An optimized Baum-Welch algorithm

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Baum-Welch algorithm

- Computes **Probability distribution** over a model
- The hidden states of a hidden Markov model
- Using expectation-maximization

We decide/are given

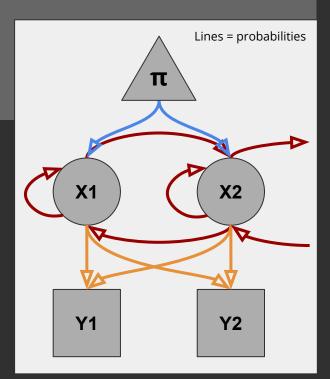
N: # hidden states

M: # observations

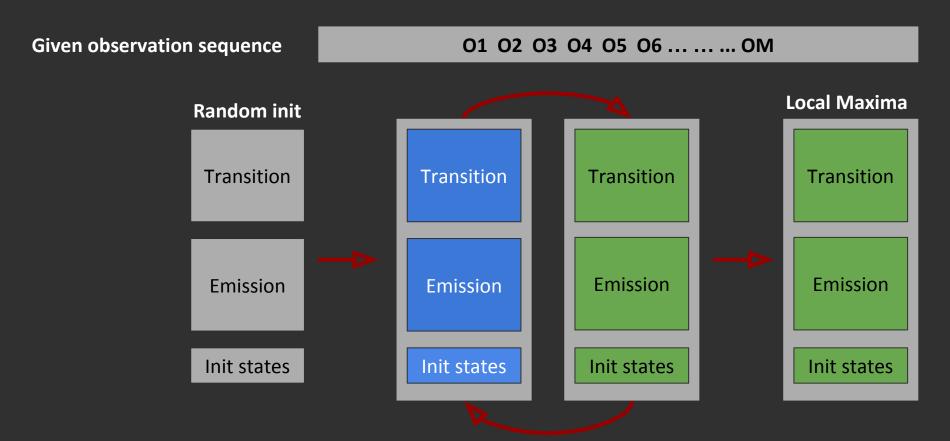
K: # observation sequences

T: # time steps

Max_iterations: # iterations to perform



Task of the Baum-Welch algorithm



Cost Analysis

Asymptotic runtime per iteration:

$$O(KTN * (M+N)) \approx O(N^2)$$

Flops per iteration:

```
9*TKNN - 5*KNN + NN + 8*TKN + 2*KNM + 3*KN + 2*TK + NM + K +N Flops
```

Memory usage:

```
(max_iterations + KTNN + KNN + NN + KTN + NM + KN + 2*KT + N)*8 + 144 Bytes
```

Featured weight: NN

Baseline Implementation + Performance

Implementation:

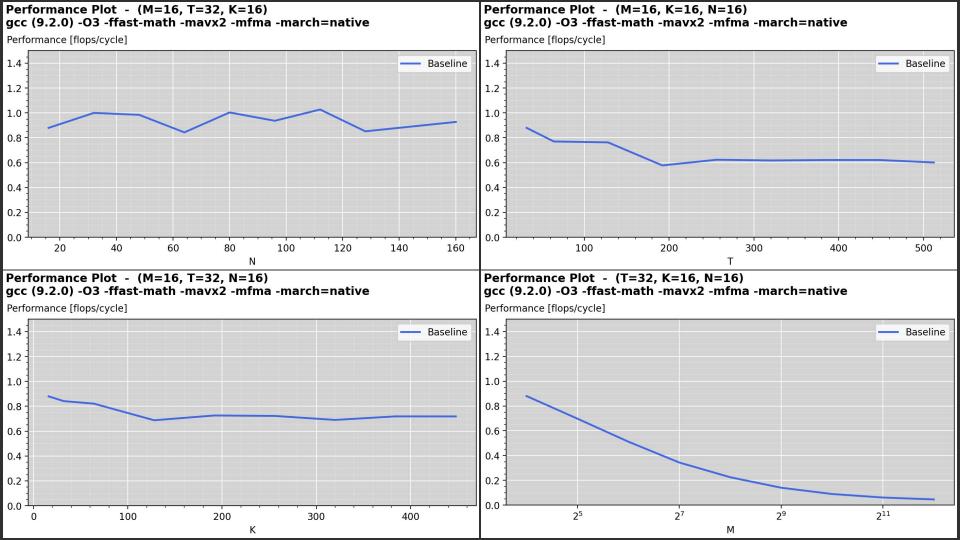
- Implemented code from the referenced tutorial slides
- Struct with pointer to arrays for convenience

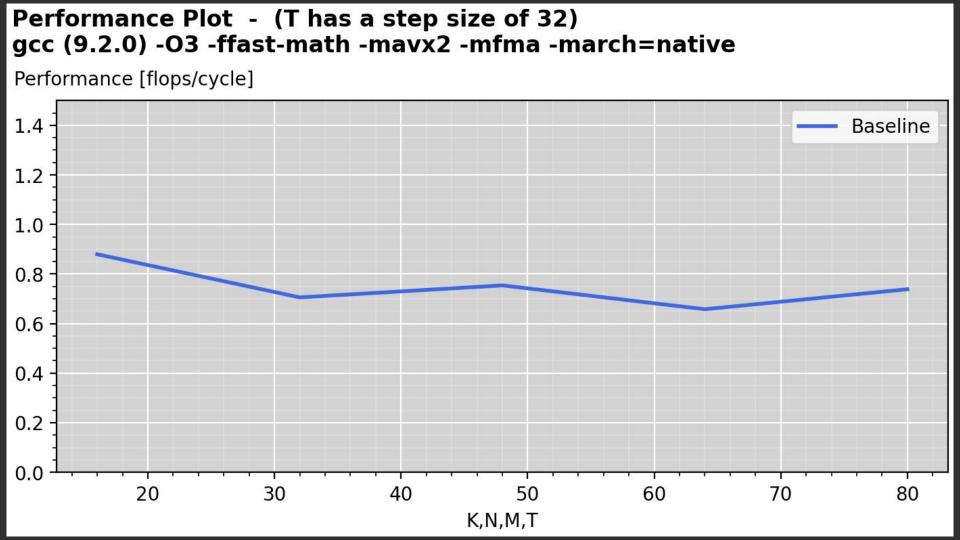
Assumptions:

- Divisibility of N, M and K by 16 and T by 32

Verification:

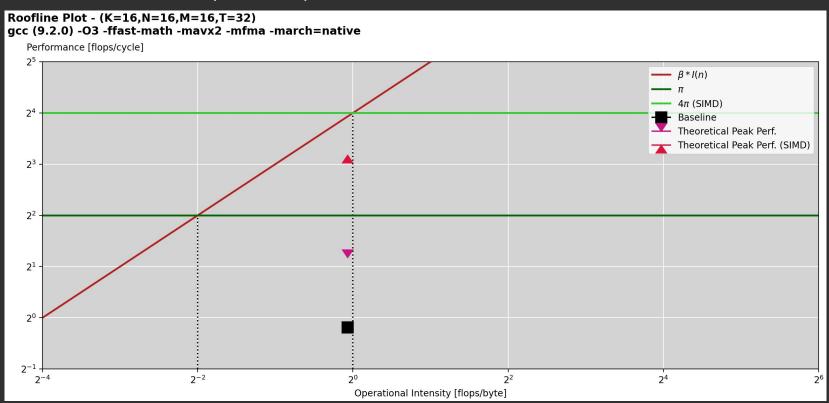
- 1. Compare baseline against other implementations known to be correct
- 2. Compare our optimizations against our baseline





Baseline Roofline Plot

Haswell i7-4710MQ, 2.5GHz, 12GB RAM



Optimizations we performed

- Precomputing (taking code out of the loop)
- Reordering of the code (combining loops, transformed some terms)
- Scalar replacement
- Unrolling
- Blocking
- Vectorization
- Using alternative input (transformed a matrix)

Optimizations we performed - reordering

Observation:

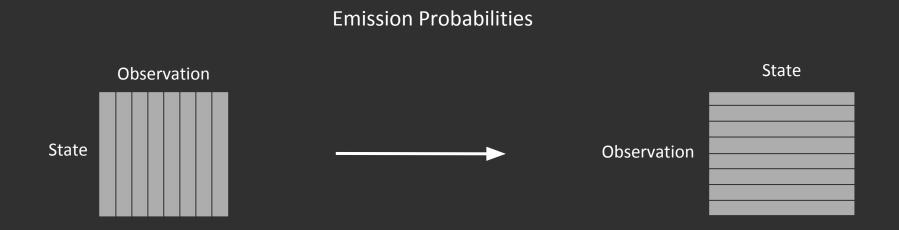
- Data dependency (e.g. forwards-step before backwards-step)
- Once all data is computed, dependency can be computed (gamma, sigma)

Conclusion: Merging of loops possible

Result:

- + Efficient loop usage
- + Less Division operations
- + Less calls to log

Optimizations we performed - alternative input



An implementation can request the input matrix for the emission probabilities to be transposed. This improves locality.

Optimizations we performed - vectorization

 Application of knowledge gained in exercises (e.g. horizontal addition)

Awareness of data dependency during unrolling
 (e.g. usage of T-1 or T+1 in calculus prevents unrolling T)

Experiments

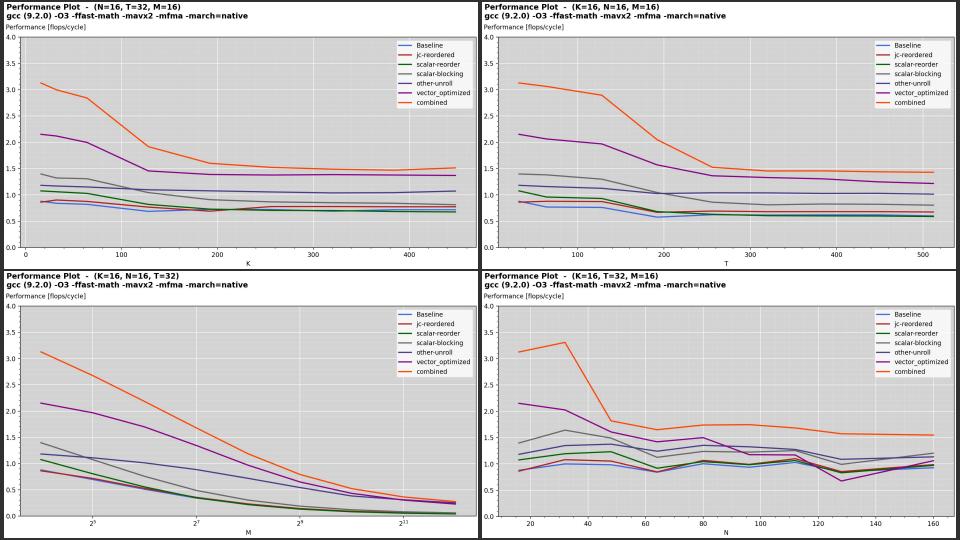
CPU: Haswell i7-4710MQ, 2.5GHz, 12GB RAM

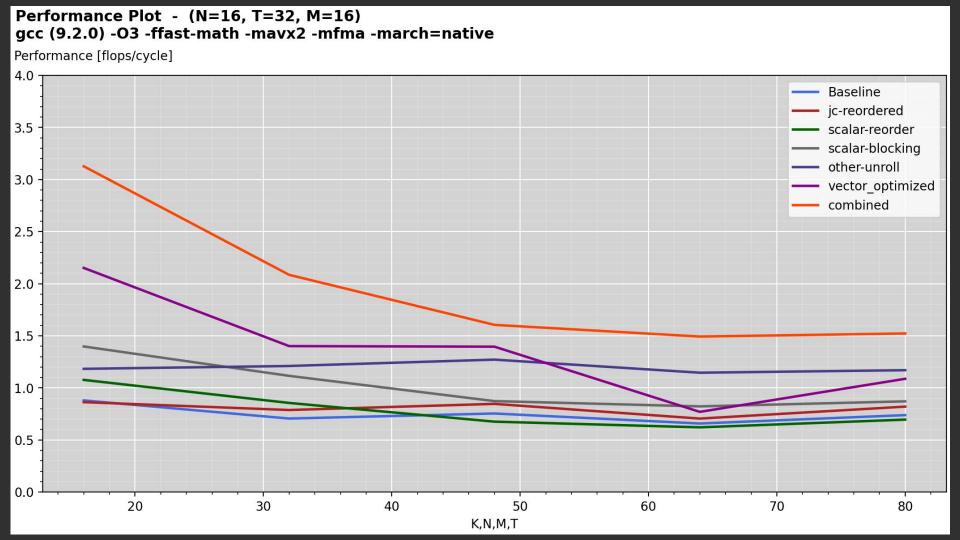
- L1: 32 KB (8-way associative, instruction+data cache)
- L3: 6 MB 12-way set associative shared cache
- AVX2 supported

Compiler: gcc 9.2.0 and clang 7.01

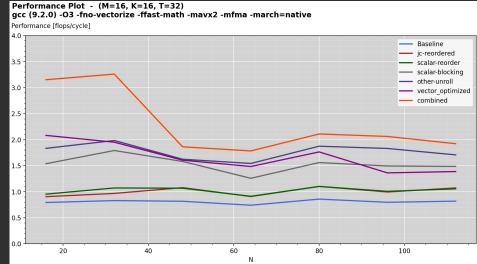
Flags:

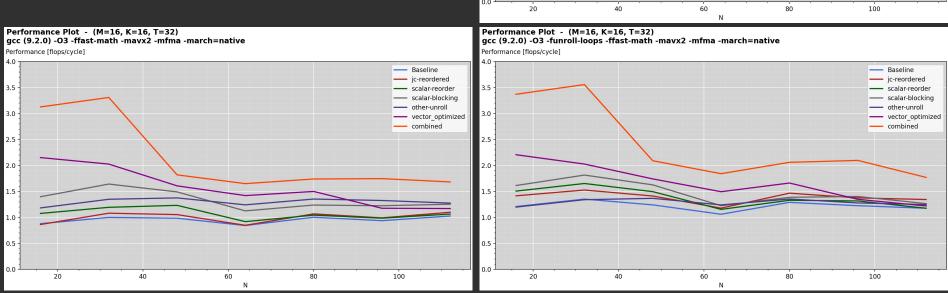
- -O3 -ffast-math -mavx2 -mfma -march=native
- -O3 -fno-vectorize -ffast-math -mavx2 -mfma -march=native
- -O3 -funroll-loops -mavx2 -mfma -march=native



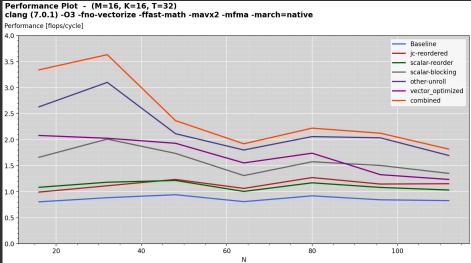


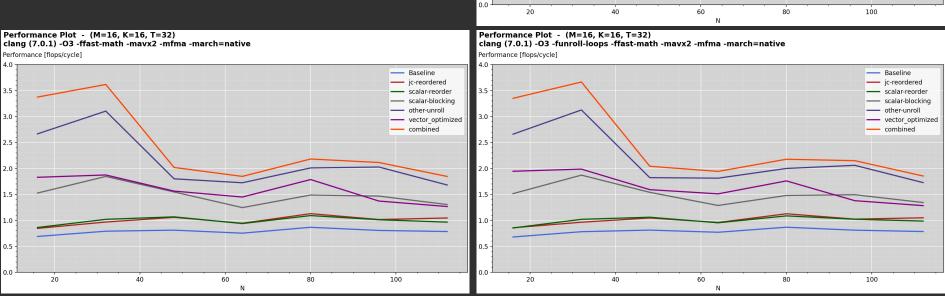
Different Flags (gcc)

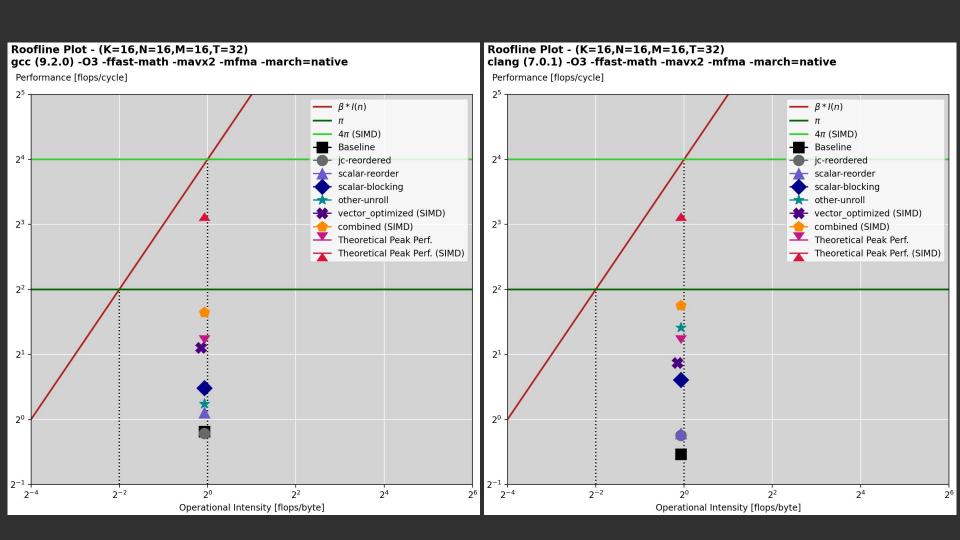


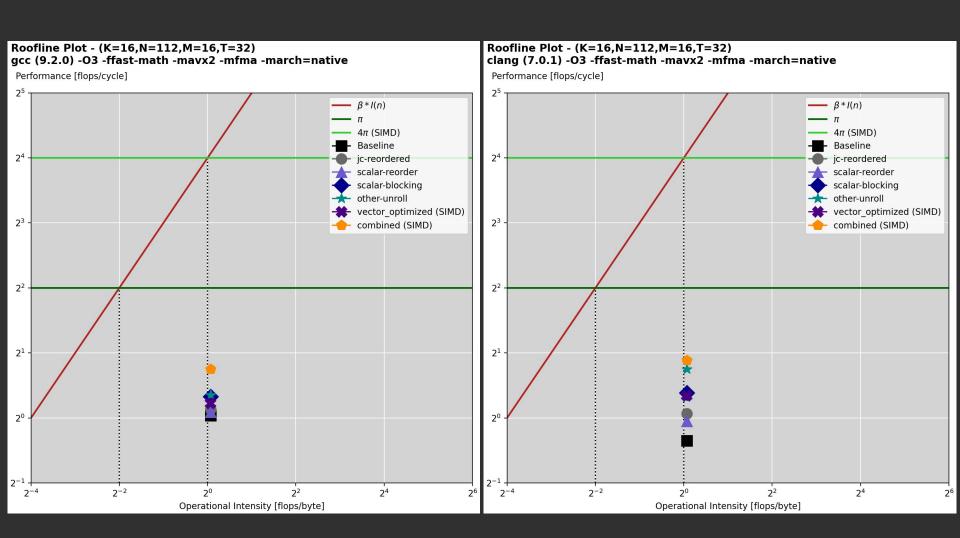


Different Flags (clang)









Conclusion

Combination makes the difference.

Dependant on the compiler and optimization flags,
optimizations can differ or even worsen the performance

Plots as analysation for further optimizations