performing convolution operations with those. To simplify hardware and keep dataflow as it is, SimCNN treats LSH Signature calculation as a part of the convolution operation. where the convolution is performed between the input vectors and some random filters (vectors). This is done separately for each channel. When the actual filters of a channel are convoluted with the input vectors, signatures are used to determine if similar computations (dot products) are already done.
Similarly, PE Set are calculated using R bit. Similarly, of PEs working on a dot product as a PE Set. Thus, signature generation process. S \( S_1 \) is convoluted with with all input vectors to produce the 1st signatures to \( 1,1 \). As shown in Figure 4, \( 1,2 \), \( 1,3 \), and \( 1,4 \). We refer to the set of PEs working on a dot product as a PE Set. Thus, PE Set 1 consists of PE1 to PE3. We use the notation \( S_{i,j} \) to indicate the \( j \)-th bit of signature \( S_{i,j} \). where, \( S_{i,j} \) is the signature for input vector \( I_i \). The sign bit of \( I_i \). \( R_1 \) is used to produce \( S_{i,1} \) bit. Similarly, PE Set 1 also calculates \( S_{2,1} \) and then, \( S_{3,1} \). Thus, \( R_1 \) is convoluted with with all input vectors to produce the 1st bit of each signature. After that \( R_2 \) is loaded and the 2nd bit of each signature is calculated. Thus, \( n \) bits of all signatures are calculated using \( n \) random vectors. As shown in Figure 4, PE Set 1 produce signatures of 3 input vectors - \( I_1, I_2, I_3 \). Similarly, PE Set 2 and PE Set 3 each produces 3 signatures. Thus, SIMCNN converts signature calculations into convolution operations between the input vectors and random filters.

1) Signature Calculation: Let us consider a \( 5 \times 5 \) input and \( n \) random vectors where each random vector, \( R_i \) for \( 1 \leq i \leq n \), is of size \( 3 \times 3 \). Also, assume that the accelerator has a 3 PE array with row-stationary data flow. Figure 4 shows the signature generation process. SIMCNN starts with the random vector, \( R_1 \) and computes dot products with each input vector from \( I_1 \) to \( I_n \). PE1 to PE3 perform 3 dot products in a streaming fashion - \( I_1, R_1, I_2, R_1, \) and then, \( I_3, R_1 \). We refer to the set of PEs working on a dot product as a PE Set. Thus, PE Set 1 consists of PE1 to PE3. We use the notation \( S_{i,j} \) to indicate the \( j \)-th bit of signature \( S_{i,j} \), where, \( S_{i,j} \) is the signature for input vector \( I_i \). The sign bit of \( I_i \). \( R_1 \) is used to produce \( S_{i,1} \) bit. Similarly, PE Set 1 also calculates \( S_{2,1} \) and then, \( S_{3,1} \). Thus, \( R_1 \) is convoluted with with all input vectors to produce the 1st bit of each signature. After that \( R_2 \) is loaded and the 2nd bit of each signature is calculated. Thus, \( n \) bits of all signatures are calculated using \( n \) random vectors. As shown in Figure 4, PE Set 1 produce signatures of 3 input vectors - \( I_1, I_2, I_3 \). Similarly, PE Set 2 and PE Set 3 each produces 3 signatures. Thus, SIMCNN converts signature calculations into convolution operations between the input vectors and random filters.

2) Data Flow of Signature Calculation: Let us continue with our example scenario in Section IV-B1. Figure 5 shows the timing of signature calculation in a row-stationary data flow machine. With \( 3 \times 3 \) input vectors, it takes 4 cycles to multiply and accumulate the result of each row and additional 2 cycles to accumulate across rows. Thus, it takes 6 cycles to generate a single bit of a signature. Similarly, the first bit of subsequent signatures takes 6 cycles each. In general, for \( x \times x \) input vectors, it takes \( 2x \) cycles to calculate each bit of a signature. However, the calculation of one bit of one signature does not overlap with that of another signature (as shown in Figure 7(a)). Note that, we are assuming a separate multiplier and adder unit in each PE. Instead, if we we assume a multiply-accumulate (MAC) unit, it takes \( 2x-1 \) cycles to calculate a single bit of a signature (because row accumulation takes one less cycle). However, still each signature is calculated in a non-overlapping fashion. We propose to overlap the calculation of one signature with another using a new data flow, called Overlapped. The core idea is to add a register, named Overlapped register (ORM), in each PE and intentionally delay the calculation starting time of PE2 and PE3 by 1 and 2 cycles respectively (as shown...
in Figure 6). This is reminiscent of software pipelining [26]. ORg register is used to hold the result of multiplying the first element of each row of input and random vectors. For example, ORg of PE1 is used to hold $i_{1,1} \times r_{1,1}$ in cycle 2 and $i_{1,2} \times r_{1,1}$ in cycle 5. When the register holds $i_{1,2} \times r_{1,1}$ in cycle 5, it frees up the adder unit which can be used to pass the row accumulation result from PE1 to PE2 in cycle 6. Similarly in cycle 6, ORg of PE2 holds $i_{3,2} \times r_{1,1}$ which frees up the adder. Therefore, the adder accumulates the result from PE1 with PE2 and passes it to PE3 in cycle 7. At cycle 7, ORg of PE3 holds $i_{3,2} \times r_{1,1}$ which frees up the adder to finish the accumulation of all rows. Thus, $Sig_{1,1}$ takes 7 cycles to calculate. However, the calculation of $Sig_{2,1}$ has already started. Therefore, following the same flow, $Sig_{2,1}$ will finish in cycle 10 i.e., it takes only 3 more cycles. Similarly, the first bit of subsequent signatures produced by the same PEs will take 3 more cycles each. In general, for $x \times y$ input vectors, the first bit of the first signature calculated by a set of PEs takes $2x + 1$ cycles while other bits of any signature takes $x$ cycles to finish. This is illustrated in Figure 7(b).

3) Signature Management: SimCNN manages signatures using three structures - signature table, SIMCACHE, and hitmap. The signature table stores the signatures, SIMCACHE keeps dot product results computed between different input vectors and a filter, and the hitmap keeps track of which signature causes a hit in SIMCACHE. The signature table is indexed by the input vector number so that SimCNN can easily find it for a particular input vector. When a signature is calculated by the PEs, SimCNN stores it in the signature table and then accesses SIMCACHE (Figure 8). SIMCACHE is indexed and tagged with the signature. SIMCACHE keeps computed dot product results so that input vectors with similar signature can reuse them. The data portion of SIMCACHE contains the results. Since signatures are calculated once per channel and repeatedly used with all filters in that channel, SIMCACHE is populated in two steps. In the first step, when signatures are calculated, SIMCACHE is accessed with each signature to initialize tags for different cache lines. Since the convolution operation between input vectors and filters have not been computed yet, the data (results) portion will be empty at this time. To accommodate initializing the data portion later, each cache line has two valid bits - Valid Tag (VT) and Valid Data (VD). When a signature is used to initialize the tag section of a cache line, its VT is set while VD remains unset. The data portion of SIMCACHE is populated and used as a filter (or derivate) is convoluted with the input vectors. Different filters populate the data portion with different results. (details in Section IV-C).

When SimCNN accesses SIMCACHE with a signature in order to initialize the tag section, the tag may or may not be present in the cache. If the tag is already present, that is a hit and the entry corresponding to the signature in the hitmap is set accordingly. On the other hand, if the tag not present yet in SIMCACHE, that is a miss. In case of a miss, it is possible that the cache set is already full. In that case, SIMCACHE does not evict any existing cache line from the set because any eviction may make earlier entries of the hitmap inconsistent. To differentiate a miss when the cache set is full from when it is not, the hitmap marks a miss as either Miss But Full (MBF) or Miss Not Full (MNF). Thus, each entry in the hitmap can be either HIT, MBF or MNF. During convolution operations, if the hitmap entry is marked as MNF, the dot product result is stored in the data portion of the appropriate cache line in SIMCACHE. If the entry is MBF, the dot product result is not stored in the cache. On the other hand, if the entry is HIT, the dot product between some earlier input vector with similar signature and the filter has already been computed and stored in the cache line. Therefore, the result can be reused.

C. Phase 2: Exploiting Computational Similarity

Here, We explain how signatures along with SIMCACHE can be utilized to skip similar computations during convolution operations. We first explain it for the forward propagation followed by the backward propagation. Finally, we explain how to adapt SimCNN as training proceeds.

1) Computation Reuse in Forward Propagation: During the forward propagation, convolution operations are performed using inputs and filters. For each channel, a 2D input convolutes with a number of filters. The 2D input consists of a number input vectors, each with the same size as a filter. Thus, for each channel, an accelerator performs a number of dot products between the input vectors and filters in that channel. The PEs load the one filter and a number of input vectors at a time and perform the dot products. The input vectors and filters are passed through the PEs in a streaming fashion. Rows of input vectors are passed through diagonally where as rows of filters are passed through horizontally. Partial sums are accumulated vertically. Figure 9 shows this flow. Here, we assume that PE1, PE2, and PE3 perform a dot product between an input vector and a filter. Thus, PE Set 1 consists of PE1, PE2, and PE3. Similarly, PE Set 2 consists of PE4 to PE6.

Each PE has an input buffer, a number of input and weight registers, a multiplier, and an adder. The input buffer holds inputs as they arrive to the PE. Input registers load values from the input buffer. As filter weights arrive, they are stored in the weight registers. The multiplier and adder work with the values from the input and weight registers. Each PE in a PE set starts
with the first input vector from its input buffer. Each PE checks whether the corresponding entry in the hitmap is a HIT. Keep in mind that the hitmap is pre-filled when signatures are first calculated for a channel. A HIT indicates that the input vector is similar to some earlier one and hence, the dot product result stored in the SimCACHE can be reused instead of calculating again. That is why, the PE skips the dot product. Instead, the result of the dot product is fetched from SimCACHE using the signature of the input vector and used as the result from the PE set. On the other hand, if the entry in the hitmap is MBF or MNF, the PEs in the PE set perform the dot product (using overlapped data flow as in Figure 6). If the hitmap entry is MNF, the dot product result is stored in SimCACHE and VD is set in the appropriate cache line. If the hitmap entry is MBF, the dot product result is not stored in the cache. The PEs in the PE set proceeds with the next input vector from the respective input buffer.

For example, if we assume the same inputs as in Section IV-B1, then PE Set1 operates on input vectors 1, 2, and 3 whereas PE Set2 operates on input vectors 4, 5, and 6 in Figure 9. Therefore, at first, the PEs in PE Set1 check entry 1 of the hitmap. Based on that entry, the PEs either reuse results from SimCACHE or compute dot products using input vector 1 and the current filter. For the example in Figure 9, PE Set1 will compute dot product because entry 1 is MNF. On the other hand, the PEs in PE Set2 check entry 4 in the hitmap and act accordingly. Note that each PE set acts independent of other PE sets. As a result, one PE set might reuse a lot of computed results and finish computations early whereas another PE set may lag behind computing many dot products. We propose two designs to address this issue - synchronous and asynchronous design.

- Synchronous Design: In synchronous design, when a PE set finishes computation, it waits until all other PE sets are done. This is facilitated by maintaining a busy bit (B) for each PE set. A controller checks all B bits. If none of them are busy (i.e., \( B = 0 \)), the controller instructs the PEs to load with the next filter and input vectors. At this point, SimCACHE may contain computed results from the previous filter and input vectors. Those results cannot be used because weights will change in the new filter. Therefore, SimCACHE flash invalidates all VD bits. Keep in mind that the input vectors remain the
same within the same channel. Therefore, VT flags and hitmap are still valid and kept as they are. When SimCNN proceeds with the next channel, the signatures in the signature table, SimCACHE, and hitmap are recalculated and repopulated.

- Asynchronous Design: The synchronous design is intuitive and simpler but suffers from limited performance improvement because the faster PE sets remain idle until the slowest one completes. Therefore, we propose an asynchronous design where the faster PE sets can work on the next filter and input vectors while the slower ones work on the previous filter and input vectors. However, this requires additional buffer and co-ordination scheme. Figure 10 shows the changes required for the asynchronous design. There are 3 major changes. First, to store new input vectors each PE is extended to have two input buffers. Each buffer has an associated valid (V) bit to indicate whether it contains valid inputs or not. Moreover, each PE has a register, named InUse, to indicate which of the two buffers is currently used. All PEs in a PE set will have the same value in the InUse register. With the extra buffer, whenever the fastest PE set completes computation, it loads next input vectors in streaming fashion as before. PEs in other PE sets store the new input vectors in the unused input buffer. That way, when those PE sets finish computations, new input vectors are already available in one of the input buffers. Second, the accelerator stores multiple filters in a shared buffer so that each PE can access it. Each filter has an associated BusyMap to indicate which PE sets are currently busy with that filter. Each PE maintains a register, named FlUse, to indicate which filter it is using. Like InUse, the FlUse register has the same value in each PE of a PE set. When all PE sets finish using a filter, it is loaded with a new filter and the BusyMap is initialized. Third, since each input vector and filter produces a new dot product result, we propose to make SimCACHE a multi-version cache where each cache line has multiple versions of data. Each data portion has a VD bit to indicate whether it is valid or not. Note that there are as many versions as the number of filters. Thus, if a PE set tries to use a new filter when there is no space to store it (because all N filters are marked busy with at least one PE set), then the PEs in the PE set will remain idle until a filter is completely used up in all PE sets. When the PEs in a PE set access a cacheline, they use FlUse register to determine which data version should be used.

2) Computation Reuse in Backward Propagation: In the backward propagation, there are two major computations - calculation of (i) weight derivatives (dW) of the current layer (say, layer i), and (ii) output derivatives of the previous layer (dO -1). Here, boldfaced letters indicate multidimensional vectors. At the high level, dW is calculated by performing convolution between the current layer’s input I and dO i.e. dW_i = I_i * CONV dO_i. On the other hand, dO -1 is calculated by convolving dO with W i.e., dO -1 = dO_i * CONV W_i. We note that for dW_i calculation, the same input that was used in the forward propagation is used again. However, the dimension of dO_i in a channel is different (usually much larger) than the filters used in the forward propagation. Therefore, the signatures produced in the forward propagation are not useful in determining similarity of input vectors. Now, let us consider the computation of dO_i -1. We observe that O_i is the same as I_i -1. Therefore, if the filters of layer i + 1 have the same dimension as those of layer i, the signatures and hitmap produced by layer i + 1 for I_i -1 can be applied to dO_i to find similarity. In that case, this computation scenario is the same as the forward propagation computation of layer i + 1. Based on this observation, we propose to save signatures and hitmap of each layer during the forward propagation and reload them during the backward propagation of the previous layer. Then, SimCNN applies the same technique as in Section IV-C1. Note that computation reuse layer i is possible in the backward propagation only when the filters of layer i and i + 1 have the same dimension. Luckily, this is true for many deep learning models. For example, filters of every layer of all VGG models have the same dimensions and this happen for in other big networks a lot that let us to have good saving for those layers.

D. Adaptation in SimCNN

As training proceeds, CNN models become more sensitive. As a result, computation reuse may introduce significant inaccuracy. To address this issue, we propose SimCNN to be adaptive in the following ways:

1) Increase in Signature Length: Signature indicates two input vectors v1 and v2 to be similar if ε = v1 - v2 is small. If signature length increases, v1 and v2 are found to be similar only when ε becomes significantly smaller. Therefore, larger signature has lesser effect on model accuracy. However, it may reduce the potential computation reuse. Therefore, SimCNN starts with smaller signature size (e.g., 20 bit long) and progressively increases signature length as the model is trained more. Towards this end, SimCNN calculates average loss in each iteration during training. If there is no change in loss for K consecutive iterations, then SimCNN increments signature length by 1. This implies that for subsequent iterations, SimCNN generates one more random vector during signature generation phase.
2) Stoppage of Similarity Detection: SIMCNN analytically determines if detecting similarity can save computations or not. If not computation can be saved then SIMCNN turns off the similarity detection phase. In order to implement this, SIMCNN calculates the total computation cost $C_T$ for signature generation and forward and backward propagation when some computations are reused. This cost is compared with the total computation cost $C_S$ of baseline system without any computation reuse. If the former cost is more than the later for $T$ consecutive batches of inputs, SIMCNN stops generating signatures.

V. IMPLEMENTATION DETAILS

Figure 10 shows the overall structure of SIMCNN. It has a PE-Array with several PEs. We used the same structure used in Eyeriss [5] for connecting PEs together for passing inputs and filters from one PE Set to the next one. We put SIMCACHE in shared memory and defined it as register in our FPGA design. So, every PE Set can access it simultaneously.

During the signature generation process, all PE Sets work simultaneously and generates the signature bits based on LSH technique. The size of each signature is based on number of random vectors. For storing those signatures, we used a FIFO called Signature Table in Figure 10, and every time that we calculate next bit of signature, we read this FIFO, add the new bit and store it again. For optimizing read access to cache lines, cache index and way number with signatures. Also, as we explained above we have a special array Hitmap for each PE-Set for storing the similarity situation for vectors and all PEs of a PE-Set have access to this Hitmap. For each vector in PE-Set, we assign 2-bits that shows there is a Hit/Miss But Full/Miss Not Full. The reason behind this, for multiplying with kernels, using Hitmap we can check the status of current vector very fast without need to check the SIMCACHE for finding similarity. Then, using FIFO, we can find the exact place in the SIMCACHE for that specific vector to load the previous result from SIMCACHE or save new result into it.

The structure of PE in proposed design is almost similar to Eyeriss As shown in Figure 10, each PE has an extra buffer enough to store one row of the input. We used block memories in FPGA for this part to decrease the overhead of that. During reading input rows from global memory or external memory, we have the same structure between PEs to pass input rows to next PE-Set and after that each PE-Set store inputs into their own specific buffer and use it for the rest of operations. In original row stationary data flow, we need enough input registers for storing one row of one vector in each PE which for them we need to use Slice Registers in FPGA that we have limited amount of them. But, in our structure we reduce this buffer to only one register to get one element of one row and store it into the memory and PE can start convolution operation using this block memory. During the second phase of convolution operation, which is multiplying with kernels, we already have Hitmap, similarity indexes, and SIMCACHE. In this phase, we use block memory to read input and based on Hitmap we decided to skip the vector or continue convolution with kernels. If Hitmap value is 11 for current vector which is a Hit, we increase the memory address by stride number to go to the next vector. But, if it’s 00 or 01, it shows that it’s a miss and we need to do normal convolution operation with kernels and we follow the same structure as Row Stationary dataflow for this operation.

For Synchronous design, since all PEs only work on one filter at a time, so, this extra block memory is enough for clustering. But, Asynchronous design, since the first phase and second phase can be done by different PE-Set independently, we need to have enough memory to load two input rows. If we consider imagenet dataset for our input, in FPGA, each block memory has 18K bit space which is enough space for storing two row of one input channel. In clustering structure, there are some PE Sets that finish the operation of current input faster than others since they have more clustered vectors. So, in Asynchronous design since we have enough space for two input row, the faster PE Set can load next input and start the first phase of that when the slower PE is still busy with second phase of previous input. We have some extra registers for storing a limited number of filters at the same time in shared memory In this way, each PE Set can work on different filters which can cause the operation of faster PE Sets to finish sooner and start the operation of next input. Also, we have a counter named FIUse in each PE Set that shows the filter number that it currently works on it.

For generating random numbers (Random Generator), SIMCNN used a standard linear-feedback shift register (LFSR) which is a shift register whose input bit is a linear function of its previous state. The most commonly used linear function of single bits is exclusive-or (XOR). An LFSR with a well-chosen feedback function can produce a sequence of bits that appears random and has a very long cycle. In this paper, we utilize CRC-16 as our polynomial function in each step of LFSR which is well-known in several applications for generating random numbers.

A. Scalability of SIMCACHE

To make SIMCACHE scalable, we make two design decisions. First, SIMCACHE is implemented in shared memory using slice registers (in FPGA) that can be accessed through id. Multiple PE Sets can read the same cache entry with a fixed delay using the id. That is why, when a signature is inserted into SIMCACHE, the id of that entry is saved along with the signature in the signature table. Since an inserted signature is not removed from the cache until a new channel starts, further access to that signature is done through the id without requiring any comparison. Second, we add a queue and a simple controller for each cache set. Thus, a cache set can be updated independent of other sets. If multiple signature insertion requests come simultaneously for a cache set, the queue records the requests, and the controller serializes them - one at a time. Multiple signature insertion requests for different cache sets can proceed simultaneously without any issue. Although these techniques are specifically for FPGA, for an ASIC accelerator, similar techniques such as banked cache,
multi-signature cache line, PE Set wise smaller cache can be used to improve its scalability.

VI. EXPERIMENTAL SETUP

For hardware implementation of SimCNN, we used ISE Design Suite [29] and Virtex 7 [30] FPGA (XC7VX980T) board from Xilinx. In our design, we used the same number of PEs (i.e., 168) that was used in the Eyeriss [5]. For off-chip memory, we utilized an external SSD (MIG 7 series DDR3 memory) to store the model’s inputs and weight. For the global buffer, we used the block memories in FPGA. The size of each block memory is 36 KB, and totally we have 1500 block memories in FPGA XC7VX980T. SimCACHE is shared among all PEs. For this purpose, we used the Slice Registers in FPGA for the implementation of SimCACHE. The FPGA has a total of 612,000 registers. For the signature table, we used the FIFO memory in FPGA. For input buffers, we used one block memory.

VII. RESULTS

A. Overall Performance Analysis

For experimental purpose, we consider 4 popular and big networks: AlexNet, GoogleNet, ResNet50, and ResNet101. That said, the proposed method is applicable to any network since it is independent of the network type. For comparison purpose, we use Eyeriss [5] Row-Stationary dataflow as our baseline. We implemented the Row-Stationary data flow on FPGA and then implement the proposed SimCNN on top of that. In this work, we only apply our clustering method in channel-level not across channels and only for layers with kernel size more than one. Working across channels has extra overhead and we leave it for future works and in this work we only consider one channel of one input for clustering purpose.

| Models  | Baseline Training | Baseline Validation | SimCNN Training | SimCNN Validation | Epochs |
|---------|-------------------|---------------------|----------------|------------------|--------|
| AlexNet | 0.9795            | 0.7012              | 0.9795         | 0.7012           | 400    |
| GoogleNet | 0.9226          | 0.7012              | 0.9671         | 0.7026           | 255    |
| ResNet50 | 0.9632           | 0.7024              | 0.9692         | 0.7154           | 88     |
| ResNet101 | 0.9794          | 0.7194              | 0.9794         | 0.7130           | 52     |

*Hyper-parameters are adjusted in training to achieve optimal accuracy.

Table II shows the accuracy comparison of proposed SimCNN method and baseline. As shown in this figure, the final validation and training accuracy is almost the same as baseline and this shows the adaptive clustering method works very well on different network and doesn’t have significant effect on the final accuracy.

Figure 11 shows the speed up comparison of SimCNN and baseline. As shown in this figure, SimCNN is able to speed up the overall training time by 32% in average. In this figure, for some bigger networks such as ResNet50 and ResNet101 that have more number of layers and also big layers, the amount of saving is more since it has more number of vectors for clustering. This shows the effectiveness of SimCNN for reducing the training time of big networks. Figure 12 shows the result of clustering mode (ON/OFF) of layers across different models. There are two limitations for turning ON or OFF the clustering for a specific channel. First, the adaptive structure that has been utilized in SimCNN and turning off the clustering of channels based on the cost of clustering. Second, we consider the total loss of training over epochs and we may turn off the whole clustering based on overall loss value. Third, we skip the clustering for layers that have kernel size less than 1 with this explanation, since AlexNet doesn’t have any layer with size 1 and the clustering percentage is good enough to keep the clustering in its layers, it has 100% clustering in layers. But, ResNet101 has higher number of layers with kernel size=1 and more number of layers, totally has only 40% clustering in its layers.

B. Adaptivity Analysis

In this section, we provided the results of Adaptivity analysis of our models. This section will let us to have a better understanding of the structure of SimCNN and for this goal we need a detailed analysis of the different layers of a network. Here we choose AlexNet for explanation purpose since it has a few layers with different input and kernel size which is more comfortable for these analysis purposes.

In proposed SimCNN because of the limitation in the cache size the higher Hit-rate shows more number of clustered vectors that will increase saving amount. Figure 13 shows the overall cache hit rates of AlexNet over more than 350 epochs. As
shown in this figure, in the beginning the overall Hit-Rate is more than last epochs. The reason behind these results is we have adaptivity in the number of random vectors in SimCNN. As mentioned in details in previous sections, since we want to keep the accuracy the same as baseline design, we increase the number of random vectors to increase the accuracy of clustering and therefore the final accuracy of the model. But, increasing the number of random vectors decrease the rate of clustering or cache hit. Figure 14 shows the average amount of saving in comparison with baseline design across different layers in several epochs. As shown in this figure, the amount of saving over layers is different because of difference in the size of each layer and also number of channels. Since layer 2 has higher number of channels in comparison with layer 1, and also the size of input is bigger than the size of input in next layers, it totally has more amount of saving. Figure 15 shows the effect of increasing the number of ways to 32 the amount of saving will increase. But, this has larger hardware overhead and as we mentioned earlier there is a trade off between these two. Here, still with 16 ways we have the saving close to 32 ways. Figure 17 shows the effect of increasing the number of random vectors on the amount of saving for different cache configurations. As shown in this figure, when we increase the number of ways to 32 the amount of saving will increase. But, this has larger hardware overhead and as we mentioned earlier there is a trade off between these two. Here, still with 16 ways we have the saving close to 32 ways.

C. Sensitivity Analysis

In this section, we provided the results of the Sensitivity analysis for different networks. As explained before, Sensitivity metrics such as the size of cache, number of ways, and number of random vectors have significant effect on the amount of clustering and as a result on the final saving. Figure 16 compared the time saving of SimCNN vs baseline design
As shown in this network the best saving is for 20 random vectors and then 25 random vectors is better than 30 random vectors. But, decreasing the number of random vectors will have the negative effect on final accuracy. So, we choose 25 as our default number of random vectors in this paper. Table III shows the results of power consumption for Baseline, Synchronous, and Asynchronous design after place and route final design in Xilinx ISE hardware design tool.

![Comparison of On-Chip Power Consumption for Different Designs](image)

**Table III**

Comparison of On-Chip Power Consumption for Different Design.

|                  | Baseline | Synchronous | Asynchronous |
|------------------|----------|-------------|--------------|
| Clocks           | 86.11    | 105.33      | 197.9        |
| Logic            | 89.79    | 112.64      | 209.94       |
| Signals          | 227.72   | 280.64      | 939.3        |
| IOs              | 2.21     | 2.26        | 2.26         |
| BlockRAM/FIFO    | 225.29   | 457.4       | 575.99       |
| MMCMs            | 105.37   | 105.37      | 105.37       |
| DSPs             | 15.35    | 15.35       | 15.35        |
| Static Power     | 222.88   | 375.78      | 385.63       |
| Total            | 971.87   | 1454.74     | 2491.74      |

As shown in this table, the synchronous and asynchronous designs have some hardware overheads that cause the increase in final power consumption. The majority of this increment is related to the power of Signals and Logic. This is because of using cache-based structure in the proposed design. Also, the other reason behind this overhead is that in the implementation of SimCNN, we didn’t separate the clustering process from regular convolution operation in layers and our method is part of that. In other words, we load random vectors similar to other filters and before them for each layer. In this way, we don’t change the dataflow and keep all the benefits and savings of it. Also, it’s evident that this part of implementation doesn’t have any hardware overhead. With this explanation, we can apply our method to any dataflow and have savings on top of that. However, as explained in scalability subsection in section V, since we fixed the cache size and number of ways to an optimal value, this overhead will be the same even by increasing the size of input image and number of PEs. Here, the experimental results are related to the Eyeriss chip [5], which has 168 PEs. So, in the case of more PEs, the overhead of our design in comparison with the baseline design will be lower. Table IV compares the resource usage and area overhead of SimCNN vs baseline design.

Similar to Table III, the majority of the SimCNN resource usage overhead is related to Slice Registers, which is related to cache structure. However, we can bring the same explanation here for the fixed overhead of the SimCNN.

Table IV

|                  | Baseline | Synchronous | Asynchronous |
|------------------|----------|-------------|--------------|
| Slice Registers  | 10969    | 13035       | 14531        |
| IOs              | 32       | 32          | 32           |
| Block RAM        | 28       | 55          | 79           |
| DSP/SAXEIs       | 30       | 36          | 36           |

**VIII. RELATED WORK**

There has been a considerable amount of efforts on CNN acceleration and their efficiency [2], [5], [9], [11], [13], [20], [21], [33]. Courbariaux et al. [9] propose BinaryNet, a network whose weights are quantized to either +1 or -1. Due to these binary weights, all arithmetic calculations in the network can be replaced by bitwise operations, thus significantly reducing the memory footprint of the model. Another line of work attempts to exploit the sparsity within the model architecture. Mahmoud et al. [20] find out that the multiply-accumulate (MAC) operations account for a significant amount of energy consumption in model training. In a MAC operation, if any of the operands is zero, it can be safely ignored. As such, they propose TensorDash, a hardware scheduler that can efficiently find and skip unnecessary MAC computations. Albericio et al. [2] show that almost half of the calculations within the convolutional layers involve multiplying with zero. As such, they present ConvLin, a CNN-centric hardware accelerator that can detect and eliminate most of these unnecessary computations. Han et al. propose Deep Compression (DC) [13], a holistic solution that combines model pruning and weight quantization. At the beginning, DC removes all connections whose weights are smaller than a preset threshold. The remaining weights are then quantized and encoded.

**IX. CONCLUSIONS**

We proposed a novel scheme based on LSH clustering technique to exploit the similarity of computations during CNN training in a hardware accelerator. The proposed scheme, called SimCNN, uses a cache (SimCACHE) to store LSH signatures of recent input vectors along with the computed results. If the LSH signature of a new input vector matches with that of an already existing vector in the SimCACHE, the already-computed result is reused for the new vector. SimCNN is the first work that exploits computational similarity for accelerating CNN training in hardware. We present a detailed design, workflow, and implementation of SimCNN. This work opens up a new direction of optimizing CNN accelerator training process. Our experimental evaluation with four different deep learning models shows that SimCNN saves a significant number of computations and therefore, improves training time by up to 43%.

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