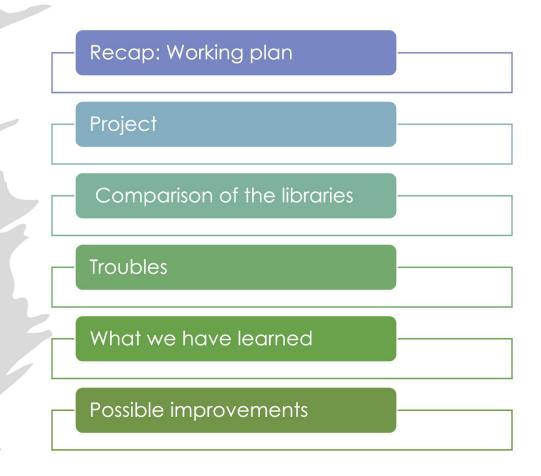


Table of content





Phase 0: Understanding of LSQR method

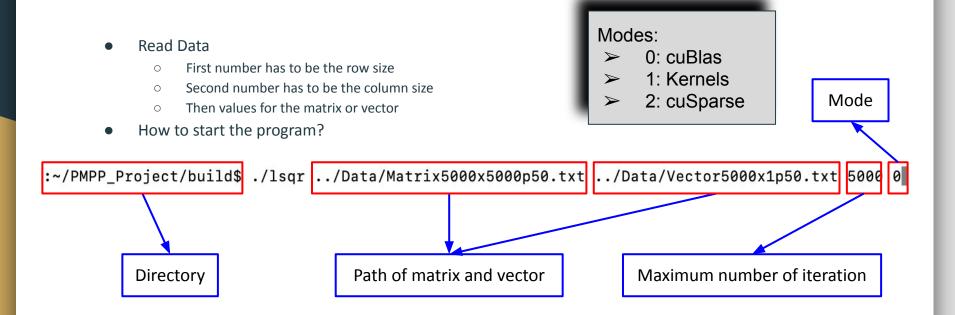
Phase 1: Programm and test of the LSQR method with a small matrix

Phase 2: Try and modify LSQR method for a matrix A that can not fully stored in the memory is really big

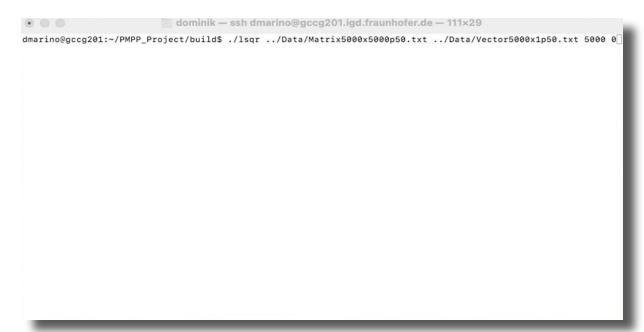
What we have done

- cuBlas implementation
 - Only using cuBlas subroutines for the lsqr implementation
- cuSparse implementation
 - Using cuSparse subroutines for the lsqr implementation
 - If there is no subroutine implemented ——— using own kernels
 - Norm kernel
 - Addition and subtraction vector kernel
 - Multiply scalar with a vector
- Kernel implementation
 - Norm kernel
 - Addition and subtraction kernel
 - Multiply scalar to vector
 - Multiply sparse matrix with vector
- Matlab and Python code for Testing and creating sparse matrices and vectors

Project - Read data and compile



Example



Sparse GPU Kernels for Deep Learning

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Abstract—Scientific workloads have traditionally exploited high levels of sparsity to accelerate computation and reduce memory requirements. While deep neural networks can be made sparse, achieving practical speedups on GPUs is difficult because these applications have relatively moderate levels of sparsity that are not sufficient for existing sparse kernels to outperform their dense counterparts. In this work, we study sparse matrices from deep learning applications and identify favorable properties that can be exploited to accelerate computation. Based on these insights, we develop high-performance GPU kernels for two sparse matrix operations widely applicable in neural networks: sparse matrix-dense matrix multiplication and sampled densedense matrix multiplication. Our kernels reach 27% of singleprecision peak on Nvidia V100 GPUs. Using our kernels, we demonstrate sparse Transformer and MobileNet models that achieve $1.2-2.1\times$ speedups and up to $12.8\times$ memory savings without sacrificing accuracy.

Index Terms—Neural networks, sparse matrices, graphics processing units

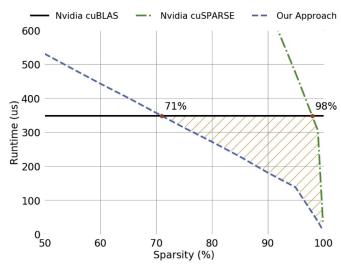
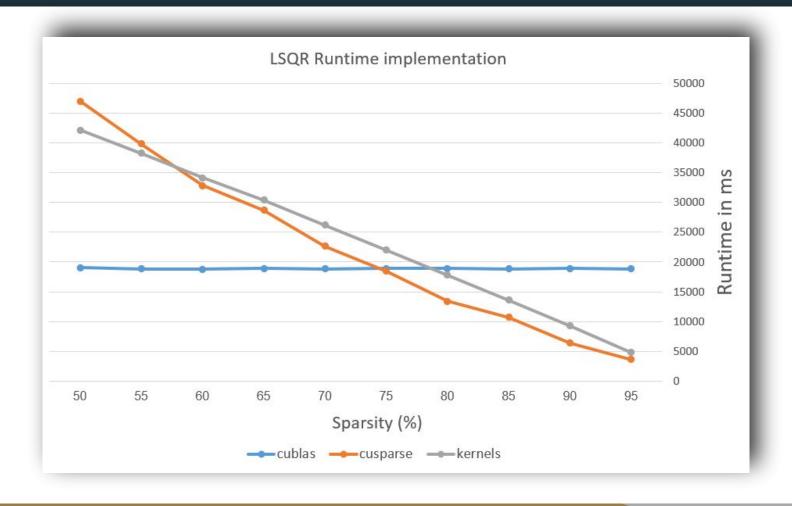
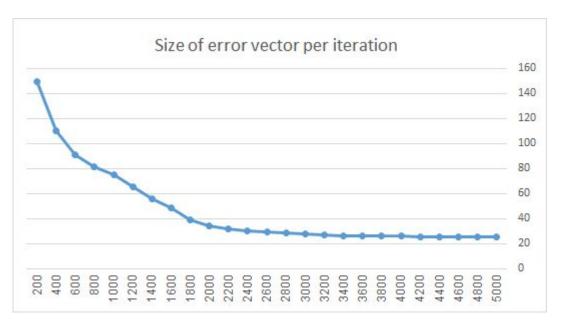


Fig. 1. Sparse matrix-matrix multiplication runtime for a weight-sparse



Convergence of the algorithm

(square matrix, 5000*5000, sparsity: 50%, values are integers in range 0-100)-> |Ax-b|



Troubles

- "Voodoo" Errors in kernels when using more than one block of threads, variables had "left over" values in shared memory
- Errors with Linking/using old libraries of cublas/cusparse
- Univertable matrices might cause weird error values
- The algorithm is working for about 150 iterations and then goes completely wrong
- Problems with cudaMallocPitch
- Problems with transposing the matrix

What we have learned

- cuBlas und cuSparse are old-fashioned and hard to work with
- Checking cuda errors after every operation
- Cuda error codes are partial and confusing
- Shared memory needs to be initialized to 0
- Memory needs to be freed as soon as possible
- It's better to avoid allocating memory and copying it
- Using sparse libraries is worth it at about 80% sparsity

```
cusparseCsr2cscEx2 bufferSize(cusparseHandle t
                                                    handle,
                              int
                                                    m,
                                                    n,
                              int
                                                    nnz,
                              const void*
                                                    csrVal,
                              const int*
                                                    csrRowPtr,
                              const int*
                                                    csrColInd,
                              void*
                                                    cscVal,
                              int*
                                                    cscColPtr,
                              int*
                                                    cscRowInd,
                              cudaDataType
                                                    valType,
                              cusparseAction t
                                                    copyValues,
                              cusparseIndexBase t idxBase,
                              cusparseCsr2CscAlg t alg,
```

```
cusparseStatus_t
cusparseCsr2cscEx2(cusparseHandle t
                                        handle,
                   int
                                        m,
                   int
                                        n,
                                        nnz,
                   const void*
                                        csrVal,
                   const int*
                                        csrRowPtr,
                   const int*
                                        csrColInd,
                   void*
                                        cscVal,
                   int*
                                        cscColPtr,
                   int*
                                        cscRowInd,
                   cudaDataType
                                        valType,
                   cusparseAction t
                                        copyValues,
                   cusparseIndexBase t idxBase.
                   cusparseCsr2CscAlg_t alg,
```

Possible improvements

- Matrix multiplication with shared memory, warps to unroll
- Working on a better stopping criteria (taking into account improvement slow-down)
- Detect if given matrix **A** is invertible
- More general use of functions, that allow for example for transpose operation

```
global__void matrix_vector_multiplication(const_int_n_rows, const_double **elements,

const_int_*rowPtr, const_int **colIdx, const_double **x, double **result) {

unsigned int_row = blockIdx.x * blockDim.x + threadIdx.x;

if (row < n_rows) {

const_int_row_start = rowPtr[row];

const_int_row_end = rowPtr[row + 1];

double sum = 0.0;

for (int_idx = row_start; idx < row_end; idx++) {

int_col = colIdx[idx];

const_int_row = elements[idx] * x[col];

result[row] = sum;

}

const_int_row = blockIdx.x * blockDim.x + threadIdx.x;
```



Do you have any questions?