ETH Lecture 401-0663-00L Numerical Methods for CSE

Main Examination

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Duration: 3h 20m (computer-based)

(Examination for Course at ETH Zurich in Autumn Term 2016)

Family name		Grade
First name		
Study program		
Computer name		
Legi no.		
Date	26.01.2016	

Points:

,

Task	1	2	3	4	5	Total
Max. pts.	18	14	19	23	10	
1st Corr.						
2nd Corr.						

See next page for detailed instructions.

Instructions:

- Fill in this cover sheet first.
- Always keep your Legi visible on the table.
- Keep your phones, tablets and computers turned off in your bag.
- Start each handwritten problem on a new sheet.
- Put your name on each sheet.
- Do not write with red/green/pencil.
- Write your solutions clearly and work carefully.
- Write all your solutions only in the folder questions!
- Any other location will not be backed-up and will be discarded.
- Files in resources may be overridden at any time.
- Make sure to regularly save your solutions.
- Time spent on restroom breaks is considered examination time.
- Never turn off or log off from your computer!

Instructions for coding problems:

- In the folder "~/questions" you will find the template files for the solution of the problems. You can use these templates to write your solution.
- We provide a "CMake" file that automatically compiles all the templates. To generate a "Makefile" for all problems, type "cmake ." in the folder "~/questions". Compile your programs with "make".
- In order to compile and run the C++ code related to a single problem, like Problem 0.3, type "make problem3". Execute the program using "./problem3".
- If you want to manually compile your code without CMake, use:

```
g++ -I./ -std=c++11 -Wno-deprecated-declarations \
-Wno-ignored-attributes filename.cpp -Wno-misleading-indentation \
-Wno-unused-variable -o program_name
```

or

```
clang++ -1./ -std=c++11 -Wno-deprecated-declarations \
        -Wno-ignored-attributes filename.cpp -Wno-misleading-indentation \
        -Wno-unused-variable -o program_name
```

We use the flags -Wno-deprecated-declarations, -Wno-ignored-attributes, -Wno-misleading-indentation and -Wno-unused-variable to suppress some unwanted EIGEN warnings.

• For each problem requiring C++ implementation, a template file named problemX.cpp is provided (where X is the problem number). For your own convenience, there is a marker TODO in the places where you are supposed to write your own code. All templates should compile even if left unchanged.

dist

Problem 0.1: Estimating point locations from distances (18 pts)

We consider a linear least squares problem from \rightarrow Chapter 3.

[This problem involves implementation in C++]

Consider n > 2 points located on the real axis, the leftmost point situated at $x_1 := 0$, the other points at unknown locations $x_i \in \mathbb{R}$, i = 2, ..., n with $x_i < x_{i+1}$, i = 1, ..., n-1. We *measure* the $m := \binom{n}{2} = \frac{n(n-1)}{2}$ distances $d_{i,j} := |x_i - x_j|$, $i, j \in 1, ..., n$, i > j. The distances are arranged in a vector according to

$$\mathbf{d} := [d_{2,1}, d_{3,1}, \dots, d_{n,1}, d_{3,2}, d_{4,2}, \dots, d_{n,n-1}]^{\top} \in \mathbb{R}^m .$$
(0.0.1)

In absence of measurement errors, the point positions x_i and the distances satisfy an overdetermined linear system of equations

$$\mathbf{A}\mathbf{x} = \mathbf{d}$$
, $\mathbf{x} = [x_2, \dots, x_n]^{\top} \in \mathbb{R}^{n-1}$. (0.0.2) {

(0.1.a) (2 pts) Show that the coefficient matrix/system matrix $\mathbf{A} \in \mathbb{R}^{m,n-1}$ from (0.0.2) has full rank.

SOLUTION of (0.1.a):

As in \rightarrow Eq. (3.0.11), we find that

$$x_{i} - x_{j} = d_{ij},$$

$$1 \le j < i \le n.$$

$$\begin{cases}
-1 & 1 & 0 & \dots & 0 \\
-1 & 0 & 1 & 0 & \dots \\
\vdots & \ddots & \ddots & \ddots & \vdots \\
-1 & \dots & 0 & 0 & 1 \\
0 & -1 & 1 & 0 & \dots & 0 \\
0 & -1 & 0 & 1 & 0 & \vdots \\
\vdots & & & & \\
0 & -1 & 1 & 0 & \dots & 0 \\
0 & -1 & 1 & 0 & & \\
0 & \dots & 0 & -1 & 1
\end{cases} \begin{bmatrix}
x_{1} \\
x_{2} \\
\vdots \\
x_{n}
\end{bmatrix} = \begin{bmatrix}
d_{2,1} \\
d_{3,1} \\
\vdots \\
d_{3,2} \\
\vdots \\
d_{4,2} \\
\vdots \\
d_{4,3} \\
\vdots \\
d_{n,n-1}
\end{bmatrix}.$$

$$(0.0.3) \quad \text{(0.0.3)}$$

[1 pts. for the correct system of eq. (at least the identity part)] Setting $x_1 := 0$ amounts to dropping the first column of the system matrix. The remaining matrix is the matrix **A** from (0.0.2), which is of the form

$$\mathbf{A} = \begin{bmatrix} \mathbf{I}_{n-1} \\ * \end{bmatrix} \in \mathbb{R}^{m,n-1}$$

[1 pts. for argument] Since the top $(n-1) \times (n-1)$ block is the identity matrix, A must have full rank.

sp:a

(0.1.b) (4 pts) [depends on (0.1.a)

Provide an implementation of a function

SparseMatrix<double> buildDistanceLSQMatrix(int n);

that initializes the system matrix A from (0.0.2). The function must be *efficient* for large n.

HINT 1 for (0.1.b): A template for the function <code>buildDistanceLSQMatrix</code> is provided within the file <code>problem1.cpp</code>. You can compile the file with <code>make problem1</code>. The executable ./problem1 tests the routine <code>buildDistanceLSQMatrix</code> by printing the resulting matrix.

SOLUTION of (0.1.b):

The matrix **A** is sparse with $2m - (n-1) = (n-1)^2 < \frac{n(n-1)^2}{2}$ non-zero entries. The signature of the function buildDistanceLSQMatrix already imposes the usage of sparse matrix data formats.

There are two alternative methods that guarantee an efficient implementation, see →Section 2.7.3.

- Matrix assembly via intermediate triplet format:
 - 1. [3 pts. for correct construction of triplet vectors] A vector of triplets is preallocated.

This is possible, because we know that A has a total of $2m - (n - 1) = (n - 1)^2$ non-zero entries. The vector is then filled with triplets.

- 2. [1 pts. for correct construction of triplet vectors] Initialization via an intermediate triplet (COO) format and EIGEN's method setFromTriplets().
- [3 pts. for correct matrix construction] Direct entry specification via SparseMatrix<T>::insert (also SparseMatrix<T>::coeffRef is accepted). [1 pts. for meaningful preallocation] To avoid unnecessary memory reallocations, SparseMatrix<T>::reserve must be called with an appropriate estimate.

C++11-code 0.0.4: Solution of Sub-problem (0.1.b).

```
SparseMatrix < double > buildDistanceLSQMatrix(int n) {
2
       SparseMatrix < double > A(n*(n-1)/2, n-1);
3
4
       // Assembly
5
       std::vector<Triplet<double>> triplets; // List of non-zeros
6
          coefficients
       triplets.reserve((n-1)*(n-1)); // Two non-zeros per row (at
7
          most), first n-1 rows only one entry
       // \rightarrow (n-1)^2 total non-zero entries
8
       // Loops over vertical blocks
10
       int row = 0; // Current row counter
11
       for(int i = 0; i < n-1; ++i) { // Block with same "-1" column
12
           for(int j = i; j < n-1; ++j) { // Loop over block</pre>
13
                triplets.push_back(Triplet <double>(row, j, 1));
14
                if(i > 0) { // Remove first column
15
                    triplets.push back(Triplet < double > (row, i - 1, -1));
16
                ł
17
                row++; // Next row
18
           }
19
```

```
20 }
21
22 // Build matrix
23 A. setFromTriplets(triplets.begin(), triplets.end());
24
25 A.makeCompressed();
26 return A;
27 }
```

sp:b

(0.1.c) (2 pts) [depends on (0.1.a)]

Give explicit formulas for the entries of the system matrix (coefficient matrix) \mathbf{M} of the normal equations corresponding to the overdetermined linear system (0.0.2).

SOLUTION of (0.1.c):

[1 pts. for off-diagonal entries] The entries of matrix $\mathbf{M} = \mathbf{A}^{\top} \mathbf{A}$ can be expressed as inner products of two different columns of \mathbf{A} :

$$\left(\mathbf{A}^{\top}\mathbf{A}\right)_{i,j} = (\mathbf{A})_{:,i}^{\top}(\mathbf{A})_{:,j}.$$

Two columns of **A** have both non-zero entries, ± 1 of opposite sign, only in a single position, hence $(\mathbf{M})_{i,j} = -1$ for $i \neq j$. [1 pts. for diagonal entries] The diagonal entries of **M** are the squares of the Euclidean norms of the columns of **A**. Every column of **A** has exactly n - 1 entries with value ± 1 , which means $(\mathbf{M})_{i,i} = n - 1$.

sp:2

(0.1.d) (3 pts) [depends on (0.1.c)]

Show that the system matrix **M** of the normal equations for the overdetermined linear system from (0.0.2), as found in Sub-problem (0.1.c), can be written as a rank-1 perturbation of a diagonal matrix.

SOLUTION of (0.1.d):

As

$$(\mathbf{M})_{i,j} = \begin{cases} -1 & , \text{ if } i \neq j ,\\ n-1 & , \text{ if } i = j \end{cases}, \quad 1 \le i, j \le n-1 , \tag{0.0.5}$$

we have [1 pts. for correct matrix] [1 pts. for correct vector(s) and for argument that modification has rank 1] that

$$\mathbf{M} = n\mathbf{I}_{n-1} - \mathbf{1} \cdot \mathbf{1}^{\top}, \quad \mathbf{1} = [1, \dots, 1]^{\top} \in \mathbb{R}^{n-1}.$$
 (0.0.6) { { \cdot \cdot c}}

[1 pts. for correct form of rank-1 perturbation] The tensor product matrix $1 \cdot 1^{\top}$ has rank 1.

5

impl

(0.1.e) (6 pts) [depends on
$$(0.1.d)$$
]

Implement an efficient C++ function

VectorXd estimatePointsPositions(const MatrixXd& D);

that computes a least squares estimate for x_2, \ldots, x_n by solving the normal equations for (0.0.2) and returns the column vector $\mathbf{x} := [x_2, \ldots, x_n]^\top$.

The distances $d_{i,i}$ are passed as entries of an $n \times n$ -matrix **D** according to

$$(\mathbf{D})_{i,j} = \begin{cases} d_{i,j} & , \text{ if } i > j , \\ 0 & , \text{ if } i = j , \\ -d_{j,i} & , \text{ if } i < j . \end{cases}$$

Use the observation made in Sub-problem (0.1.d).

HINT 1 for (0.1.e): A template for the function <code>estimatePointsPositions</code> is provided in the file <code>problem1.cpp</code>. You can compile the file with <code>make problem1</code>. The generated executable ./problem1 tests the routine <code>estimatePointsPositions</code>. The program prints a test matrix **D**. Then, the program prints the vector **x** obtained using the function <code>estimatePointsPositions</code> on the measured distances given by **D**.

Example output:

```
The matrix D is:
          -3 -4.2
                       -5
  0 -2.1
2.1
        0 -0.9 -2.2 -3.3
  3
           0 -1.3 -1.1
      0.9
4.2
      2.2
            1.3
                0 -1.1
  5
      3.3
            1.1
                 1.1
                         0
The positions [x_2, \ldots, x_n] obtained from the LSQ system are:
2
3.16
4.18
4.96
```

SOLUTION of (0.1.e):

We rely on the techniques introduced in \rightarrow § 2.6.13 and apply the [1 pts. for stating the correct SMW formula and realize it can be used] Sherman-Morrison-Woodbury formula from \rightarrow Lemma 2.6.22 to the normal equations

$$(n\mathbf{I}_{n-1}-\mathbf{1}\cdot\mathbf{1}^{\top})\mathbf{x}=\mathbf{A}^{\top}\mathbf{d}$$
.

Then →Eq. (2.6.23) yields

$$\mathbf{x} = \frac{1}{n}\mathbf{b} + \frac{\frac{1}{n}\mathbf{1}\cdot\mathbf{1}^{\top}\mathbf{b}}{n-\mathbf{1}^{\top}\mathbf{1}} = \frac{1}{n}\left(\mathbf{b}+\mathbf{1}\cdot\mathbf{1}^{\top}\mathbf{b}\right), \quad \mathbf{b} := \mathbf{A}^{\top}\mathbf{d}.$$
(0.0.7)

Note that the entries of the vector $\mathbf{b} \in \mathbb{R}^{n-1}$ can be computed by summing the entries of the last n-1 rows of \mathbf{D} (the intermediate points of the distances cancel each other out) [2 pts. correct r.h.s., also valid to use matrix-vector multiplication]. [3 pts. for correct application of SMW, including matrix inversion with $\frac{1}{n}$]

C++11-code 0.0.8: Solution of Sub-problem (0.1.e).

```
VectorXd estimatePointsPositions(const MatrixXd& D) {
    VectorXd x;
    // Vector of sum of columns of A
    ArrayXd b = D.rowwise().sum().tail(D.cols()-1);
    // Vector 1
    ArrayXd one = ArrayXd::Constant(D.cols()-1, 1);
    // Apply SMW formula
    x = (b + one * b.sum()) / D.cols();
    return x;
}
```

sp:6

(0.1.f) (1 pts) [depends on (0.1.e)]

What is the asymptotic complexity of the function <code>estimatePointsPositions</code> implemented in Sub-problem (0.1.e) for $n \to \infty$?

SOLUTION of (0.1.f):

2

5

6

7

8

9

10

11 12

13

14

An implementation of (0.0.7) involves SAXPY operations and inner products for vectors of length n - 1, all of which can be carried out with asymptotic complexity O(n).

[1 pts. for noticing that complexity is dominated by r.h.s. and specify it correctly] However, forming the vector **b** has to access all distances and involves computational cost $O(n^2)$, which dominates the total asymptotic complexity.

End Problem 0.1

Problem 0.2: Zero finding in two dimensions (14 pts)

This problem studies Newton's method for a 2×2 non-linear system of equations.

[This problem involves implementation in C++]

Let f be a strictly increasing, positive, continuously differentiable function $f \in C^1(\mathbb{R})$, f(t) > 0.

We seek two real numbers $a, b \in \mathbb{R}$ such that

$$\int_{a}^{b} f(t) dt = a + b , \qquad (0.0.9a) \quad \text{(Vop}$$

$$\int_{a}^{b} e^{f(t)} dt = 1 + a^{2} + b^{2} . \qquad (0.0.9b) \quad \text{(Vop}$$

stem

(0.2.a) (2 pts) Eq. (0.0.9) is a nonlinear system of equations which can be rewritten as

 $F(\mathbf{x}) = \mathbf{0}$

Give an explicit formula for $F(\mathbf{x})$ still involving the generic function $f : \mathbb{R} \to \mathbb{R}$. What are the components of \mathbf{x} ?

SOLUTION of (0.2.a):

[0.5 pts. for formula for x]]

[1.5 pts. for formula for F]]

We have $\mathbf{x} = [a, b]^{\top}$ and

$$F: \left\{ \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \rightarrow \begin{bmatrix} x_2 \\ \int_{x_1}^{x_2} f(t) \, \mathrm{d}t \end{bmatrix} - x_1 - x_2 \\ \begin{pmatrix} x_2 \\ \int_{x_1}^{x_2} \mathrm{e}^{f(t)} \, \mathrm{d}t \end{pmatrix} - 1 - x_1^2 - x_2^2 \end{bmatrix} \right\}$$

sp:2

(0.2.b) (4 pts) [depends on Sub-problem (0.2.a)]

State the Newton's iteration for solving Eq. (0.0.9) as explicitly as possible.

HINT 1 for (0.2.b): The explicit formula for the inverse of a 2×2 matrix is

$$\mathbf{A} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \implies \mathbf{A}^{-1} = \frac{1}{ad - bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}, \text{ if } ad - bc \neq 0.$$

SOLUTION of (0.2.b):

[2 pts. for Jacobian of F]]

[2 pts. for inverse of Jacobian]]

Using the fundamental theorem of calculus $\frac{d}{dx} \int_{a}^{x} g(t) dt = g(x)$, we find for the Jacobian of *F*:

$$\mathsf{D} F(\mathbf{x}) = \begin{bmatrix} -f(x_1) - 1 & f(x_2) - 1 \\ -e^{f(x_1)} - 2x_1 & e^{f(x_2)} - 2x_2 \end{bmatrix}$$

Using this and the formula for the inverse of a regular 2×2 -matrix, we can write the Newton iteration

as

$$\mathbf{x}^{(k+1)} = \mathbf{x}^{(k)} - \frac{1}{(-f(x_1) - 1)(\mathbf{e}^{f(x_2)} - 2x_2) - (f(x_2) - 1)(-\mathbf{e}^{f(x_1)} - 2x_1)} \begin{bmatrix} \mathbf{e}^{f(x_2)} - 2x_2 & -f(x_2) + 1 \\ \mathbf{e}^{f(x_1)} + 2x_1 & -f(x_1) - 1 \end{bmatrix} \cdot \begin{bmatrix} \begin{pmatrix} x_2 \\ \int x_1 \\ x_1 \end{pmatrix} - x_1 - x_2 \\ \begin{pmatrix} \int x_2 \\ x_1 \end{bmatrix} + \frac{1}{(-f(x_1) - 1)(\mathbf{e}^{f(x_2)} - 2x_2)} \end{bmatrix} \cdot \frac{1}{(-f(x_1) - 1)(\mathbf{e}^{f(x_1)} - 2x_1)} \begin{bmatrix} \mathbf{e}^{f(x_2)} - 2x_2 & -f(x_2) + 1 \\ \mathbf{e}^{f(x_1)} + 2x_1 & -f(x_1) - 1 \end{bmatrix} \cdot \frac{1}{(-f(x_1) - 1)(\mathbf{e}^{f(x_2)} - 2x_2)} \begin{bmatrix} \begin{pmatrix} x_2 \\ x_1 \end{pmatrix} - x_1 - x_2 \\ \begin{pmatrix} x_2 \\ x_1 \end{pmatrix} \end{bmatrix} \cdot \frac{1}{(-f(x_1) - 1)(\mathbf{e}^{f(x_2)} - 2x_2)} \begin{bmatrix} x_1 + x_2 \\ x_2 \end{bmatrix} \cdot \frac{1}{(-f(x_1) - 1)(\mathbf{e}^{f(x_2)} - 2x_2)} \end{bmatrix} \cdot \frac{1}{(-f(x_1) - 1)(\mathbf{e}^{f(x_2)} - 2x_2)} = \frac{1}{(-f(x_1) - 1)(\mathbf{e}^{f(x_2)} - 2x_2)} + \frac{1}{(-f(x_1) - 2x_2)} + \frac{1}{$$

sp:3

(0.2.c) (8 pts) [depends on Sub-problem (0.2.b)]

Implement a C++ function

that solves Eq. (0.0.9) by means of Newton's method with initial guess $a^{(0)} = 0$, $b^{(0)} = 1$.

The argument qr provides a quadrature rule **on** [0, 1] in terms of weights and nodes. Use it for the evaluation of all occurring definite integrals.

Use a correction-based termination criterion controlled by relative tolerance rtol and absolute tolerance atol. The variable maxit specifies the maximum number of iterations.

HINT 1 for (0.2.c): Recall the definition of the QuadRule class

```
struct QuadRule {
    VectorXd nodes;
    VectorXd weights;
};
```

For numerical quadrature based on the quadrature rule <code>QuadRule</code>, you may implement an auxiliary function

which takes the integration bounds as argument vector \mathbf{x} .

```
HINT 2 for (0.2.c): A template for the functions getIntv and integrate is provided within the file problem2.cpp. You can compile the file with make problem2. The executable ./problem2 tests the routine getIntv by printing the approximate (a, b) (for a given function f(t) := t) and the reference solution.
```

SOLUTION of (0.2.c):

[2 pts. for correct function integrate or an equivalent correct integration]

[2 pts. for correct transformation of QuadRule on [0, 1]]

[4 pts. for correct function getIntv]

For the correction-based a posteriori termination criterion, look at →Section 8.4.1.

```
C++11-code 0.0.10: Function integrate.
  template < class Function, class QuadRule>
2
  double integrate (const Function& f, const QuadRule& gr, const
3
      Vector2d & x) {
       double I = 0;
5
6
       VectorXd
                   nodes = qr.nodes;
7
       VectorXd weights = qr weights;
8
       assert(nodes.size() == weights.size() &&
q
              "Nodes and weights of QuadRule have different lengths");
10
       for (unsigned i=0; i < nodes.size(); ++i) {</pre>
11
            double t = (x(1)+x(0))/2. + (x(1)-x(0)) * (nodes(i) - 0.5);
12
            // Adjust nodes of [0,1]-QuadRule to domain [x_1, x_2].
13
14
            I += f(t) * weights(i);
15
       }
16
17
       I = x(1)-x(0); // Adjust weights of [0,1]-QuadRule to domain
18
          |x_1, x_2|.
19
       return I;
20
  }
21
```

ector-32

C++11-code 0.0.11: Function getIntv.

```
template < class Function, class QuadRule>
2
   std::pair<double, double> getIntv(const Function& f, const QuadRule&
3
      qr,
                                         double atol, double rtol,
4
                                         unsigned maxit=10) {
5
       std::pair<double,double> x end;
6
7
       Vector2d x;
       x << 0, 1;
9
10
       Vector2d x_new = x;
11
       auto exp f = [\&] (double t) {return std::exp(f(t));};
12
13
       for (unsigned i=0; i<maxit; ++i) {</pre>
14
15
           // Compute inverse of Jacobian.
16
           Matrix2d invDF;
17
```

```
invDF << \exp_f(x(1)) - 2 x(1), -f(x(1)) + 1,
18
                       \exp_f(x(0)) + 2 x(0), -f(x(0)) - 1;
19
            invDF /= (-f(x(0))-1)*(exp_f(x(1))-2*x(1)) -
20
                (f(x(1))-1)*(-exp_f(x(0))-2*x(0));
21
            // Evaluate F(\mathbf{x}^{(k)}).
            Vector2d F;
23
            F \ll integrate(f, qr, x) - (x(0)+x(1)),
24
                  integrate (\exp_f, qr, x) - (1+x(0)*x(0)+x(1)*x(1));
25
26
            // Newton's iteration.
27
            x_new = x - invDF*F;
28
29
            // Correction-based termination (relative and absolute).
30
            double r = (x_new - x).norm();
31
            if(r < atol || r < rtol * x_new.norm()) {
32
                 break:
33
            }
34
35
            x = x_{new};
       }
37
38
       x_end = \{x_new(0), x_new(1)\};
39
40
       return x_end;
41
  }
42
```

ankk

End Problem 0.2

Problem 0.3: Low rank approximation (19 pts)

A causal, linear, time-invariant and finite (LT-FIR) channel has the impulse response

$$(0, \dots, 0, h_0, \dots, h_{n-1}, 0, \dots, 0)$$
 (0.0.12)

of duration $(n-1)\Delta t$. When we feed into it a signal $\mathbf{x} := (0, \dots, 0, x_0, \dots, x_{n-1}, 0, \dots, 0)$ of duration $(n-1)\Delta t$, the filter produces an output signal $\mathbf{y} := (0, \dots, 0, y_0, \dots, y_{2n-2}, 0, \dots, 0)$ of duration $(2n-2)\Delta t$. The linear mapping

$$l: \begin{cases} \mathbb{R}^n & \to \mathbb{R}^{2n-1} \\ (x_j)_{j=0}^{n-1} & \to (y_j)_{j=0}^{2n-2} \end{cases}$$

can be represented by the matrix-vector product

$$(y_j)_{j=0}^{2n-2} = \mathbf{C} (x_j)_{j=0}^{n-1}$$
, (0.0.13) {\delta(x_j)_{j=0}^{n-1}}

which can be expressed as the following matrix×vector multiplication, see →Rem. 4.1.17:

$$\begin{bmatrix} y_0 \\ \vdots \\ h_1 & h_0 & 0 & \cdots & 0 \\ h_1 & h_0 & 0 & \cdots & 0 \\ \vdots & \ddots & \ddots & & \vdots \\ h_{n-1} & h_{n-2} & \cdots & h_1 & h_0 \\ 0 & h_{n-1} & \ddots & h_1 \\ \vdots & \ddots & \ddots & & \vdots \\ 0 & \cdots & 0 & h_{n-1} \end{bmatrix} \begin{bmatrix} x_0 \\ \vdots \\ \vdots \\ x_{n-1} \end{bmatrix}$$

sp:0

(0.3.a) (2 pts)

Using EIGEN, implement a C++ function with signature

MatrixXd buildLTFIRMatrix(const VectorXd &h);

that initializes the matrix C from (0.0.13). The vector h specifies the entries of C.

HINT 1 for (0.3.a): You will find a template for the function buildLTFIRMatrix within the file problem3.cpp. You can compile the file with make problem3. The executable ./problem3 tests the routine buildLTFIRMatrix by printing the resulting matrix. The correct matrix (for n = 6) is reported as a comment in the code (within main of problem3.cpp).

SOLUTION of (0.3.a):

[2 pts. Many ways to do this]

```
C++11-code 0.0.14: Function buildDistanceLSQMatrix.
```

```
MatrixXd buildLTFIRMatrix(const VectorXd & h)
2
   {
3
       // Initialization
4
       unsigned int n = h.size();
5
       MatrixXd C(2*n-1, n);
6
7
       C. setZero();
8
q
       for (unsigned i=0; i<n; ++i) {</pre>
10
            C.col(i).segment(i,n) = h;
11
       }
12
13
       return C;
14
   }
15
```

Now the goal is to implement a compressed model for the channel. Consider the class

▲

```
class LTFIR_lowrank {
public:
    LTFIR_lowrank(const VectorXd& h, unsigned k);
    VectorXd operator()(const VectorXd& x) const;
private:
    // TODO: private members of class LTFIR_lowrank
};
```

whose evaluation operator realizes $\mathbf{y} = \tilde{\mathbf{C}}\mathbf{x}$, where $\tilde{\mathbf{C}} \in \mathbb{R}^{2n-1,n}$ is the rank-*k* best approximation of \mathbf{C} , and $k \in \{1, ..., n\}$ is passed as the second argument of the constructor.

(0.3.b) (9 pts) [depends on Sub-problem (0.3.a)]

Implement both member funcions of the class LTFIR_lowrank such that a call of the evaluation operator involves as little computational effort as possible (asymptotically, for $n \to \infty$).

HINT 1 for (0.3.b): You may use the function buildLTFIRMatrix from Sub-problem (0.3.a).

HINT 2 for (0.3.b): A template for the class LTFIR_lowrank is provided within the file problem3.cpp. You can compile the file with make problem3. The executable ./problem3 tests the routine operator() by printing the resulting vector $\mathbf{y} = \mathbf{\tilde{C}} \mathbf{x}$ for specific inputs \mathbf{h} , \mathbf{c} and k. The correct result is reported as a comment in the code.

SOLUTION of (0.3.b):

[6 pts. for efficient constructor and private members. Economical SVD should be used.]

[3 pts. for efficient operator()]

```
C++11-code 0.0.15: Constructor of class LTFIR lowrank.
       LTFIR_lowrank(const VectorXd& h, unsigned int k) {
2
            MatrixXd C = buildLTFIRMatrix(h);
3
           JacobiSVD<MatrixXd> svd(C, ComputeThinU | ComputeThinV);
5
           // With Eigen::svd you can ask for thin U or V to be
6
               computed.
           // In case of a rectangular m \times n matrix,
7
           // with j the smaller value among m and n,
8
           // there can only be at most j singular values.
9
           // The remaining columns of \boldsymbol{U} and \boldsymbol{V} do not correspond
10
            // to actual singular vectors and are not computed in thin
11
               format.
12
           VectorXd s = svd.singularValues();
13
           s.conservativeResize(k);
14
           auto S = s.asDiagonal(); // kxk
15
16
           MatrixXd U = svd.matrixU();
17
           MatrixXd V = svd.matrixV();
18
           U_{-} = U.leftCols(k) * S; // nxk
19
            // Already optimised product between dense and diagonal
20
               matrix
            Vt_ = V.leftCols(k).transpose(); // kxn
21
22
```

C++11-code 0.0.16: Function operator (). VectorXd operator()(const VectorXd& x) const { 2 VectorXd y; 3 assert(x.size() == Vt_.cols() && 5 "x must have same length of h"); 6 7 VectorXd tmp = Vt_ * x; 8 $y = U_{-} * tmp;$ 9 // Complexity is O(kn + nk) = O(nk). 10 // Given precomputed $Ck = U \cdot Vt_{-}$, 11 // complexity would have been O(nn). 12 return y; 13 ł 14



C++11-code 0.0.17: Private members of class LTFIR_lowrank.

MatrixXd U_; // nxk MatrixXd Vt_; // kxn

sp:2

(0.3.c) (2 pts) [depends on Sub-problem (0.3.b)]

What is the asymptotic complexity of your implementation of the constructor and the evaluation operator for $n \to \infty$ and $k \to \infty$ (separately, assuming $k \le n$)?

SOLUTION of (0.3.c):

[1 pts. for complexity of SVD]

[1 pts. for complexity of operator()]

The rank-*k* approximation performed by the constructor involves a singular value decomposition. The complexity of an SVD is $O(n^3)$.

The evaluation operator carries out two matrix-vector multiplications, by $k \times n$ matrix \mathbf{V}^{\top} and $(2n - 1) \times k$ matrix \mathbf{U} . The complexity is therefore $\mathcal{O}(kn + nk) = \mathcal{O}(nk)$. On the other hand, given the full $(2n - 1) \times n$ approximation matrix $\tilde{\mathbf{C}}$, the complexity would have been $\mathcal{O}(n^2)$.



(0.3.d) (3 pts)

Decide which of the following properties does the new filter (realized by the evaluation operator of LTFIR_lowrank) still enjoy for any $(h_j)_{j=0}^{n-1}$: linearity, causality, and finiteness.

Linearity [1 pts.] Yes: it is ultimately a matrix-vector multiplication.

Causality [1 pts.] Yes: $y_j = 0 \forall j < 0$.

Finiteness [1 pts.] Yes: the number of nonzero y_i is up to 2n - 1.

sp:4

(0.3.e) (3 pts)

Another way to build a compressed model of the channel is frequency filtering, which is implemented in the following LTFIR_freq class.

```
C++11-code 0.0.18: Constructor of class LTFIR freq.
       LTFIR_freq(const VectorXd& h, unsigned k) {
2
            n_{-} = h.size();
3
            k_{-} = k;
4
5
            VectorXd h = h;
6
               h_.conservativeResizeLike(VectorXd::Zero(2*n_-1));
7
            // Forward DFT
8
            FFT<double> fft;
9
            ch_{-} = fft.fwd(h_{-});
10
       }
11
```

```
C++11-code 0.0.19: Function operator ().
       VectorXd operator()(const VectorXd& x) const {
2
           assert(x.size() == n_ && "x must have same length of h");
3
4
           VectorXd x_{-} = x;
5
              x_.conservativeResizeLike(VectorXd::Zero(2*n_-1));
           // Forward DFT
6
           FFT<double> fft;
           VectorXcd cx = fft.fwd(x);
8
           VectorXcd c = ch_.cwiseProduct(cx);
9
           // Set high frequency coefficients to zero
10
           VectorXcd clow = c;
11
           for (int j=-k_; j <=+k_; ++j) clow (n_+j) = 0;
12
           // Inverse DFT
13
           return fft.inv(clow).real();
14
       }
15
```

Rankk-43

C++11-code 0.0.20: Private members of class LTFIR_freq.

2 int n_;
3 int k_;
4 VectorXcd ch_;

What is the asymptotic complexity of the evaluation operator **operator** () for $n \to \infty$?

You can find the implementation of the class LTFIR_freq in the file problem3.cpp.

SOLUTION of (0.3.e):

[3 pts.] The most expensive steps of the implemented low-pass filter are the Fourier transforms. For *n*-dimensional input vectors **x**, the complexity of a fast Fourier transform is $O(n \log n)$.

: ODE

End Problem 0.3

Problem 0.4: Single step method (23 pts)

This problem concerns numerical integration \rightarrow Chapter 11 with single step methods.

[This problem involves implementation in C++]

We consider the initial value problem for $\mathbf{y}(t) := [y_1(t), y_2(t)]^\top$:

$$\dot{\mathbf{y}} = \begin{bmatrix} -\theta(y_2) \\ y_1 \end{bmatrix}, \quad \theta \in C^1(\mathbb{R}), \quad \mathbf{y}(0) = \begin{bmatrix} 0 \\ y_0 \end{bmatrix}. \tag{0.0.21}$$

(0.4.a) (2 pts)

Denote by $\xi \in C^2(\mathbb{R})$ the principal of θ , that is $\xi' = \theta$.

Show that $I(\mathbf{y}(t)) = \text{const.}$ for $I(\mathbf{z}) = \frac{1}{2}z_1^2 + \xi(z_2)$, $\mathbf{z} = [z_1, z_2]^{\top}$ and any solution $t \mapsto \mathbf{y}(t)$ of (0.0.21).

HINT 1 for (0.4.a): What is an equivalent condition for $I(\mathbf{y}(t)) = \text{const.}$?

SOLUTION of (0.4.a):

[2 pts.] Consider $I(\mathbf{y}) = \frac{1}{2}y_1^2 + \xi(y_2)$. We have that $I(\mathbf{y}) = \text{const} \iff \frac{d}{dt}I(\mathbf{y}(t)) = 0$. By the scalar chain rule and the product rule we can conclude:

$$I'(\mathbf{y}) = y_1 \dot{y}_1 + \xi'(y_2) \dot{y}_2 = \dot{y}_2 \dot{y}_1 + heta(y_2) \dot{y}_2 = \dot{y}_2 \dot{y}_1 - \dot{y}_1 \dot{y}_2 = 0$$
 .

(**0.4.b**) (4 pts)

Give the concrete defining equation for the discrete evolution Ψ of the implicit midpoint rule \rightarrow Eq. (11.2.18) for (0.0.21).

SOLUTION of (0.4.b):

[4 pts.] The discrete evolution operator $\Psi : \mathbb{R} \times \mathbb{R}^2 \to \mathbb{R}^2$ according to \Rightarrow § 11.3.1 is defined as the solution operator of the following non-linear system of equations: for a generic autonomous ODE $\dot{y} = f(y)$ it reads

$$\Psi(h, \mathbf{y}) := \mathbf{z}: \quad \mathbf{z} = \mathbf{y} + h\mathbf{f}\left(\frac{1}{2}(\mathbf{y} + \mathbf{z})\right)$$

and, concretely, for (0.0.21),

$$\Psi(h, \mathbf{y}) := \mathbf{z} = \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} \text{ such that } \mathbf{z} = \mathbf{y} + h \begin{bmatrix} -\theta \left(\frac{1}{2} (y_2 + z_2) \right) \\ \frac{1}{2} (y_1 + z_1) \end{bmatrix} , \quad \mathbf{y} \in \mathbb{R}^2.$$
 (0.0.22)

For sufficiently small *h* there is a unique solution $\mathbf{z} = \mathbf{z}(h, \mathbf{y})$.

(0.4.c) (5 pts) [depends on Sub-problem (0.4.b)]

State the explicit formulas for the Newton's iteration that can be used to approximately evaluate the discrete evolution of the implicit midpoint rule for (0.0.21). Specify a meaningful initial value in the case of small time steps.

HINT 1 for (0.4.c): The explicit formula for the inverse of a 2×2 matrix is

$$\mathbf{A} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \implies \mathbf{A}^{-1} = \frac{1}{ad - bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}, \text{ if } ad - bc \neq 0.$$

SOLUTION of (0.4.c):

[1 pts. for functional *F*. Note that there are several ways to recast the implicit midpoint rule as a non-linear equations, among them also the stage form discussed in class.]

- [1 pts. for Jacobian of *F*]
- [1 pts. for inverse of Jacobian]
- [1 pts. for complete Newton's iteration]

[1 pts. for initial guess]

The non-linear 2 \times 2 system of equations (0.0.22) can be recast into the standard form

$$F(\mathbf{z}) = \mathbf{0} \quad , \quad F(\mathbf{z}) := \mathbf{z} - \mathbf{y} - h \begin{bmatrix} -\theta \left(\frac{1}{2} (y_2 + z_2) \right) \\ \frac{1}{2} (y_1 + z_1) \end{bmatrix} . \tag{0.0.23}$$

For the Jacobian of F we find

$$\mathsf{D} F(\mathbf{z}) = \begin{bmatrix} 1 & \frac{1}{2}h\theta'(\frac{1}{2}(y_2 + z_2)) \\ -\frac{1}{2}h & 1 \end{bmatrix}.$$
 (0.0.24)

Using the formula for the inverse of a 2×2 -matrix, the Newton's iteration reads

$$\mathbf{z}^{(k+1)} = \mathbf{z}^{(k)} - \frac{1}{1 + \frac{1}{4}h^{2}\theta'\left(\frac{1}{2}\left(y_{2} + z_{2}^{(k)}\right)\right)} \begin{bmatrix} 1 & -\frac{1}{2}h\theta'\left(\frac{1}{2}\left(y_{2} + z_{2}^{(k)}\right)\right) \\ \frac{1}{2}h & 1 \end{bmatrix} \begin{bmatrix} z_{1}^{(k)} - y_{1} + h\theta\left(\frac{1}{2}\left(y_{2} + z_{2}^{(k)}\right)\right) \\ z_{2}^{(k)} - y_{2} - \frac{1}{2}h\left(y_{1} + z_{1}^{(k)}\right) \end{bmatrix}$$

$$(0.025)$$

For small *h* we expect $\Psi(h, \mathbf{y}) \approx \mathbf{y}$. Hence $\mathbf{z}^{(0)} := \mathbf{y}$ is the natural initial guess for the Newton's iteration.

Since the implicit midpoint rule is a Runge-Kutta single step method, it can also be cast in stage form, see \rightarrow Rem. 12.3.21. Then one can use Newton's method to solve for the stages g_i , see \rightarrow Rem. 12.3.24.

p: 3 (0.4.d) (4 pts) [depends on Sub-problem (0.4.c)]

```
Implement a function
```

that approximately realizes the discrete evolution operator of the implicit midpoint rule for (0.0.21) using, internally, two Newton's steps. The parameter h specifies the step size. The variable theta resp. theta_d represent the function θ and its derivative θ' . The vector y passes the value y at the previous step.

HINT 1 for (0.4.d): A template for the function psi is provided within the file problem4.cpp. You can compile the file with make problem4. The executable ./problem4 tests the routine psi by comparing the discrete evolution for $\theta(\xi) = e^{\xi}$ with a reference solution. The test performs a single evolution step of size h = 0.1 starting from the initial data $\mathbf{y}(0)$.

SOLUTION of (0.4.d):

[4 pts.]

```
C++11-code 0.0.26: Solution of (0.4.d).
  template < typename Functor, typename Jacobian >
2
  Vector2d psi(Functor& theta, Jacobian& theta_d,
3
                 double h, const Vector2d& y) {
4
       Vector2d z;
5
       Z = Y;
6
       for (unsigned i=0; i<2; ++i) {
8
           Matrix2d invDF:
10
           invDF << 1., -0.5*h*theta_d(0.5*(y(1)+z(1))),
11
                      0.5*h, 1.;
12
           invDF /= 1 + 0.25*h*h*theta d(0.5*(y(1)+z(1)));
13
14
           Vector2d F;
15
           F \ll z(0) - y(0) + h*theta(0.5*(y(1)+z(1))),
16
                 z(1) - y(1) - 0.5 * h * (y(0) + z(0));
17
18
           z = z - invDF*F;
19
```

sp:4

(0.4.e) (3 pts) The following function lfevl implements an explicit Runge-Kutta single step method for Eq. (0.0.21) and for some (unknown) smooth function θ (passed as theta). The code applies a Runge-Kutta method on N equidistant steps of size h, starting from the initial value $y_0 := y(0)$.

```
C++11-code 0.0.27: Function lfev1.
  template < typename Function >
2
   Vector2d IfevI(const Function& theta, Vector2d y0,
3
                   double h, unsigned int N) {
4
       auto f = [&theta] (const Vector2d& y) -> Vector2d {
5
           Vector2d y_dot;
6
           y_dot << -theta(y(1)), y(0);
           return y_dot;
8
       };
9
       Vector2d yk = y0;
10
       for (unsigned k=0; k < N; ++k) {
11
           Vector2d k1 = f(yk);
12
           Vector2d k^2 = f(yk + h/2.*k1);
13
           Vector2d k3 = f(yk - h*k1 + 2.*h*k2);
14
15
           yk += h/6.*k1 + 2.*h/3.*k2 + h/6.*k3;
16
       }
17
       return yk;
18
  }
19
```

Write down the Butcher scheme for this method.

SOLUTION of (0.4.e):

[3 pts.] The code closely follows the structure of the increment equations from \rightarrow Def. 11.4.9 and one can simply read off the coefficients.

	$\frac{1}{6}$	$\frac{2}{3}$	$\frac{1}{6}$
Ī	-1	2	0
$\frac{1}{2}$	$\frac{1}{2}$	0	0
0	0	0	0

```
(0.4.f) (5 pts) [depends on Sub-problem (0.4.e)]
```

Consider the C++ function lfevl of Sub-problem (0.4.e) and let $\theta(\xi) = e^{\xi}$ and $\mathbf{y}(0) = [0, 1]^{\top}$. Empirically determine the order of convergence of the single step method implemented by lfevl by studying the errors of the numerical solutions at the final time T = 10 and their dependence on the number N of equidistant steps of the single-step method.

HINT 1 for (0.4.f): Use suitable sequences of numbers of steps N ranging between 50 and $2 \cdot 10^4$.

HINT 2 for (0.4.f): Implement your code in the main function of the file problem4.cpp. You can compile the file with make problem4. The executable ./problem4 should print the error and the estimated order of convergence of lfev1, for every value of N.

SOLUTION of (0.4.f):

The empiric order of the method is 3. The smartest choice of a sequence of numbers of steps is geometric progression, doubling N in turn, e.g., $N = 2^6, \ldots, 2^{14}$.

[4 pts. for correct implementation]

[1 pts. for correct order of convergence]

C++11-code 0.0.28: Solution of (0.4.f).

```
// Vector of number of steps (each entry is twice the previous
2
          entry).
       std::vector<unsigned> N = \{128, 256, 512, 1024, 2048, 4096, 
3
          8192, 16384};
       std::cout << std::setw(15) << "N"
4
                  << std::setw(15) << "error"
5
                  << std::setw(15) << "rate"
                  << std :: endl;
       double err old;
8
       for (unsigned int i=0; i < N. size(); ++i) {
9
           double h = T/N[i];
10
           auto yk = lfevl(theta, y0, h, N[i]);
11
           double err = (yk - y_exact).norm();
12
           std::cout << std::setw(15) << N[i]
13
                      << std::setw(15) << err;
14
           if(i > 0) {
15
                std::cout << std::setw(15) << std::log2(err old / err);</pre>
16
           }
17
           err_old = err;
18
           std::cout << std::endl;</pre>
19
       }
20
```

End Problem 0.4

Problem 0.5: Polar decomposition of a matrix (10 pts)

This problem addresses a special matrix factorization and its numerical realization.

[This problem involves implementation in C++]

The following result is obtained in linear algebra:

Theorem 0.0.29. Polar decomposition

Given $\mathbf{M} \in \mathbb{R}^{n,n}$, there is a symmetric positive semidefinite matrix $\mathbf{A} \in \mathbb{R}^{n,n}$ and an orthogonal matrix $\mathbf{Q} \in \mathbb{R}^{n,n}$ such that

$$\mathbf{M} = \mathbf{A}\mathbf{Q} \ . \tag{0.0.30}$$

The matrix factorization (0.0.30) is called the polar decomposition of **M**.

(0.5.a) (4 pts) Give a proof of Thm. 0.0.29.

HINT 1 for (0.5.a): Use the singular value decomposition of M.

SOLUTION of (0.5.a):

[1 pts. for correct usage of SVD]

[1 pts. for proven symmetry of A]

[1 pts. for proven positive definiteness of A]

[1 pts. for proven orthogonality of Q]

Given $\mathbf{M} \in \mathbb{R}^{n,n}$, there always exists a singular value decomposition $\mathbf{M} = \mathbf{U} \Sigma \mathbf{V}^{\top}$, where $\mathbf{U}, \mathbf{V} \in \mathbb{R}^{n,n}$ are orthogonal and $\Sigma \in \mathbb{R}^{n,n}$ is diagonal. Consider the property of orthogonal matrices $\mathbf{U}^{\top}\mathbf{U} = \mathbf{I}$. Hence:

$$\mathbf{M} = \mathbf{U} \mathbf{\Sigma} \mathbf{U}^ op \mathbf{U} \mathbf{V}^ op = \Big(\mathbf{U} \mathbf{\Sigma} \mathbf{U}^ op \Big) \Big(\mathbf{U} \mathbf{V}^ op \Big) \equiv \mathbf{A} \mathbf{Q}$$
 ,

where we defined $A := U\Sigma U^{\top}$ and $Q := UV^{\top}$. We just need to prove that A is symmetric positive semidefinite and Q is orthogonal.

For the first part, we have that $\mathbf{A}^{\top} = (\mathbf{U}\Sigma\mathbf{U}^{\top})^{\top} = \mathbf{U}\Sigma\mathbf{U}^{\top} = \mathbf{A}$, hence \mathbf{A} is symmetric. Furthermore, the singular values of \mathbf{M} are the eigenvalues of \mathbf{A} (diagonal of Σ) and singular values are always nonnegative. Hence, the eigenvalues of \mathbf{A} are nonnegative and \mathbf{A} must be positive semidefinite.

For the second part, we have that $\mathbf{Q}^{\top} = (\mathbf{U}\mathbf{V}^{\top})^{\top} = (\mathbf{V}^{\top})^{\top}\mathbf{U}^{\top} = (\mathbf{V}^{\top})^{-1}\mathbf{U}^{-1} = (\mathbf{U}\mathbf{V}^{\top})^{-1} = \mathbf{Q}^{-1}$, which means that \mathbf{Q} is also orthogonal.

(0.5.b) (5 pts) [depends on (0.5.a)]

Using EIGEN's numerical linear algebra facilities, write a C++ function

```
std::pair<MatrixXd, MatrixXd> polar(const MatrixXd& M);
```

that computes the polar decomposition (0.0.30) of **M**, returning the tuple (\mathbf{A}, \mathbf{Q}) .

HINT 1 for (0.5.b): You may use EIGEN's methods for numerical singular value decomposition (SVD). \Box

HINT 2 for (0.5.b): A template for the function <code>polar</code> is provided within the file <code>problem5.cpp</code>. You can compile the file with <code>make problem5</code>. The executable ./problem5 tests the routine <code>polar</code>. In <code>main()</code>, for the specified matrix

	1	2	3]	
$\mathbf{M} =$	2	1	3	
	6	3	11	

the program computes and prints the matrices A and Q.

Example output:

```
Matrix A is:
  2.11118 0.847555 2.97062
0.847555
           1.31722 3.39803
 2.97062
           3.39803 12.0677
Matrix Q is:
-0.352666
              0.910956
                         0.213977
 0.872437
              0.402776
                       -0.276811
           -0.0890599
  0.338348
                         0.936797
```

The function testPolar is also provided. This function uses an implementation of polar and checks whether it returns a true polar decomposition.

SOLUTION of (0.5.b):

[5 pts.]

```
C++11-code 0.0.31: Solution of Sub-problem (0.5.b).
  std::pair<MatrixXd, MatrixXd> polar(const MatrixXd& M) {
2
       assert(M.rows() == M.cols() && "M must be square!");
3
       unsigned n = M.rows();
4
       JacobiSVD<MatrixXd> svd(M, ComputeThinU | ComputeThinV);
5
6
       VectorXd s = svd.singularValues();
       MatrixXd S; S.setZero(s.size(),s.size());
8
       S.diagonal() = s;
9
       MatrixXd U = svd.matrixU();
10
       MatrixXd V = svd.matrixV();
11
12
       return std::make pair(U * S * U.transpose(), U * V.transpose());
13
  }
14
```

▲

(0.5.c) (1 pts) [depends on (0.5.b)]

What is the asymptotic complexity of your implementation of polar for $n \to \infty$?

SOLUTION of (0.5.c):

[1 pts.] The most expensive step of a polar decomposition is to compute a singular value decomposition. For $(n \times n)$ square matrices, the complexity of an SVD is $\mathcal{O}(n^3)$.

End Problem 0.5

,