

Recapitulation: How to deal with pdfs?

Example: Consider a RV with pdf $p(\mathbf{x})$! How to calculate the pdf $p(\mathbf{y})$ of a RV $\mathbf{y} = \mathbf{t}[\mathbf{x}]$ resulting from \mathbf{x} by a transformation $\mathbf{t} : \mathbf{x} \mapsto \mathbf{t}[\mathbf{x}]$?

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$$\begin{aligned} p(\mathbf{y}) &= \int d\mathbf{x} p(\mathbf{x}, \mathbf{y}) && \text{marginalize: bring } \mathbf{x} \text{ into the play!} \\ &= \int d\mathbf{x} p(\mathbf{y}|\mathbf{x}) p(\mathbf{x}) && \text{notion of a conditional pdf} \end{aligned}$$

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For Dirac-distributions: “integration formula”: $\int dx \delta(x - y) f(x) = f(y)$.

Assumption: invertable transformation $\mathbf{t} : \mathbf{x} \mapsto \mathbf{z} = \mathbf{t}[\mathbf{x}]$! Substitute in the integral: $\mathbf{x} = \mathbf{t}^{-1}[\mathbf{z}]$.

Remember: substitution rule for volume integrals

$$\varphi : y \mapsto \varphi[y] = x \quad \int_a^b dx f(x) = \int_{\varphi[a]}^{\varphi[b]} dy \frac{d\varphi[y]}{dy} f(\varphi[y])$$

$$\varphi : \mathbf{y} \mapsto \varphi[\mathbf{y}] = \mathbf{x} \quad \int_X d\mathbf{x} f(\mathbf{x}) = \int_{\varphi[X]} d\mathbf{y} \left| \frac{\partial \varphi[\mathbf{y}]}{\partial \mathbf{y}} \right| f(\varphi[\mathbf{y}])$$

Jacobian = matrix of the first derivatives of a vector-variate function

$$\varphi : \mathbf{x} \mapsto \varphi[\mathbf{x}] = (\varphi_1[\mathbf{x}], \dots, \varphi_m[\mathbf{x}])^\top, \mathbf{x} = (x_1, \dots, x_n)^\top :$$

$$\Phi = \begin{pmatrix} \frac{\partial \varphi_1[\mathbf{x}]}{\partial x_1} & \dots & \frac{\partial \varphi_m[\mathbf{x}]}{\partial x_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial \varphi_1[\mathbf{x}]}{\partial x_n} & \dots & \frac{\partial \varphi_m[\mathbf{x}]}{\partial x_n} \end{pmatrix} =: \frac{\partial \varphi[\mathbf{x}]}{\partial \mathbf{x}}$$

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Corresponding Jacobi determinant: $|\mathbf{T}^{-1}(\mathbf{z})|$ mit $|\mathbf{T}^{-1}(\mathbf{z})| = \frac{\partial \mathbf{t}^{-1}[\mathbf{z}]}{\partial \mathbf{z}}$.

$$\begin{aligned} p(\mathbf{y}) &= \int d\mathbf{z} |\mathbf{T}^{-1}(\mathbf{z})| \delta(\mathbf{y} - \mathbf{z}) p(\mathbf{t}^{-1}[\mathbf{z}]) \\ &= |\mathbf{T}^{-1}(\mathbf{y})| p(\mathbf{t}^{-1}[\mathbf{y}]) =: \mathcal{T}[p](\mathbf{y}) && \mathcal{T} \text{ is called “Transfer-Operator”} \end{aligned}$$

To be generalized under certain assumptions!

Let \mathbf{x} be a Gaussian RV with $p(\mathbf{x}) = \mathcal{N}(\mathbf{x}; \mathbb{E}[\mathbf{x}], \mathbb{C}[\mathbf{x}])$.
Show for the pdf of the RV $\mathbf{y} = \mathbf{t}[\mathbf{x}]$, resulting from \mathbf{x} by
an *affine* transformation $\mathbf{t}[\mathbf{x}] = \mathbf{a} + \mathbf{A}\mathbf{x}$:

Exercise (voluntary)

$$\begin{aligned} p(\mathbf{y}) &= \left| \frac{\partial \mathbf{t}^{-1}[\mathbf{y}]}{\partial \mathbf{y}} \right| p(\mathbf{t}^{-1}[\mathbf{y}]) \\ &= \mathcal{N}(\mathbf{y}; \mathbf{a} + \mathbf{A}\mathbb{E}[\mathbf{x}], \mathbf{A}\mathbb{E}[\mathbf{x}]\mathbf{A}^\top) \end{aligned}$$

\mathbf{a} , \mathbf{A} : vector/matrix of suitable dimension (constant),

$$\mathbf{t}^{-1} : \mathbf{y} \mapsto \mathbf{t}^{-1}[\mathbf{y}] = \mathbf{A}^{-1}(\mathbf{y} - \mathbf{a}), \quad \frac{\partial \mathbf{t}^{-1}[\mathbf{y}]}{\partial \mathbf{y}} = \mathbf{A}^{-1}$$

Remember some rules for dealing with matrices:

$$|\mathbf{A}||\mathbf{B}| = |\mathbf{AB}|, \quad |\mathbf{A}^{-1}| = |\mathbf{A}|^{-1}$$

$$(\mathbf{AB})^\top = \mathbf{B}^\top \mathbf{A}^\top, \quad (\mathbf{AB})^{-1} = \mathbf{B}^{-1} \mathbf{A}^{-1}$$