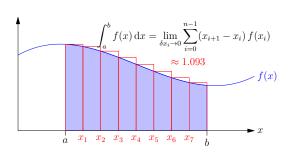
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Integral Calculus



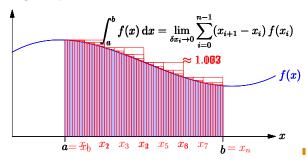
Riemann Integration, integration by parts, gaussian integrals

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Riemann Integral

• Integrals represent area beneath a curve



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Fundamental Law of Calculus

Let

$$I(a,x) = \int_{a}^{x} f(z) dz = \lim_{\delta z_{i} \to 0} \sum_{i=0}^{n-1} (z_{i+1} - z_{i}) f(z_{i})$$

• Now for small δx

$$I(a, x + \delta x) = \int_{a}^{x + \delta x} f(z) dz = \lim_{\delta z_{i} \to 0} \sum_{i=0}^{n-1} (z_{i+1} - z_{i}) f(z_{i}) + \delta x f(x)$$

Thus

$$\frac{\mathrm{d}I(a,x)}{\mathrm{d}x} = \lim_{\delta x \to 0} \frac{I(x+\delta x) - I(x)}{\delta x} \\ = \lim_{\delta x \to 0} \frac{\delta x f(x)}{\delta x} \\ = f(x) \\ = f(x)$$

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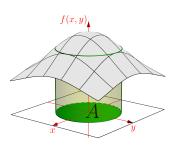
Indefinite Integrals

- So far we have considered **definite integrals** where we integrate between two points (a and b)
- However, when think about integration as an anti-derivative, it is useful to think of a function $F(x) = \int f(x) dx$
- So that F'(x) = f(x)
- However the function F(x), F(x)+1, $F(x)+\pi$, etc. all have the same derivative so F(x) is only defined up to an additive constant
- Note that the definite integral is given by

$$\int_{a}^{b} f(x) \mathrm{d}x = F(b) - F(a)$$

Outline

- 1. Defining Integrals
- 2. Doing Integrals
- 3. Gaussian Integrals



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Linearity of Integration

• Integration is a linear operator

$$\begin{split} \int_{a}^{b} (rf(x) + sg(x)) \, \mathrm{d}x &= \lim_{\delta x_{i} \to 0} \sum_{i=0}^{n-1} (x_{i+1} - x_{i}) \, (rf(x_{i}) + sg(x_{i})) \mathbb{I} \\ &= \lim_{\delta x_{i} \to 0} \left(\sum_{i=0}^{n-1} (x_{i+1} - x_{i}) rf(x_{i}) + \sum_{i=0}^{n-1} (x_{i+1} - x_{i}) sg(x_{i}) \right) \mathbb{I} \\ &= \lim_{\delta x_{i} \to 0} \left(r \sum_{i=0}^{n-1} (x_{i+1} - x_{i}) f(x_{i}) + s \sum_{i=0}^{n-1} (x_{i+1} - x_{i}) g(x_{i}) \right) \mathbb{I} \\ &= r \lim_{\delta x_{i} \to 0} \sum_{i=0}^{n-1} (x_{i+1} - x_{i}) f(x_{i}) + s \lim_{\delta x_{i} \to 0} \sum_{i=0}^{n-1} (x_{i+1} - x_{i}) g(x_{i}) \mathbb{I} \\ &= r \int_{a}^{b} f(x) \, \mathrm{d}x + s \int_{a}^{b} f(x) \, \mathrm{d}x \mathbb{I} \end{split}$$

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The Other Way Around

Consider

$$\begin{split} \int_{a}^{b} \frac{\mathrm{d}f(x)}{\mathrm{d}x} \mathrm{d}x &= \int_{a}^{b} \lim_{\delta x \to 0} \frac{f(x + \delta x) - f(x)}{\delta x} \mathrm{d}x \\ &= \lim_{x_{i+1} - x_{i} \to 0} \sum_{i=0}^{n-1} (x_{i+1} - x_{i}) \frac{f(x_{i+1}) - f(x_{i})}{x_{i+1} - x_{i}} \\ &= \lim_{x_{i+1} - x_{i} \to 0} \sum_{i=0}^{n-1} (f(x_{i+1}) - f(x_{i})) \mathbb{I} \\ &= (f(x_{1}) - f(x_{0})) + (f(x_{2}) - f(x_{1})) + (f(x_{3}) - f(x_{2})) + \cdots \\ &+ (f(x_{n-1}) - f(x_{n-2})) + (f(x_{n}) - f(x_{n-1})) \mathbb{I} \\ &= f(x_{n}) - f(x_{0}) \mathbb{I} = f(b) - f(a) \mathbb{I} \end{split}$$

 We can think of integration as an anti-derivative it undoes differentiation

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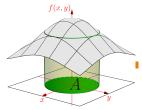
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Multiple Integrals

- For functions involving many independent variables (e.g. f(x,y), f(x,y,z), f(x)) we can integrate over multiple dimensions
- For example

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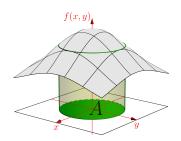




• It gets tedious writing multiple integral signs and I tend to write just one

$$\int \cdots \int f(x_1, x_2, \dots, x_n) dx_1 dx_2 \cdots dx_n = \int f(x) dx$$

- 1. Defining Integrals
- 2. Doing Integrals
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Is Integration Straightforward?

- We saw due to the product and chain rules that we can differentiate almost anything. Given integration is the anti-derivative can we integrate anything?
- Products and compositions

$$\int f(x)g(x)dx = ? \qquad \qquad \int f(g(x))dx = ? \mathbf{1}$$

- Unfortunately, unlike differentiation we don't have a small parameter we can expand in
- In general integration is hard

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Example of Integration by Parts

Consider

$$\begin{split} \Pi(z) &= \int_0^\infty x^z \mathrm{e}^{-x} \mathrm{d}x = \int_0^\infty x^z \frac{\mathrm{d}(-\mathrm{e}^{-x})}{\mathrm{d}x} \mathrm{d}x \\ &= \left[x^z (-\mathrm{e}^{-x}) \right]_0^\infty - \int_0^\infty \frac{\mathrm{d}x^z}{\mathrm{d}x} (-\mathrm{e}^{-x}) \mathrm{d}x \\ &= \int_0^\infty (zx^{z-1}) \mathrm{e}^{-x} \mathrm{d}x = z \int_0^\infty x^{z-1} \mathrm{e}^{-x} \mathrm{d}x = z \Pi(z-1) \end{split}$$

 \bullet Thus $\Pi(z)=z\Pi(z-1)$, but

$$\Pi(0) = \int_0^\infty \mathrm{e}^{-z} \mathrm{d}z = \left[-\mathrm{e}^{-x} \right]_0^\infty \mathbf{I} = -\mathrm{e}^{-\infty} - (-\mathrm{e}^0) \mathbf{I} = 1 \mathbf{I}$$

Now

$$\Pi(n) = n\Pi(n-1) = n(n-1)\Pi(n-2) = n(n-1)(n-2)...1 = n!$$

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Example of Integration by Substitution

- We consider $I(n) = \int_{0}^{\infty} x^n e^{-x^2/2} dx$
- Let $u(x) = x^2/2$ or $x(u) = \sqrt{2u}$ so that

$$\frac{\mathrm{d}x(u)}{\mathrm{d}u} = \frac{1}{\sqrt{2u}} \qquad u(0) = 0 \qquad u(\infty) = \infty$$

Thus

$$\begin{split} I(n) &= \int_0^\infty \left(\sqrt{2u}\right)^n \mathrm{e}^{-u} \frac{1}{\sqrt{2u}} \mathrm{d}u \\ &= 2^{\frac{n-1}{2}} \int_0^\infty u^{\frac{n-1}{2}} \mathrm{e}^{-u} \mathrm{d}u = 2^{\frac{n-1}{2}} \Pi\left(\frac{n-1}{2}\right) \end{split}$$

$$\begin{array}{l} \bullet \ I(1) = 1 \ \ \, I(3) = 2 \times 1! = 2 \ \ \, I(5) = 2^2 \times 2! = 8 \ \ \, \text{but} \\ I(0) = \Pi(-1/2)/\sqrt{2} \ \ \, I(2) = \sqrt{2}\Pi(1/2) = \Pi(-1/2)/\sqrt{2} \ \ \, I(2) = \sqrt{2}\Pi(1/2) = \Pi(-1/2)/\sqrt{2} \ \ \, I(2) = 1 \ \ \, I(1) = 1$$

- A key method for performing integrals is through knowledge of the anti-derivative
- If we know F'(x) = f(x) then $F(x) + c = \int f(x) dx$
- E.g. we know that $dx^n/dx = nx^{n-1}$ therefore

$$\int x^{n-1} dx = \frac{1}{n} \int \frac{dx^n}{dx} dx = \frac{x^n}{n} + c$$

and

$$\int_{a}^{b} x^{n-1} \mathrm{d}x = \frac{b^n}{n} - \frac{a^n}{n}$$

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Integration by Parts

- \bullet Recall the product rule $\frac{\mathrm{d}f(x)g(x)}{\mathrm{d}x} = \frac{\mathrm{d}f(x)}{\mathrm{d}x}g(x) + f(x)\frac{\mathrm{d}g(x)}{\mathrm{d}x}$
- Integrating we get

$$\int_{a}^{b} \frac{\mathrm{d}f(x)g(x)}{\mathrm{d}x} \mathrm{d}x = \int_{a}^{b} \frac{\mathrm{d}f(x)}{\mathrm{d}x} g(x) \mathrm{d}x + \int_{a}^{b} f(x) \frac{\mathrm{d}g(x)}{\mathrm{d}x} \mathrm{d}x$$
$$= \left[f(x)g(x) \right]_{a}^{b} = f(b)g(b) - f(a)g(a)$$

• Unfortunately we get two integrals, but we can turn this around

$$\int_{a}^{b} f(x) \frac{\mathrm{d}g(x)}{\mathrm{d}x} \mathrm{d}x = [f(x)g(x)]_{a}^{b} - \int_{a}^{b} \frac{\mathrm{d}f(x)}{\mathrm{d}x} g(x) \mathrm{d}x$$

whether this is helpful depends on f(x) and g(x)

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Substitution

• We can make a transformation from x to u = u(x)

$$\begin{split} \int_{a}^{b} f(x) \mathrm{d}x &= \lim_{\delta x_{i} \to 0} \sum_{i=0}^{n-1} f(x_{i}) (x_{i+1} - x_{i}) \mathbf{I} \\ &= \lim_{\delta u_{i} \to 0} \sum_{i=0}^{n-1} f(x(u_{i})) \frac{x(u_{i+1}) - x(u_{i})}{u_{i+1} - u_{i}} (u_{i+1} - u_{i}) \mathbf{I} \\ &= \int_{u(a)}^{u(b)} f(x(u)) \frac{\mathrm{d}x(u)}{\mathrm{d}u} \mathrm{d}u \mathbf{I} \end{split}$$

- * where u_i is such that $x(u_i) = x_i$ or $u_i = u(x_i)$ where u(x) is the inverse of x(u)
- the inverse of x(u). * using $\lim_{\delta u_i \to 0} \frac{x(u_{i+1}) - x(u_i)}{u_{i+1} - u_i} = \frac{\mathrm{d}x(u_i)}{\mathrm{d}u}$.

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Changing Variables in Multidimensional Space

ullet When changing variables in many dimensions x o u the change of variables involves the Jacobian

$$\int f(\boldsymbol{x}) \mathrm{d}\boldsymbol{x} = \int f(\boldsymbol{x}(\boldsymbol{u})) |\det(\mathbf{J})| \mathrm{d}\boldsymbol{u}, \qquad \boldsymbol{J} = \begin{pmatrix} \frac{\partial x_1}{\partial u_1} & \frac{\partial x_1}{\partial u_2} & \cdots & \frac{\partial x_n}{\partial u_n} \\ \frac{\partial x_1}{\partial u_1} & \frac{\partial x_2}{\partial u_2} & \cdots & \frac{\partial x_2}{\partial u_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial x_n}{\partial u_n} & \frac{\partial x_n}{\partial u_n} & \cdots & \frac{\partial x_n}{\partial u_n} \end{pmatrix}$$

• E.g. transforming from Cartesian coordinates (x,y) to polar coordinates (r,θ) then $x=r\cos(\theta)$ and $y=r\sin(\theta)$

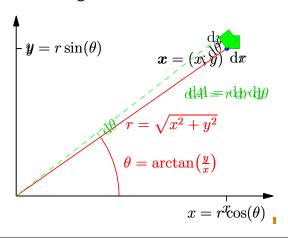
$$\begin{split} |\det(\mathbf{J})| &= \left| \det \left(\frac{\frac{\partial r \cos(\theta)}{\partial r}}{\frac{\partial r \sin(\theta)}{\partial r}} \right. \left. \frac{\frac{\partial r \cos(\theta)}{\partial \theta}}{\frac{\partial \theta}{\partial r} \sin(\theta)} \right) \right| \mathbf{I} = \left| \det \left(\frac{\cos(\theta)}{\sin(\theta)} \right. \left. -r \sin(\theta) \right) \right| \mathbf{I} \\ &= r \left(\cos^2(\theta) + \sin^2(\theta) \right) \mathbf{I} = r \mathbf{I} \end{split}$$

• That is, $dxdy = rdrd\theta$

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Change of Variables in Pictures



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Cumulant Generating Function

- Note that $e^{\ell x} = 1 + \ell x + \frac{1}{2}\ell^2 x^2 + \frac{1}{3!}\ell^3 x^3 + \cdots$
- So

$$Z(\ell) = \int_{-\infty}^{\infty} \mathrm{e}^{\ell x} f_X(x) \, \mathrm{d}x = 1 + \ell M_1 + \frac{1}{2} \ell^2 M_2 + \frac{1}{3!} \ell^3 M_3 + \cdots$$

- Now using $\log(1+\epsilon) = \epsilon \frac{1}{2}\epsilon^2 + \frac{1}{3}\epsilon^3 + \cdots$ $G(\ell) = \log(Z(\ell)) = \ell M_1 + \frac{1}{2}\ell^2 (M_2 M_1^2) + \frac{1}{2!}\ell^3 (M_3 3M_2M_1 + 2M_1^3) + \cdots$
- So that $\kappa_n=G^{(n)}(0)$, with $\kappa_1=M_1$ (the mean), $\kappa_2=M_2-M_1^2$

• So that $\kappa_n = G^{(n)}(0)$, with $\kappa_1 = M_1$ (the mean), $\kappa_2 = M_2 - M_1$ (the variance), $\kappa_3 = M_3 - 3M_2M_1 + 2M_1^3$ (the third cumulant related to the skewness)

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Special Functions

- There are integrals with no known closed form solution
- We saw that $\Pi(z)=\int\limits_0^\infty x^z{\rm e}^{-x}{
 m d}x$ satisfies $\Pi(z)=z\Pi(z-1)$
- For integer n then $\Pi(n)=n!$ but for general z, the integal $\Pi(z)$ can't be written in terms of elementary functions
- ullet We consider $\Pi(z)$ as a special function in its own right
- Although, history has left us with the gamma function instead

$$\Gamma(z) = \int_0^\infty x^{z-1} e^{-x} dx = \Pi(z-1)$$

• Other special function defined by integrals exist (e.g. the Bessel , Aire, hypergeometric, elliptic, error functions, . . .)

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Gaussian Integrals

ullet Gaussian integrals are integrals involving e^{-x^2} , e.g.

$$\int_{-\infty}^{\infty} e^{-x^2} dx \qquad \qquad \int_{-\infty}^{\infty} x^4 e^{-ax^2 - bx} dx$$

 They are important in computing integrals with respect to the normal distribution

$$\mathcal{N}(x|\mu,\sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(x-\mu)^2/(2\sigma^2)}$$

- The great news is that these integrals are all doable
- The bad news is that they are quite tricky to do

Differentiating Through the Integral

 A trick that sometimes works is differentiating through an integral, e.g. consider finding moments

$$M_n = \mathbb{E}[X^n] = \int_{-\infty}^{\infty} x^n f_X(x) \, \mathrm{d}x$$

• We can define a momentum generating function

$$Z(\ell) = \int_{-\infty}^{\infty} e^{\ell x} f_X(x) dx$$

• Then $M_n = Z^{(n)}(0)$

$$\left. \frac{\mathrm{d}^n Z(\ell)}{\mathrm{d}\ell^n} \right|_{\ell=0} = \int_{-\infty}^{\infty} \frac{\mathrm{d}^n \mathrm{e}^{\ell x}}{\mathrm{d}\ell^n} \left| f_X(x) \mathrm{d}x \right| = \int_{-\infty}^{\infty} x^n f_X(x) \mathrm{d}x = M_n \mathbf{e}^{\ell x}$$

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More Integration

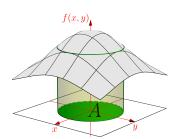
- Although we have a few tricks, integration is hard
- Surprisingly integration sometimes is easier when carried out in the complex plane!
- This is a beautiful part of mathematics! (due largely to Cauchy)!—but beyond the scope of this course!
- Interestingly, also there is an algorithm that allows us to integrate
 a lot of function. It is sufficiently complicated that you need to
 write a computer algorithm of considerable complexity to
 implement it. Most symbolic manipulation packages (e.g.
 Mathematica) have implemented some part of this algorithm.

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Outline

- 1. Defining Integrals
- 2. Doing Integrals
- 3. Gaussian Integrals



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The Gaussian Integral

• The integral over a Gaussian is surprisingly difficult

$$I_1 = \int_{-\infty}^{\infty} e^{-x^2/2} dx$$

• There is a nice trick which is to consider

$$I_1^2 = \int_{-\infty}^{\infty} \mathrm{e}^{-x^2/2} \mathrm{d}x \int_{-\infty}^{\infty} \mathrm{e}^{-y^2/2} \mathrm{d}y = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \mathrm{e}^{-(x^2+y^2)/2} \mathrm{d}x \mathrm{d}y$$

• Making the change of variables $r=\sqrt{x^2+y^2}$ and $\theta=\arctan(y/x)$ (so that $x=r\cos(\theta),\,y=r\sin(\theta)$ and $x^2+y^2=r^2$)

$$I_1^2 = \int_0^{2\pi} d\theta \int_0^{\infty} re^{-r^2/2} dr = 2\pi \int_0^{\infty} re^{-r^2/2} dr$$

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The Gaussian Integral Continued

• From before

$$I_1^2 = 2\pi \int_0^\infty re^{-r^2/2} dr$$

ullet Finally let $u=r^2/2$ so that $\mathrm{d}u/\mathrm{d}r=r$ or $\mathrm{d}u=r\mathrm{d}r$ we get

$$I_1^2 = 2\pi \int_0^\infty e^{-u} du = 2\pi$$

- So that $I_1 = \sqrt{2\pi}$
- Incidentally, $I_1 = \sqrt{2}\Pi(-1/2)$ so $\Pi(-1/2) = \Gamma(1/2) = \sqrt{\pi}$

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Multi-dimensional Gaussians

Consider

$$I_3 = \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} e^{-\frac{1}{2} \|\boldsymbol{x}\|_2^2} dx_1 \cdots dx_n$$

where $x = (x_1, x_2, ..., x_n)^{\mathsf{T}}$

• Note that $\|x\|_2^2 = x_1^2 + x_2^2 + \dots + x_n^2$ and using $\mathrm{e}^{\sum_i a_i} = \prod_i \mathrm{e}^{a_i}$

$$I_3 = \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} e^{-\frac{1}{2} \sum_{i=1}^{n} x_i^2} dx_1 \cdots dx_n$$

$$= \prod_{i=1}^{n} \int_{-\infty}^{\infty} e^{-x_i^2/2} dx_i = \prod_{i=1}^{n} \sqrt{2\pi} = (2\pi)^{n/2}$$

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Determinants

 \bullet Using the facts, that $\Xi = V \Lambda V^{\mathsf{T}}$ then

$$\det(\boldsymbol{\Xi}) = \det(\boldsymbol{V}\boldsymbol{\Lambda}\boldsymbol{V}^{\mathsf{T}}) \boldsymbol{\mathbb{I}} = \det(\boldsymbol{V})\det(\boldsymbol{\Lambda})\det(\boldsymbol{V}^{\mathsf{T}}) \boldsymbol{\mathbb{I}} = \det(\boldsymbol{\Lambda}) \boldsymbol{\mathbb{I}} = \prod_{i=1}^n \lambda_i \boldsymbol{\mathbb{I}}$$

using $\det(A\,B) = \det(A)\det(B)$ and $\det(V) = 1$

- Recall $I_4 = \prod_i \sqrt{2\pi\lambda_i} = (2\pi)^{n/2} \sqrt{\det(\Xi)}$
- ullet We note for an n imes n matrix ${f M}$ then $\det(c{f M}) = c^n \det({f M})$ so that

$$I_4 = (2\pi)^{n/2} \sqrt{\det(\Xi)} = \sqrt{\det(2\pi\Xi)}$$

• Finally, we get that for the PDF of a normal to integrate to 1

$$\mathcal{N}(\boldsymbol{x} \mid \boldsymbol{\mu}, \boldsymbol{\Xi}) = \frac{1}{\sqrt{\det(2\pi\boldsymbol{\Xi})}} e^{-\frac{1}{2}(\boldsymbol{x} - \boldsymbol{\mu})^{\mathsf{T}} \boldsymbol{\Xi}^{-1}(\boldsymbol{x} - \boldsymbol{\mu})}$$

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Normal Distribution

We consider

$$I_2 = \int_{-\infty}^{\infty} e^{-(x-\mu)^2/(2\sigma^2)} dx$$

• Making the change of variables $z=(x-\mu)/\sigma$ so that $\mathrm{d}z=\mathrm{d}x/\sigma$ or $\mathrm{d}x=\sigma\mathrm{d}z$. Then

$$I_2 = \sigma \int_{-\infty}^{\infty} e^{-z^2/2} dz = \sigma I_1 = \sqrt{2\pi} \sigma$$

 Note that the probability density function (PDF) for a normally distributed random variable is given by

$$\mathcal{N}(x \mid \mu, \sigma^2) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(x-\mu)^2/(2\sigma^2)}$$

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Full Multi-variate Normal

Consider

$$I_4 = \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} e^{-\frac{1}{2}(\boldsymbol{x} - \boldsymbol{\mu})^{\mathsf{T}} \boldsymbol{\Xi}^{-1}(\boldsymbol{x} - \boldsymbol{\mu})} dx_1 \cdots dx_n$$

- ullet Let $oldsymbol{\Xi}^{-1} = \mathbf{V} oldsymbol{\Lambda}^{-1} \mathbf{V}^\mathsf{T}$ and make the change of variables $y = \mathbf{V}^\mathsf{T} (x \mu)$
- ullet The Jacobian ${\sf J}$ has elements (note that $x={\sf V}y+\mu$)

$$J_{ij} = \frac{\partial x_i}{\partial y_j} = \frac{\partial}{\partial y_j} \left(\sum_{k=1}^n V_{ik} y_k + \mu_i \right) = V_{ij} \mathbf{I}$$

 \bullet So that J=V and consequently $|{\rm det}(J)|=|{\rm det}(V)|=1$ then

$$I_4 = \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} e^{-\frac{1}{2} \mathbf{y}^\mathsf{T} \mathbf{A}^{-1} \mathbf{y}} \, \mathrm{d}y_1 \cdots \mathrm{d}y_n. = \prod_{i=1}^n \int_{-\infty}^{\infty} e^{-y_i^2/(2\lambda_i)} \, \mathrm{d}y_i = \prod_i \sqrt{2\pi\lambda_i} \mathbf{I}_i$$

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Summary

- Integration is extra-ordinarily useful as a tool of analysis
- It occurs when you work with probabilities densities for continuous random variables!
- Integration is beautiful, but hard

 —often impossible

 ■
- Normal distributions lucky almost always give raise to integrals that can be computed in closed form, although often it requires quite a bit of work.
- Making friends with integration will give you a super-power that not too many people share!