

```
In [1]: import numpy as np
```

```
In [17]: def function1(X):
v = np.zeros(X.shape)
for j in range(X.shape[0]):
    y = np.zeros(X.shape[1])
    for i in range(j):
        r = np.inner(X[j], v[i])
        y += r * v[i]
    v[j] = (X[j] - y)/np.linalg.norm(X[j] - y)
return v
```

```
In [18]: def function2(X):
v = np.zeros(X.shape)
for j in range(X.shape[0]):
    w = X[j]
    for i in range(j):
        r = np.inner(w, v[i])
        w = w - r * v[i]
    v[j] = (w)/np.linalg.norm(w)
return v
```

```
In [19]: def GenerateHilbert(n):
H = np.zeros((n,n))
for i in range(1, n+1):
    h = [1/(i + j) for j in range(n)]
    H[i-1] = h
return H
```

```
In [ ]:
```

```
In [63]: n = 1000
```

```
In [64]: H = GenerateHilbert(n)
```

```
In [65]: R1 = function1(H)
```

```
In [66]: R2 = function2(H)
```

```
In [67]: R3 = function1(R1)
```

```
In [68]: R4 = function1(R2)
```

Since  $R_1^T R_1$  and  $R_2^T R_2$  are supposed to be equal to the identity matrix, the sum of all off diagonal entry should be zero, therefore  $G_k := R_k^T R_k - \mathbb{I}$ ,  $\Sigma_k = \sum_{i=1}^n \sum_{j=1}^n |g_{ij}^k|$  hast to be zero. Due to numerical / rounding errors, this does not hold for the computed matrices above. Large  $\Sigma_k$  indicates, that the according matrix  $R_k$  is not orthogonal.

```
In [69]: np.sum(abs(np.matmul(R1.T, R1) - np.identity(n)))
```

```
Out[69]: 319615.3517070741
```

```
In [70]: np.sum(abs(np.matmul(R2.T, R2) - np.identity(n)))
```

```
Out[70]: 4228.080270900577
```

```
In [71]: np.sum(abs(np.matmul(R3.T, R3) - np.identity(n)))
```

```
Out[71]: 555770.9540641983
```

```
In [72]: np.sum(abs(np.matmul(R4.T, R4) - np.identity(n)))
```

```
Out[72]: 1.3740774860795175e-06
```

Function2 yields better results, since the orthogonalization inside the inner loop is not directly based on the according vector  $x_j$ , the numerical errors are taken into account during the process. This results in a more orthogonal matrix

```
In [ ]:
```

```
In [ ]:
```

```
In [ ]:
```