Vector API: Writing own-vector algorithms in OpenJDK* for faster performance

In this paper, we discuss insights into Vector API, which is being developed as part of OpenJDK* under Project Panama. First, we’ll go over some Vector API fundamentals, basic functionalities, and tips. We’ll then show you some code samples of vector algorithms for standard Machine Learning routines and financial benchmarks, and go over some ways to increase performance. These examples should give you some guidelines and best practices for vector programming in Java*, to help you to write successful vector versions of your own compute-intensive algorithms.

INTRODUCTION

Modern microprocessors offer parallelism at various granularities in order to deliver high performance. These granularities are at the thread, instruction, data, and pipeline level. Thread- and Instruction-level parallelism is delivered by the CPU itself (via hyper-threading and out-of-order execution). Data-level parallelism is achieved using Single Instruction Multiple Data (SIMD) instructions. Processors can leverage application-level parallelization by simultaneously processing the same operation on multiple data items. Application-level parallelization allows for higher performance speeds by orders of magnitude.

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ACKNOWLEDGMENTS
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CHALLENGES: LIMITED SIMD SUPPORT IN JAVA*

SIMD in Java* opens up ways for developers to explore new opportunities in areas like high performance computing (HPC), machine learning (ML) linear algebra-based algorithms, deep learning (DL) and artificial intelligence (AI) frameworks, DL training workloads, and financial services that operate on huge data sets.

Right now there is limited SIMD support in Java, with some new optimizations in the Java Virtual Machine 9 (JVM 9). However, even though SIMD optimization is supported in Java (via auto-vectorization and Super-word optimizations), that support is currently limited to simple expressions and/or loops. Fortunately, these optimizations don’t require you to do additional work. However, you do need to write your Java code in certain ways, in order to take advantage of auto-vectorization.

Because of this, big data applications typically use Unsafe or Java Native Interface (JNI) wrapper packages, in order to have access to faster native libraries. Such big data applications include Apache Flink*, Apache Spark* ML libraries, and BigDL (big data distributed deep learning on Spark). Unfortunately, JNI remains hard to develop, hard to maintain, and adds performance overhead.

Vector API and Project Panama

To address these challenges, Project Panama offers a Vector API. Vector API supports the more complex expressions used in ML and DL (such as basic linear algorithm subprogram, or BLAS), as well as in the financial services industry (FSI) and HPC programs.

Vector API makes it possible to develop compute-intensive machine and deep learning algorithms, financial algorithms, and training workloads all in Java. Even better, Vector API enables this without needing non-portable native code or incurring JNI overhead. It introduces a set of methods for data-parallel operations on sized vector-types for programming directly, typically without requiring knowledge of an underlying CPU. APIs are further efficiently mapped to SIMD instructions on modern CPUs by the JVM JIT. Also, BLAS algorithms can run up to 3x to 4x faster when implemented using Vector API.

How to use Vector API in Java

A vector interface is bundled as part of the com.oracle.vector package. To begin using Vector API, you need to import the following lines into your program. Depending on the Vector type, you can choose to import FloatVector, IntVector etc. See code sample 1, above.

The Vector type (Vector<E, S>) takes two parameters:

- E The element type, broadly supporting the int, float, and double primitive types.
- S Specifies the shape or bitwise size of the vector.

Vector operations live as virtual methods of a vector instance. Before using vector operations, you must create a primordial instance which captures the element type and vector shape. Using that instance, you can then create other vectors of that particular size and shape. See code sample 2, above.

Once you have created the primordial instance, you can create vector instances of the FloatVector<Shapes.S256Bit> type. If necessary, your program should also create first instances of other vector elements and shape types, such as DoubleVector<Shapes.S512Bit>.

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Vector class hierarchy

First, let’s look at the Vector API class hierarchy. At the top level, the Vector interface `Vector<E, S>` takes the parameters Element and Shape of the vector. Further down we have abstract classes `IntVector<S>`, `FloatVector<S>`, and so on. The abstract classes specialize the Element type to Double, Integer, and so on. These abstract classes are inherited into classes like `Int128Vector`, `Float512Vector`. In turn, those classes specialize the Shape (bitwise size) of the vectors for each Element type for concrete vectors where vector operations reside.

Vector API has broad support for Float, Integer, and Double types, since most SIMD features revolve around these primitive data types. See Figure 1.

A prototype implementation for a Vector interface is shown in code sample 3.

At the top level, there is a vector interface. Moving down through the hierarchy, we start to specialize with an IntVector, with a shape that has yet to be determined. See code sample 4.

When we drill down to the bottom of the hierarchy, we start getting vector classes which are specific to the particular Element types (E) and Shapes (S), as shown in code sample 5.

Vector-Vector functionality

As we mentioned earlier, Vector is an immutable interface. All the methods in the vector interface provide the result in a new object. They do not modify the input’s objects.

The Vector interface supports most of the basic arithmetic and trigonometric operations in both masked and unmasked form. You can see this support in code sample 6.
Support for advanced vector operations

Advanced vector operations are also supported. These include horizontal reductions, broadcasting primitives, blend/shuffle operations, masked comparisons, and array load/stores. You can see the supported operations in code sample 7.

The next code sample shows the vector addition of two arrays. AddArrays creates two Vectors of Float Element type and 256-bit Shape (size). In this example, we use the fromArray (array, index) operation to load the vectors from arrays left [] and right [], followed by the vector add () operation. We also use the intoArray (array, index) operation to store the result of the computation into res []]. See code sample 8.

Write loop kernels independent of vector size.

Vector API lets you write loop kernels independent of vector size. While writing loop kernels, you can simply query the Vector API for the vector size:species.length (). You can then use that size for striding through arrays and byte-buffers. This allows you to make your code portable across multiple vector sizes.

In code sample 9, you can see that user-defined classes must extend Vector.Shape<Vector<?, ?>>. Within the class definition, you must include a primordial instance spec as field of final type. Once you do that, you can then use the spec vector instance to create vector instances that are length-agnostic.

The next code sample (sample 10) shows a loop kernel for the vector addition of two arrays. In this example, the Shape of the vector is parameterized by FloatVector<S> in the loop kernel.
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Note that, after writing the vectorized version of the loop, you still need to iterate over the remaining array elements in a scalar fashion. The example above shows this in the tail cleanup loop.

While creating objects of AddClass type, you will need the primordial vector instance species specialized by Shape. As part of the object definition, you must explicitly specify the Vector shape as AddClass<Shapes.S256Bit>. See code sample 11.

**Loops with conditional statements**

Loops with conditional statements can also be written as vector versions using masked operations. In this next example, we first generate Vector.Mask<Float, Shapes.S256Bit> using the greaterThan () operation. Mask is used for the mul () operation.

Code sample 12 shows the scalar code.

Code sample 13 shows the vector loop.

We'll show you several other vector programming tips and tricks using code samples in the next discussion.

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**Code sample 11. Explicitly specifying the Vector shape.**

```java
FloatVector.FloatSpecies<Shapes.S256Bit> species = (FloatVector.FloatSpecies<Shapes.S256Bit>)
Vector.speciesInstance (Float.class, Shapes.S_256_BIT);
AddClass<Shapes.S256Bit> myAddObject = new AddClass<> (species);
```

**Code sample 12. Scalar code for loops with conditional statements.**

```java
for (int i = 0; i < SIZE; i++) {
    float res = b[i];
    if (a[i] > 1.0) {
        res = res * a[i];
    }
    c[i] = res;
}
```

**Code sample 13. Vector loop.**

```java
public void useMask (float [] a, float [] b, float [] c, int SIZE) {
    FloatVector.FloatSpecies<Shapes.S256Bit> species = (FloatVector.FloatSpecies<Shapes.S256Bit>)
Vector.speciesInstance Float.class, Shapes.S_256_BIT);
    FloatVector<Shapes.S256Bit> tv = species.broadcast (1.0f);
    int i = 0;
    for (; i + species.length() < SIZE; i += species.length()){
        FloatVector<Shapes.S256Bit> rv = species.fromArray (b,i);
        FloatVector<Shapes.S256Bit> av = species.fromArray (a,i);
        Vector.Mask<Float,Shapes.S256Bit> mask = av.greaterThan (tv);
        rv.mul (av, mask).intoArray (c,i);
    }
    //tail processing
}
```
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The BLAS sub-program contains a set of low-level linear algebra routines. These routines can take advantage of both Vector operations and SIMD instructions. BLAS algorithms are used in most common ML algorithms and utilities. For example, BLAS-3 GEMM is a ubiquitous algorithm used in DL and neural networks.

This discussion focuses on how to implement Vector API for few of the BLAS routines. Most of the BLAS algorithms can be fully expressed using Vector API. You can find more code samples here.

**The BLAS-1 DDOT routine**

Our first example uses the BLAS-1 DDOT routine. This routine computes the dot product of two vectors or arrays (A*B). Its product is returned as a scalar value.

The Vector program VecDdot uses the vector `mul()` routine to multiply both vectors and perform the horizontal reduction `sumAll()` on the result of the multiplication. The vector loop will need a tail/post loop to iterate over the remaining scalar values until it reaches the end of the arrays.

```
static void VecDdot (double [] a, int a_offset, double [] b, int b_offset) {
    DoubleVector.DoubleSpecies<Shapes.S512Bit> spec =
    (DoubleVector.DoubleSpecies<Shapes.S512Bit>) Vector.speciesInstance (Double.class, Shapes.S_512_BIT);
    int i = 0; double sum = 0;
    for (; i + spec.length () < a.length; i += spec.length ()) {
        DoubleVector<Shapes.S512Bit> l = spec.fromArray (a, i + a_offset);
        DoubleVector<Shapes.S512Bit> r = spec.fromArray (b, i + b_offset);
        sum += l.mul(r).sumAll();
    }
    for (; i < a.length; i++) sum += a[i + a_offset] * b[i + b_offset]; //tail
}
```

**Code sample 14.** The Vector program VecDdot multiplies two vectors and performs the horizontal reduction `sumAll()` on the result of the multiplication.

```
static void VecDaxpy (double [] a, int a_offset, double [] b, int b_offset, double alpha) {
    DoubleVector.DoubleSpecies<Shapes.S512Bit> spec =
    (DoubleVector.DoubleSpecies<Shapes.S512Bit>) Vector.speciesInstance (Double.class, Shapes.S_512_BIT);
    DoubleVector<Shapes.S512Bit> alphaVec = spec.broadcast (alpha); int i = 0;
    for (; (i + spec.length ()) < a.length; i += spec.length ()) {
        DoubleVector<Shapes.S512Bit> bv = spec.fromArray (b, i + b_offset);
        DoubleVector<Shapes.S512Bit> av = spec.fromArray (a, i + a_offset);
        bv.add (av.mul (alphaVec)).intoArray (b, i + b_offset);
    }
    for (; i < a.length; i++) b[i + b_offset] += alpha * a[i + a_offset]; //tail of the loop
}
```

**Code sample 15.** Using the DAXPY algorithm to broadcast the alpha scalar value outside the loop using `broadcast()`.

When implemented using vectors and when run on a platform that supports Intel® Advanced Vector Extensions 2 (Intel® AVX2), the performance of the SDOT routine (which operates on two float vectors) can be increased by up to 3.25x. See code sample 14.

**Horizontal reductions are platform-specific**

Horizontal reductions like `sumAll()` and `subAll()` are platform-specific operations. This is because different CPUs may have different instruction support at the hardware level.

You must be careful while handling horizontal reductions for `Float` and `Double`-based custom types in Java applications. The order of operations matters, and your implementation must be explicit for your specific reduction.

**The DAXPY algorithm in vector loops**

DAXPY is a BLAS level-1 algorithm used to compute a constant multiplied by a vector, plus a vector. When writing vector loops, you should broadcast all constant scalars into vectors before entering the loop kernel for better performance. (This helps you avoid generating unnecessary garbage.)

In this next example, we broadcast the alpha scalar value outside the loop using `broadcast()`. The result is computed from two arithmetic operations `add()` and `mul()`. The result is stored in array `b[]`, using `intoArray()`. See code sample 15.
void VecDgemm (String transa, String transb, int m, int n, int k, double alpha, double[] a, int a_offset, int lda, double[] b, int b_offset, int ldb, double beta, double[] c, int c_offset, int ldc, boolean nota, boolean nobt) {
  DoubleVector[DoubleSpecies<Shapes.S512Bit>] spec = Vector.speciesInstance (Double.class, Shapes.S_512_BIT);
  double temp;
  if (notb && nobt) { for (j = 0; j < n; j++) {
    if (b[l + j * ldb + b_offset] != 0.0) {
      temp = alpha * b[l + j * ldb + b_offset];
      DoubleVector<Shapes.S512Bit> tv = spec.broadcast (temp);
      for (i = 0; (i + spec.length ()) < m; i += spec.length ()) {
        DoubleVector<Shapes.S512Bit> av = spec.fromArray (a, i + l * lda + a_offset);
        DoubleVector<Shapes.S512Bit> cv = spec.fromArray (c, i + j * ldc + c_offset);
        tv.fma (av, cv).intoArray (c, i + spec.length () + j * ldc + c_offset);
      }
    }
  }
  }
}

public double getOptionPrice (double Sval, double Xval, double T) {
  double temp;
  Shapes.S_512_BIT);
  double MuByT = (riskFree + 0.5 * volatility * volatility) * T;
  double VBySqrtT = volatility * Math.sqrt (T);
  double MuByT = (riskFree - 0.5 * volatility * volatility) * T;
  //Simulate Paths
  for (int path = 0; path < numberOfPaths; path++) {
    double callValue = Sval * Math.exp (MuByT + VBySqrtT * z[path]) - Xval;
    callValue = (callValue > 0) ? callValue : 0;
    val += callValue;
    val2 += callValue * callValue;
  }
  double optPrice = 0.0;
  optPrice = val / numberOfPaths;
  return (optPrice);
}

Code sample 16. DGEMM: C = alpha*A*B+beta*C. Here, A and B are non-zero matrices that are not transposed; while alpha is a non-zero scalar, and beta scalars as 1.

In the presence of nested loops, it is possible to broadcast scalars in the outer loop — provided the inner compute loop doesn’t modify the scalar value. In our example with BLAS-3, temp is broadcast outside, since it is unchanged inside the compute kernel.

When you use vector implementation with Intel® AVX2 support, you can boost the performance of BLAS-II routines such as SSYR by up to 2.5x, and SSPR by up to 4x. You can boost the performance of typical BLAS-III routines like SGEMM by about 4.25x.

The example above also uses the fma () vector (fused multiply-add) operation. You could express the original vector operation cv.add (av.mul (tv)) as tv.fma (av, cv), using the FMA library function in Java. To speed up performance, you should leverage the Intel AVX FMA instructions. Several BLAS-2 and BLAS-3 routines can be written using these vector operations.

Code examples: Financial services applications

Vector API is highly applicable to benchmarks and use cases in the financial services industry. For example, the getOptionPrice () program is used for Monte Carlo European simulations to get the option price. In this program, loop-independent scalar values (like VBySqrtT, MuByT, Sval, and Xval) can be broadcast first. Within the loop, the z[path] array is loaded into a vector. That is followed by a trigonometric math exp () operation on the vectors that were created from VBySqrtT, MuByT and z[path].

You can write a vector version of this over a number of paths. Code sample 17 shows the code in scalar form.

Code sample 17. Vector version of trigonometric math exp () operation on the vectors created from VBySqrtT, MuByT and z[path].

In this example, A and B are non-zero matrices that are not transposed; while alpha is a non-zero scalar, and beta scalars as 1.

You can find a VecDgemm example of this here.

Vector-matrix and matrix-matrix operations

BLAS-2 and BLAS-3 routines, such as DSYR and DGEMM respectively, perform vector-matrix or matrix-matrix operations. Code sample 16 showcases DGEMM: C = alpha*A*B+beta*C.
Note that, when writing mathematical expressions, you must be careful to maintain operator precedence. See code sample 18.

Code sample 19 shows the vector loop kernel.

**Java ternary operations: Use the blend () routine**

The Vector API provides a blend () routine for Java ternary operations (such as maxVal=a>0? a: 0) of two Vectors.

If you look at the previous code sample, blend () takes a second operand as zero vector instance zeroVec, and the masked output from greaterThan (zeroVec) of the first vector. This is then followed by a horizontal reduction sumAll (). In turn, that accumulates the scalar results in the val and val2 variables.

Code sample 20 shows the relevant line from the previous code sample.

**Using a Binomial Lattice**

The BinomialOptions () FSI algorithm uses a binomial lattice model (Cox, Ross and Rubenstein method) to price the European call option. At every step, the value of stock “S” can go up by u*S or down by v*S. This leads to a simple loop going over all leaf nodes in order to calculate the payoff at the expiry.

Code sample 21 shows the scalar algorithm.
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As shown in our previous examples, we broadcast the scalar constants and/or function parameters outside the loop. See code sample 22.

### Addressing the challenge of type casting

You can write a vector version of the algorithm over the number of nodes. In this case, one of the challenges of writing the vector code is type casting.

We use `cast (Double.class)` to explicitly type cast `Vector<Integer, Shapes.S512Bit>` to `Vector<Double, Shapes.S512Bit>`. Here, our program uses `blend()` for ternary operations on profit values. We store values greater than zero into `stepsArray`.

See code sample 23.

Code sample 24 shows a vector version of the first loop that computes profit.

The second loop can also be expressed in vector form. Moreover, you can write the expression using `fma()`. Look at code sample 25.

You can see the Vector API implementation for these algorithms at [https://software.intel.com/en-us/articles/vector-api-developer-program-for-java](https://software.intel.com/en-us/articles/vector-api-developer-program-for-java).

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**Code sample 22. Broadcasting scalar constants and/or function parameters outside the loop.**

```
DoubleVector<Shapes.S512Bit> sv = spec.broadcast(s);
DoubleVector<Shapes.S512Bit> vsdtVec = spec.broadcast (vsdt);
DoubleVector<Shapes.S512Bit> xv = spec.broadcast (x);
DoubleVector<Shapes.S512Bit> pdv = spec.broadcast (pdByr);
DoubleVector<Shapes.S512Bit> puv = spec.broadcast (puByr);
DoubleVector<Shapes.S512Bit> xv = spec.broadcast (0.0D);
IntVector<Shapes.S512Bit> inc = ispec.fromArray (new int[] {0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15}, 0);
IntVector<Shapes.S512Bit> nSV = ispec.broadcast (numSteps);
```

**Code sample 23. Addressing the challenge of type casting.**

```
int j;
for (j = 0; (j + spec.length()) < STEPS_CACHE_SIZE; j += spec.length()) {
  IntVector<Shapes.S512Bit> jv = ispec.broadcast (j);
  Vector<Double, Shapes.S512Bit> tv = jv.add (inc).cast (Double.class).mul (spec.broadcast (2.0D)).sub (nSV.cast (Double.class));
  DoubleVector<Shapes.S512Bit> pftVec = sv.mul (vsdtVec.mul (tv).exp ()).sub (xv);
  pftVec.blend (zv, pftVec.greaterThan (zv)).intoArray (stepsArray, j);
}
for (; j < STEPS_CACHE_SIZE; j++) { //tail processing
  double profit = s * Math.exp (vsdt * (2.0D * j - numSteps)) - x;
  stepsArray[j] = profit > 0.0D? profit : 0.0D;
}
```

**Code sample 24. Vector version of the first loop that computes profit.**

```
for (j = 0; j < numSteps; j++) {
  int k;
  for (k = 0; k + spec.length() < NUM_STEPS_ROUND; k += spec.length()) {
    DoubleVector<Shapes.S512Bit> sv0 = spec.fromArray (stepsArray, k);
    DoubleVector<Shapes.S512Bit> sv1 = spec.fromArray (stepsArray, k + 1);
    pdv.mul (sv1).add (puv.mul (sv0)).intoArray (stepsArray, k);
    //sv0 = pdv.fma (sv1, puv.mul (sv0)); sv0.intoArray (stepsArray, k);
  }
  for (; k < NUM_STEPS_ROUND; ++k) {
    stepsArray[k] = pdByr * stepsArray[k + 1] + puByr * stepsArray[k];
  }
}
```

**Code sample 26. Expressing the second loop (that computes profit) in vector form, using fma().**

```java
2.0D * j – numSteps; //scalar form (implicit cast)
Vector<Double, Shapes.S512Bit> tv = jv.add (inc).cast (Double.class).mul (spec.broadcast (2.0D)).sub (nSV.cast (Double.class));
```
Conclusion

Big data applications, distributed deep learning programs, and artificial intelligence solutions can run directly on top of existing Spark or Apache Hadoop clusters, and can benefit from efficient scale out. The OpenJDK Project Panama enables data parallelism, by including a rich set of Vector API methods to enrich machine learning and deep learning support.

Using Vector API, you can boost the performance of several BLAS algorithms (up to Level 3 routines) by 3x to 4x when running them on Intel® AVX-enabled platforms. Using this API, you can now write your own vector algorithms in Java itself, to achieve higher performance and leverage the advanced SIMD features provided by modern CPUs.

Although the Vector API is available for use, it is an evolving project, and JVM support for Vector API is still in progress. Currently, Vector API provides a comprehensive set of methods for basic arithmetic and advanced vector operations. It is available for use under experimental Panama and JVM flags, and will be published soon once more progress is made on the implementation.

Where to get started with Vector API

You can download Vector API under the experimental flags in Project Panama. We suggest you download the latest Project Panama Vector API sources using Mercurial* source-control, by cloning http://hg.openjdk.java.net/panama/panama/. JVM flags for real-world use are expected to be published soon.

You can find Vector interface implementations in the vector-draft-spec directory, under com/oracle/java. Several vector API examples are available inside the src/test/java folder.

We recommend using the JetBrains IntelliJ IDEA* community edition as the integrated development environment (IDE) for related development. You can find detailed instructions for using IntelliJ IDEA at the Vector API developer Program webpage.

About the Author

Rahul Kandu is a senior software engineer in the Intel Software and Services Group (SSG). He focuses on Java runtime and SOC performance analysis and Hotspot compiler optimizations.

To learn more about using Vector API to write your own vector algorithms, visit the Vector API developer program site