

e) Basically, we need to state the conditions under which the transformation \mathbf{T} complies with $p(\underline{x}_0 | N(\underline{\mu}, \underline{\Sigma})) = p(\mathbf{T}\underline{x}_0 | N(\mathbf{T}^T \underline{\mu}, \mathbf{T}^T \underline{\Sigma} \mathbf{T}))$. Let's start by looking at the right hand side of the previous equation:

$$\frac{1}{(2\pi)^{d/2} |\underline{\Sigma}|^{1/2}} \exp \left[-\frac{1}{2} (\underline{x} - \underline{\mu})^T \underline{\Sigma}^{-1} (\underline{x} - \underline{\mu}) \right] \xrightarrow[\underline{\mu} \rightarrow \mathbf{T}^T \underline{\mu}]{\underline{\Sigma} \rightarrow \mathbf{T}^T \underline{\Sigma} \mathbf{T}} \frac{1}{(2\pi)^{d/2} |\mathbf{T}^T \underline{\Sigma} \mathbf{T}|^{1/2}} \exp \left[-\frac{1}{2} (\mathbf{T}^T (\underline{x} - \underline{\mu}))^T (\mathbf{T}^T \underline{\Sigma} \mathbf{T})^{-1} (\mathbf{T}^T (\underline{x} - \underline{\mu})) \right]$$

Let's expand the exponent of the transformed Gaussian:

$$-\frac{1}{2} (\mathbf{T}^T (\underline{x} - \underline{\mu}))^T (\mathbf{T}^T \underline{\Sigma} \mathbf{T})^{-1} (\mathbf{T}^T (\underline{x} - \underline{\mu})) \xrightarrow[\text{Use } (\mathbf{AB})^{-1} = \mathbf{A}^{-1} \mathbf{B}^{-1}]{\text{Use } (\mathbf{AB})^T = \mathbf{A}^T \mathbf{B}^T} -\frac{1}{2} (\underline{x} - \underline{\mu})^T \mathbf{T} (\mathbf{T}^{-1} \underline{\Sigma}^{-1} (\mathbf{T}^T)^{-1}) \mathbf{T}^T (\underline{x} - \underline{\mu})$$

Now, observe that the matrix multiplications associated with the transformation \mathbf{T} all reduce to the identity matrix, which finally gives us the expression $-\frac{1}{2} (\underline{x} - \underline{\mu})^T \underline{\Sigma}^{-1} (\underline{x} - \underline{\mu})$, which is nothing more than what we had as the exponent of the original distribution. In order to complete this explanation, we also need to prove that $|\underline{\Sigma}|^{1/2} = |\mathbf{T}^T \underline{\Sigma} \mathbf{T}|^{1/2}$. A property of the determinants states that $|\mathbf{AB}| = |\mathbf{A}| |\mathbf{B}|$, so $|\underline{\Sigma}| = |\mathbf{T}^T \underline{\Sigma} \mathbf{T}| = |\underline{\Sigma}| |\mathbf{T}^T \mathbf{T}|$ is true only when $|\mathbf{T}^T \mathbf{T}| = 1$. This means that $\mathbf{T}^T \mathbf{T} = \mathbf{I}$ or $\mathbf{T}^T = \mathbf{T}^{-1}$. This is a property that the orthogonal matrices have. We conclude that for $p(\underline{x}_0 | N(\underline{\mu}, \underline{\Sigma})) = p(\mathbf{T}\underline{x}_0 | N(\mathbf{T}^T \underline{\mu}, \mathbf{T}^T \underline{\Sigma} \mathbf{T}))$ to be true, the transformation \mathbf{T} must be orthogonal.

f) If the application of \mathbf{A}_w to a Gaussian distribution transforms its covariance matrix into the identity matrix, then the following must be true:

$$\frac{1}{(2\pi)^{d/2} |\mathbf{A}_w^T \underline{\Sigma} \mathbf{A}_w|^{1/2}} \exp \left[-\frac{1}{2} (\mathbf{A}_w^T (\underline{x} - \underline{\mu}))^T (\mathbf{A}_w^T \underline{\Sigma} \mathbf{A}_w)^{-1} (\mathbf{A}_w^T (\underline{x} - \underline{\mu})) \right] = \frac{1}{(2\pi)^{d/2} |\mathbf{I}|^{1/2}} \exp \left[-\frac{1}{2} (\mathbf{A}_w^T (\underline{x} - \underline{\mu}))^T (\mathbf{I})^{-1} (\mathbf{A}_w^T (\underline{x} - \underline{\mu})) \right].$$

Which implies nothing but $\mathbf{A}_w^T \underline{\Sigma} \mathbf{A}_w = \mathbf{I}$. To prove this is true, we use the definition of the whitening transformation $\mathbf{A}_w = \Phi \Lambda^{-1/2} \Phi^T$ and get:

$$\begin{aligned} \mathbf{A}_w^T \underline{\Sigma} \mathbf{A}_w &= (\Phi \Lambda^{-1/2} \Phi^T)^T \underline{\Sigma} (\Phi \Lambda^{-1/2} \Phi^T) \\ &= ((\Phi^T)^T \Lambda^{-1/2} \Phi^T) \underline{\Sigma} (\Phi \Lambda^{-1/2} \Phi^T) = (\Phi \Lambda^{-1/2} \Phi^T) \underline{\Sigma} (\Phi \Lambda^{-1/2} \Phi^T) \end{aligned}$$

Matrix fundamentals tell us that $\mathbf{D} = \mathbf{X}^{-1} \mathbf{A} \mathbf{X}$ is a diagonal matrix, with the eigenvalues of \mathbf{A} as entries if the columns of \mathbf{X} are the eigenvectors of \mathbf{A} . Note that Φ is a matrix which columns are the eigenvectors of $\underline{\Sigma}$ and because $\underline{\Sigma}$ is symmetric (covariance matrix) its eigenvectors form an orthonormal basis. That is, the matrix Φ is orthogonal ($\Phi^{-1} = \Phi^T$). Now we can see that:

$$\mathbf{A}_w^T \Sigma \mathbf{A}_w = \Phi \Lambda^{-1/2} \underbrace{\Phi^T \Sigma \Phi}_{\Lambda} \Lambda^{-1/2} \Phi^T = \mathbf{I}$$

where Λ is a diagonal matrix with the eigenvalues of Σ as entries. Further development states:

$$\Phi \Lambda^{-1/2} \Lambda \Lambda^{-1/2} \Phi^T = \Phi \Lambda^{-1/2} \Lambda^{1/2} \Phi^T = \Phi \mathbf{I} \Phi^T = \mathbf{I}$$

The first part of the problem is checked. Now we have to check if the normalization is preserved by the \mathbf{A}_w transformation. We know from e) that only orthogonal transformations will keep normalization. In order to see if \mathbf{A}_w is orthogonal, we take the norm of the transformation. If it is equal to one, normalization is preserved (implying \mathbf{A}_w is orthogonal). Else, there will be a scaling factor equal to the norm of the transformation.

$$\|\mathbf{A}_w^T \mathbf{A}_w\| = \left\| \Phi \Lambda^{-1/2} \underbrace{\Phi^T \Phi}_{\mathbf{I}} \Lambda^{-1/2} \Phi^T \right\| = \|\Phi \Lambda^{-1} \Phi^T\| = \|\Lambda^{-1}\|$$

Finally we conclude that \mathbf{A}_w is not orthogonal, and does not preserve normalization. The whitening transform introduces a scaling factor of $\|\Lambda^{-1}\|$.