## DEMONSTRATION OF TRIANGULARIZATION BY CHOLESKY AND GAUSSIAN ELIMINATION

This worksheet reduces a Hermition matrix to triangular factors by Cholesky and by the simpler Gaussian elimination, and shows numerically that they are equivalent.

## Generate a Random Hermitian Matrix

$$
\mathrm{N}:=5 \quad \mathrm{i}:=0 . . \mathrm{N}-1 \quad \mathrm{j}:=0 . . \mathrm{N}-1
$$

$X_{i, j}:=\operatorname{rnd}(2)-1 \quad<===$ click once here, press F9, to get new matrix

$$
\mathbf{R}:=\overline{\left(\mathrm{X}^{\mathrm{T}}\right)} \cdot \mathrm{X} \quad \text { make it Hermitian }
$$

Here it is:

$$
\mathbf{R}=\left[\begin{array}{ccccc}
3.385 & 0.344 & -0.223 & 0.458 & 0.533 \\
0.344 & 1.975 & 0.638 & -0.334 & -0.191 \\
-0.223 & 0.638 & 1.938 & -0.301 & 0.208 \\
0.458 & -0.334 & -0.301 & 1.088 & 0.364 \\
0.533 & -0.191 & 0.208 & 0.364 & 1.482
\end{array}\right]
$$

## Cholesky Factorization

$$
\mathbf{F}:=\operatorname{cholesky}(\mathbf{R})
$$

F is lower triangular

$$
\mathbf{F}=\left[\begin{array}{ccccc}
1.84 & 0 & 0 & 0 & 0 \\
0.187 & 1.393 & 0 & 0 & 0 \\
-0.121 & 0.474 & 1.303 & 0 & 0 \\
0.249 & -0.273 & -0.108 & 0.97 & 0 \\
0.29 & -0.176 & 0.251 & 0.279 & 1.107
\end{array}\right]
$$

and it factors $\mathbf{X}$ :

$$
\mathbf{F} \cdot \mathbf{F}^{\mathrm{T}}-\mathbf{R}=\left[\begin{array}{ccccc}
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0
\end{array}\right]
$$

Its inverse is also lower triangular

$$
\mathbf{F}^{-1}=\left[\begin{array}{ccccc}
0.544 & 0 & 0 & 0 & 0 \\
-0.073 & 0.718 & 0 & 0 & 0 \\
0.077 & -0.261 & 0.767 & 0 & 0 \\
-0.151 & 0.173 & 0.086 & 1.031 & 0 \\
-0.133 & 0.13 & -0.195 & -0.26 & 0.903
\end{array}\right]
$$

and it diagonalizes the noise covariance matrix

$$
\mathbf{F}^{-1} \cdot \mathbf{R} \cdot \mathbf{F}^{-1}{ }^{\mathrm{T}}=\left[\begin{array}{ccccc}
1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1
\end{array}\right]
$$

## Gaussian Elimination

To factor $\mathbf{R}$ by Gaussian elimination, we augment it with the identity matrix, then do row reductions. Mathcad's column-oriented notation makes it easier to perform Gaussian elimination on the transpose, so it's column reductions.

$$
\operatorname{Gauss}(\mathbf{R}):=\left\lvert\, \begin{aligned}
& \mathbf{Z} \leftarrow \operatorname{augment}(\mathbf{R}, \text { identity }(\mathrm{N}))^{\mathrm{T}} \\
& \text { for } \mathrm{i} \in 0 . . \mathrm{N}-2 \\
& \text { for } \mathrm{j} \in \mathrm{i}+1 . . \mathrm{N}-1 \\
& \quad \mathbf{Z}^{<\mathrm{j}>} \leftarrow \mathbf{Z}^{<\mathrm{j}>}-\frac{\mathbf{Z}_{\mathrm{i}, \mathrm{j}}}{\mathbf{Z}_{\mathrm{i}, \mathrm{i}}} \cdot \mathbf{Z}^{<\mathrm{i}>} \\
& \mathbf{Z}^{\mathrm{T}}
\end{aligned}\right.
$$

Upper and lower factors are then extracted by

$$
\begin{aligned}
& \text { temp }:=\operatorname{Gauss}(\mathbf{R}) \\
& \mathbf{U}:=\operatorname{submatrix}(\operatorname{temp}, 0, \mathrm{~N}-1,0, \mathrm{~N}-1) \quad \mathbf{L}:=\operatorname{submatrix}(\operatorname{temp}, 0, \mathrm{~N}-1, \mathrm{~N}, 2 \cdot \mathrm{~N}-1)
\end{aligned}
$$

They are

$$
\begin{aligned}
& \mathbf{U}=\left[\begin{array}{ccccc}
3.385 & 0.344 & -0.223 & 0.458 & 0.533 \\
0 & 1.94 & 0.661 & -0.38 & -0.246 \\
0 & 0 & 1.699 & -0.141 & 0.327 \\
0 & 0 & 0 & 0.94 & 0.271 \\
0 & 0 & 0 & 0 & 1.227
\end{array}\right] \\
& \mathbf{L}=\left[\begin{array}{cccccc}
1 & 0 & 0 & 0 & 0 \\
-0.102 & 1 & 0 & 0 & 0 \\
0.101 & -0.341 & 1 & 0 & 0 \\
-0.147 & 0.168 & 0.083 & 1 & 0 \\
-0.147 & 0.144 & -0.216 & -0.288 & 1
\end{array}\right]
\end{aligned}
$$

and they satisfy $\quad \mathbf{L} \cdot \mathbf{R}=\mathbf{U} \quad$ as seen below

$$
\mathbf{L} \cdot \mathbf{R}-\mathbf{U}=\left[\begin{array}{lllll}
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0
\end{array}\right]
$$

The effect of applying $\mathbf{L}$ to the noise covariance matrix is to whiten, but not normalize, the noise components:

$$
\mathbf{L} \cdot \mathbf{R} \cdot \mathbf{L}^{\mathrm{T}}=\left[\begin{array}{ccccc}
3.385 & 0 & 0 & 0 & 0 \\
0 & 1.94 & 0 & 0 & 0 \\
0 & 0 & 1.699 & 0 & 0 \\
0 & 0 & 0 & 0.94 & 0 \\
0 & 0 & 0 & 0 & 1.227
\end{array}\right]
$$

It is easy to show (and to see) that this matrix is just the diagonal of $\mathbf{U}$ above. Thus the SNR on each bit decision, assuming correct decisions fed back, is

$$
\gamma_{\mathrm{i}}:=\mathbf{U}_{\mathrm{i}, \mathrm{i}} \quad \text { assuming unit noise variance }
$$

Now compare with Cholesky. Because it normalizes, as well as whitens, the noise, the SNR on each decision is the square of the diagonal entries of $\mathbf{F}$ (again assuming unit noise variance).

$$
\gamma_{\mathrm{ch}_{\mathrm{i}}}:=\left(\mathbf{F}_{\mathrm{i}, \mathrm{i}}\right)^{2}
$$

They are the same

$$
\begin{aligned}
& \gamma^{\mathrm{T}}=\left(\begin{array}{lllll}
3.385 & 1.94 & 1.699 & 0.94 & 1.227
\end{array}\right) \\
& \gamma_{\mathrm{ch}}^{\mathrm{T}}=\left(\begin{array}{lllll}
3.385 & 1.94 & 1.699 & 0.94 & 1.227
\end{array}\right)
\end{aligned}
$$

