# Final project for the Course High Performance Programming, Philipp Noel von Bachmann

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# 1 Introduction

Machine Learning and Data analysis are some of the most influencial fields in our current society. One of the main task in Machine Learning is to give a prediction based on some input variables. A common algorithm to use is linear-least-square, which finds the best fit for a linear model. Here, we need an efficient way to calculate this fit. In Data analysis, a common tool is the Principal Component analysis, which tries to reduce the dimensionality of the data in a way, that the reconstruction error gets minimized. PCA relies on an eigenvalue decomposition. For both methods, we can use the QR decomposition too speed up the computation.

# 2 Problem description

Suppose A is a real, square matrix. Then it can be shown that A can be decomposed into

$$A = QR \tag{1}$$

where Q is orthogonal and R is upper triangular. Finding Q and R is the task of the algorithm.

## 3 Solution

We will implement an algorithm known as **Givens Rotation**. This algorithm relies on construction a sequences of matrices  $G_i$ , such that when multiplying A with  $G_i$ , we get a new matrix with a zero at a predefined place. Choosing  $G_i$  such that we eliminate the lower diagonal of A, we end up with a R and by multiplying all  $G_i$  with Q. We will first show how to eliminate one value at the time by constructing  $G_i$  and then how to combine these.

3.1 Givens rotation 3 SOLUTION

## 3.1 Givens rotation

First, we define a Givens rotation matrix as

$$G(i,j,\theta) = \begin{bmatrix} 1 & & & & \\ & \ddots & & & \\ & & c_{ii} & \cdots & -s_{ij} \\ & & \vdots & \ddots & \vdots \\ & & s_{ji} & \cdots & c_{jj} \\ & & & \ddots & \\ & & & & 1 \end{bmatrix}$$
 (2)

where  $c = \cos(\theta)$ ,  $s = \sin(\theta)$  and any not filled out values are 0. Note: Therefore we can equally represent G by G(i, j, c, s)

# 3.2 Eliminating one value

We will how to find  $\theta$  to solve

$$G(i, j, \theta)^{T} \begin{bmatrix} \times \\ \vdots \\ a \\ \vdots \\ b \\ \vdots \\ \times \end{bmatrix} = \begin{bmatrix} \times \\ \vdots \\ r \\ \vdots \\ 0 \\ \vdots \\ \times \end{bmatrix}$$
(3)

where  $\times$  are arbitrary numbers  $a, b \in \mathbb{R}$ ,  $r = \sqrt{a^2 + b^2}$ . A trivial solution would be

$$c = -\frac{a}{r} \tag{5}$$

However, r is prone to overflow, so we can instead store it in a different way. If

- $\begin{array}{l} \bullet \ |b| \geq |a| : \\ t = \frac{a}{b}, \ s = \frac{sgn(b)}{\sqrt{1+t^2}}, c = st \end{array}$
- else:  $t = \frac{b}{a}, c = \frac{sgn(a)}{\sqrt{1+t^2}}, s = ct$

## 3.3 Final algorithm

## Algorithm 1 Givens rotation

```
1: procedure STEP

2: set R = A, Q = I

3: for j in 1 to n do

4: for i in n down to j + 1 do

5: compute the Givens rotation G(i, j, c, s) eliminating R_{ij} with a = i, b = i - 1.

6: set R = G(i, j, c, s)R, Q = QG(i, j, c, s)
```

Note that we have to do it in this order, since each update affects row and row above.

# 4 Experiments

## 4.1 Check for correctness

## 4.2 Results

#### 4.2.1 Format

In the following section, we will show timing results for different matrix sizes. We denote the sizes by i, j, which we defined as decomposing the matrix  $A \in \mathbb{R}^{i \times j}$ .

### 4.2.2 Baseline Results

i $j$	10	25	50
10	0.0005	0.0008	0.001
25	0.018	0.034	0.049
50	0.235	0.611	1.076

We see that the if we vary i, we get a superlinear increase of runtime. If we increase j instead, we see that we get a nearly linear increase in runtime.

(We should only get a minor increase in runtime for j, since we dont need to calculate new 0s). (For i this makes sense, since increasing i by one adds i new 0s to compute.)

## 5 Random

- we can order them by affecting row and above
- best is probably to create tasks because upper rows require less work
- maybe need memory optimizations, but most of the operations seem to be near anyway

### TODO:

- implement checks
- implement good storage of G
- implement efficient matmul of G
- implement one givens rotation
- implement outer loop
- serial optimizations
- parallelizations, probably with openmp

- 6 Experiments
- 7 Conclusion
- 8 References