LLM-VECTORIZER: LLM-based Verified Loop vectorizer

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Programmer's Dilemma in the World of Compute

Problem: Write fast code.

Solution:

- 1. Write unoptimized code and leave the rest on compiler optimizations (such as Auto Vectorization)
- 2. Write SIMD code by hand

Challenges

Problem in Auto-Vectorizers

- Conservative approach
- Misses a lot of optimization opportunities
- Error-prone

Problem in manually writing SIMD code

- Time-consuming
- Error-prone
- Limited to expert programmers who understand vector intrinsics

Problem Statement

Can advances in LLMs and formal verification be leveraged to automatically optimize scalar C programs into equivalent vectorized programs using AVX2 intrinsics?

Motivating Example

Vectorize with Clang

\$ clang -O3 -mavx2 -fstrict-aliasing -fvectorize -fslp-vectorize-aggressive -Rpass-missed=loop-vectorize -Rpass-analysis=loop-vectorize -lm test.c

Vectorize with GCC

```
jubi@DESKTOP-A49C4F9:~/rise/vectorizationGPT/src$ gcc -W -O3 -mavx2 -lm -ftree-vectorizer-verbose=3 -ftree-vectorize -fopt-info-vec-missed ../test/final-results/perf/src.c -o src36 ../test/final-results/perf/src.c:12:5: missed: couldn't vectorize loop ../test/final-results/perf/src.c:13:14: missed: not vectorized, possible dependence between data-refs *_3 and *_12 ../test/final-results/perf/src.c:52:5: missed: couldn't vectorize loop ../test/final-results/perf/src.c:13:14: missed: not vectorized: complicated access pattern. ../test/final-results/perf/src.c:12:5: missed: couldn't vectorize loop ../test/final-results/perf/src.c:13:14: missed: not vectorized, possible dependence between data-refs *_18 and *_27 ../test/final-results/perf/src.c:51:13: missed: statement clobbers memory: start_8 = clock (); ../test/final-results/perf/src.c:55:11: missed: statement clobbers memory: end_10 = clock (); /usr/include/x86_64-linux-gnu/bits/stdio2.h:100:10: missed: statement clobbers memory: __fprintf_chk (stdout.0_3, 1, "%f", cpu_time_used_11);
```

\$ gcc -W -O3 -mavx2 -lm -ftree-vectorizer-verbose=3 -ftree-vectorize -fopt-info-vec-optimized test.c

Vectorize with GPT-4

```
#include <immintrin.h>
void src36(int n, int *a, int *b, int *c, int *d) {
    int i = 0:
    for (; i \le n - 2 - 7; i += 8) {
        m256i va = mm256 loadu si256(( m256i *)&a[i]);
        __m256i va_next = _mm256_loadu_si256((__m256i *)&a[i + 1]);
        m256i \ vc = mm256 \ loadu \ si256(( \ m256i \ *)&c[i]);
        m256i \ vd = mm256 \ loadu \ si256(( \ m256i \ *)&d[i]);
        m256i \text{ vb} = mm256 \text{ loadu si256(( } m256i *)&b[i]);
        va = mm256 mullo epi32(va, vc);
        _mm256_storeu_si256((__m256i *)&a[i], va);
        va_next = _mm256_mullo_epi32(va_next, vd);
        vb = mm256 add epi32(vb, va next);
        mm256 storeu si256((__m256i *)&b[i], vb);
    for (; i < n - 1; i++) {
        a[i] *= c[i];
        b[i] += a[i + 1] * d[i];
```

Is there a backward loop carried dependence?

Is the LLM-based vectorized code correct?

Checksum-based Testing

- Randomly initialize the input arrays
- Execute the function
- Compare the output values written into the arrays from both unvectorized and vectorized programs.

Is the testing criterion sufficient?

Motivating Example for Symbolic Verification

```
void s124(int *a, int *b, int *c, int *d, int *e, int n) {
     int j;
     j = 1;
     for (int i = 0; i < n; i++) {
         if (b[i] > 0) {
             j++;
             a[j] = b[i] + d[i] * e[i];
         } else {
             j++;
             a[j] = c[i] + d[i] * e[i];
```

```
void s124 ( int *a, int *b, int *c, int *d, int *e, int n) {
    int j = 0;
    <u>__m256i</u> increment = <u>_mm256_set1_epi32 (1)</u>;
    <u>__m256i</u> zero = <u>_mm256_setzero_si256 ();</u>
    for ( int i = 0; i < n; i +=8) {
        _{m256i} \text{ vbi} = _{mm256} loadu_si256 (( __m256i *)&b[i]);
        __m256i vci = _mm256_loadu_si256 (( __m256i *)&c[i]);
        __m256i vdi = _mm256_loadu_si256 (( __m256i *)&d[i]);
        __m256i vei = _mm256_loadu_si256 (( __m256i *)&e[i]);
        m256i \text{ vprod} = mm256 \text{ mullo epi32 (vdi , vei );}
        <u>__m256i</u> vsum_b = _mm256_add_epi32 (vbi , vprod );
        <u>__m256i</u> vsum_c = _mm256_add_epi32 (vci , vprod );
        __m256i vmask = _mm256_cmpgt_epi32 (vbi , zero );
        <u>__m256i</u> va = _mm256_blendv_epi8 ( vsum_c , vsum_b , vmask );
        mm256 storeu si256 (( m256i *)&a[j], va);
        j +=8;
```



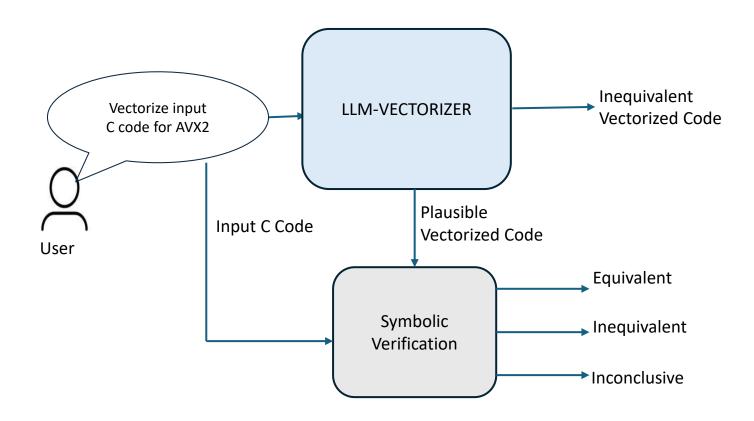
Symbolic Verification



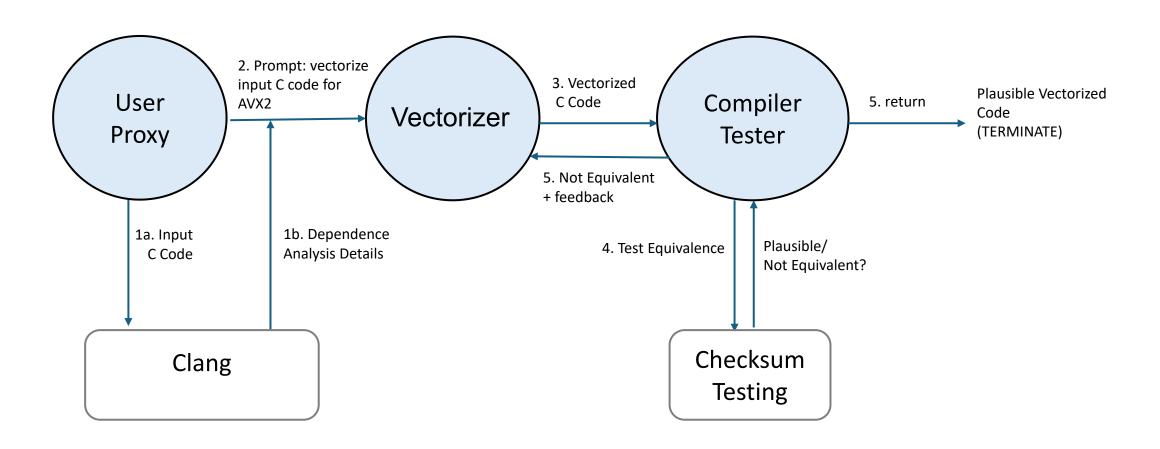
```
void s124(int *a, int *b, int *c, int *d, int *e, int n) {
     int j;
     j = 1;
     for (int i = 0; i < n; i++) {
         if (b[i] > 0) {
             j++;
             a[j] = b[i] + d[i] * e[i];
         } else {
             j++;
             a[j] = c[i] + d[i] * e[i];
```

```
void s124 ( int *a, int *b, int *c, int *d, int *e, int n) {
    int j = 0;
    m256i increment = _mm256_set1_epi32 (1) ;
    <u>__m256i</u> zero = <u>_mm256_setzero_si256 ();</u>
    for ( int i = 0; i < n; i +=8) {
        _{m256i} vbi = _{mm256}loadu_si256 (( ___m256i *)&b[i]);
        m256i vci = _mm256_loadu_si256 (( __m256i *)&c[i]);
        m256i \ vdi = mm256_loadu_si256 (( m256i *)&d[i]);
        _{m256i} vei = _{mm256}loadu_si256 (( _{m256i} *)&e[i]);
        m256i \text{ vprod} = mm256 \text{ mullo epi32 (vdi , vei );}
        __m256i vsum_b = _mm256_add_epi32 (vbi , vprod );
        m256i vsum c = mm256 add epi32 (vci , vprod );
        m256i \text{ vmask} = mm256 \text{ cmpgt epi32 (vbi, zero)};
        __m256i va = _mm256_blendv_epi8 ( vsum_c , vsum_b , vmask );
        mm256 storeu si256 (( m256i *)&a[j], va);
        i +=8;
```

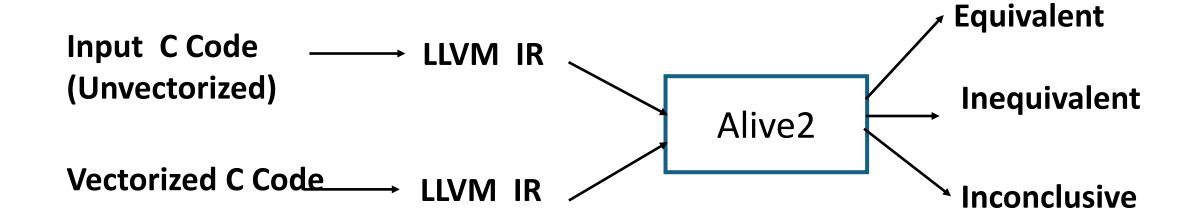
Overview of LLM-VECTORIZER



Detailed Overview of LLM-VECTORIZER



Symbolic Verification with Alive2



Symbolic Verification with Alive2

```
for (int i = 0; i < n; i++) {
    a[i] = b[i] + c[i];
}</pre>
```

```
for (int i = 0; i < n - 8; i += 8) {
b_vec = _mm256_loadu_si256 (( __m256i *) &b[i]);
c_vec = _mm256_loadu_si256 (( __m256i *) &c[i]);
a_vec = _mm256_add_epi32 (b_vec , c_vec );
_mm256_storeu_si256 (( __m256i *) &a[i], a_vec );
}</pre>
```

Symbolic Verification with Alive2

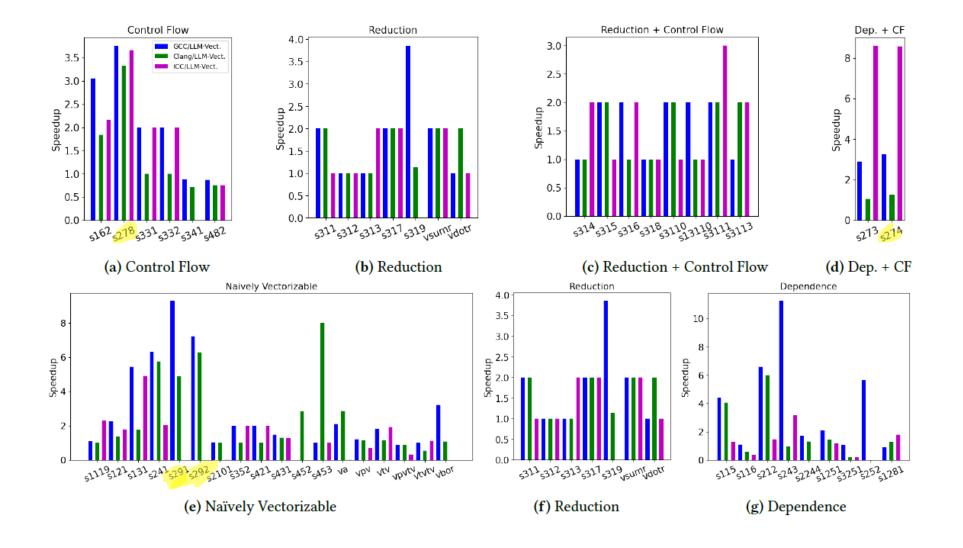
- Bounded loop verification
- Loop Alignment by unrolling unvectorized and vectorized loops
- Unrolling loops at LLVM IR level leads to larger solver queries and solver returns inconclusive results
- Scaling Techniques:
 - C-level unrolling
 - Spatial-case splitting

[RQ] How well can GPT4 vectorize the code on its own?

Techniques	Total tests	Equivalent	Not Equivalent	Inconclusive
Checksum- based Testing	149	0	24	125 [Plausible]
Alive2	125	26	17	82
C-level Unroll	82	28	18	36
Splitting	36	3	2	31
All	149	57	61	31

38.2% tests proven equivalent

[RQ] Is LLM-vectorized code faster?



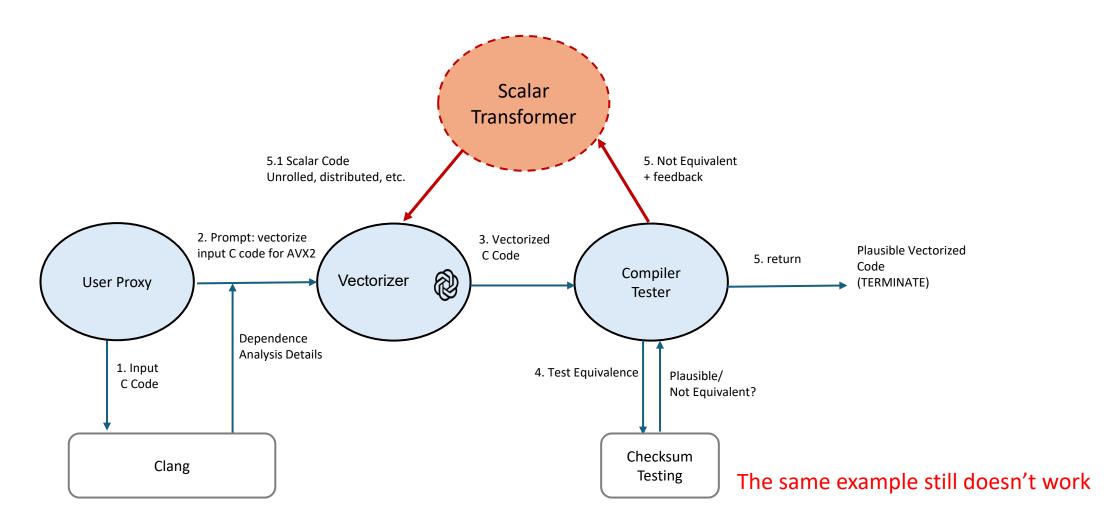
When LLMs fail?

```
void src7(int *a, int *b, int n) {
       for (int i = 0; i < n; i++) {
           a[i] = a[n/2] + b[i];
void src7(int *a, int *b, int n) {
     m256i va half = mm256 set1 epi32(a[n / 2]);
    for (int I = 0; i <= n - 8; i += 8) {
         _{m256i} vb = _{mm256}loadu_{si256((_{m256i} *)(b + i));
          m256i vres = mm256 add epi32(va half, vb);
        _mm256_storeu_si256(( m256i *)(a + i), vres);
```

When LLMs fail?

```
void src7(int *a, int *b, int n) {
       for (int i = 0; i < n; i++) {
           a[i] = a[n/2] + b[i];
a[0] = a[4] + b[0]
a[1] = a[4] + b[1]
a[2] = a[4] + b[2]
     = a[4] + b[3]
            + b[4]
     \neq a[4] + b[5]
            + b[6]
```

Repair with Scalar Transformation Agent



Conclusion

Problem:

Auto-vectorization in modern compilers remains conservative.

Our approach:

Leverage LLMs (GPT-4, no fine-tuning) and Formal Verification to generate correct vectorized code.

Conclusion

What we achieved?

LLMs produced vectorized code with up to **9.4**× **speedups** over compilers, while formal verification (Alive2) ensured correctness for **38.2**% of the tests.

Next Steps:

Unbounded loop verification remains an open problem. Feedback loop from symbolic verification

Conclusion

Rethinking Compiler Design:

Blending LLMs (AI agents and feedback loops), Formal Methods, Synthesis and human intuition? Thoughts?

Can LLMs generate fast code?

How can we guarantee LLM-based transformations are both fast and correct?

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Backup

Successful Repair Experience

```
//Input code

void s453(int *a, int *b, int n) {
  int s = 0;
  for (int i = 0; i < n; i++) {
    s += 2;
    a[i] = s * b[i];
  }
}</pre>
```

```
// First Attempt, incorrect code
void s453(int *a, int *b, int n) {
m256i s vec = mm256 set1 epi32(0);
 m256i two_vec = _mm256_set1_epi32(2);
m256i s increment = mm256 set1 epi32(16);
int i = 0;
for (; i \le n - 8; i += 8) {
s_vec = _mm256_add_epi32(s_vec, two_vec);
__m256i b_vec = _mm256_loadu_si256((___m256i*)&b[i]);
m256i a_vec = _mm256_mullo_epi32(s_vec, b_vec);
_mm256_storeu_si256((__m256i*)&a[i], a_vec);
s_vec = _mm256_add_epi32(s_vec, s_increment);
```

Repair Experience

```
//Input code

void s453(int *a, int *b, int n) {
  int s = 0;
  for (int i = 0; i < n; i++) {
    s += 2;
    a[i] = s * b[i];
  }
}
```

```
// Second Attempt, plausible code
void s453(int *a, int *b, int n) {
  m256is vec = mm256 setr epi32(2, 4, 6, 8, 10, 12, 14, 16);
 m256i two vec = mm256 set1 epi32(16);
int i = 0:
for (; i \le n - 8; i += 8)
 m256i b vec = mm256 loadu si256(( m256i*)&b[i]);
__m256i a_vec = _mm256<mark>_mullo_epi32(s_vec, b_vec);</mark>
_mm256_storeu_si256((__m256i*)&a[i], a_vec);
s_vec = _mm256_add_epi32(s_vec, two_vec);
```

[RQ] Does Al-agents design help?

1. Can we reduce the number of LLM invocations?

2. Can we repair the programs using auxiliary tools (like clang's dependence information) and agents in LLM-Vectorizer?

[RQ] Number of LLM invocations

- For k=1 (one code completion), previously we found
 72 plausible tests. With Al-agents, we found 24 new
 tests => 96 plausible tests with k=1
- With Al-agents, we found 4 unique tests for which 100 code completions (k=100) couldn't find a plausible solution, but agents finds it in k=1.