

# Moment matching approximation

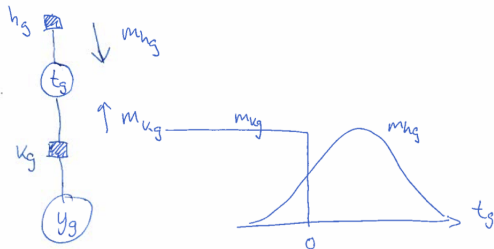
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# Key concepts

- in practise, we can (more or less) only compute with Gaussians
- but the game outcomes are binary
- how can we approximate a binary variable with a Gaussian?
- key idea: **moment matching** approximates the **effect** of the binary variable

# Approximating a step by a Gaussian?



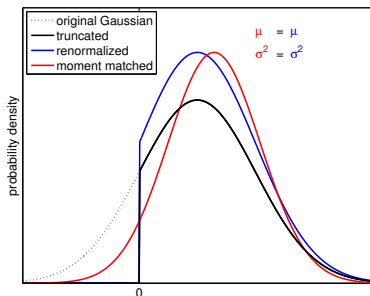
Q: How do we approximate  $m_{kg}$  by a Gaussian?

Does that even make sense?

# Moments of a truncated Gaussian density (1)

Consider the truncated Gaussian density function

$$p(t) = \frac{1}{Z_t} \delta(y - \text{sign}(t)) \mathcal{N}(t; \mu, \sigma^2) \quad \text{where } y \in \{-1, 1\} \text{ and } \delta(x) = 1 \text{ iff } x = 0.$$



We want to *approximate*  $p(t)$  by a Gaussian density function  $q(t)$  with mean and variance equal to the first and second central moments of  $p(t)$ . We need:

- First moment:  $\mathbb{E}[t] = \langle t \rangle_{p(t)}$
- Second central moment:  $\mathbb{V}[t] = \langle t^2 \rangle_{p(t)} - \langle t \rangle_{p(t)}^2$

# Moments of a truncated Gaussian density (2)

We have seen that the normalisation constant is  $Z_t = \Phi(\frac{y\mu}{\sigma})$ .

**First moment.** We take the derivative of  $Z_t$  wrt.  $\mu$ :

$$\begin{aligned}\frac{\partial Z_t}{\partial \mu} &= \frac{\partial}{\partial \mu} \int_0^{+\infty} \mathcal{N}(t; y\mu, \sigma^2) dt = \int_0^{+\infty} \frac{\partial}{\partial \mu} \mathcal{N}(t; y\mu, \sigma^2) dt \\ &= \int_0^{+\infty} y\sigma^{-2}(t - y\mu) \mathcal{N}(t; y\mu, \sigma^2) dt = yZ_t \sigma^{-2} \int_{-\infty}^{+\infty} (t - y\mu) p(t) dt \\ &= yZ_t \sigma^{-2} \langle t - y\mu \rangle_{p(t)} = yZ_t \sigma^{-2} \langle t \rangle_{p(t)} - \mu Z_t \sigma^{-2} y^2\end{aligned}$$

where  $\langle t \rangle_{p(t)}$  is the expectation of  $t$  under  $p(t)$ . We can also write:

$$\frac{\partial Z_t}{\partial \mu} = \frac{\partial}{\partial \mu} \Phi\left(\frac{y\mu}{\sigma}\right) = y\mathcal{N}(y\mu; 0, \sigma^2)$$

Combining both expressions for  $\frac{\partial Z_t}{\partial \mu}$  we obtain

$$\langle t \rangle_{p(t)} = y\mu + \sigma^2 \frac{\mathcal{N}(y\mu; 0, \sigma^2)}{\Phi(\frac{y\mu}{\sigma})} = y\mu + \sigma \frac{\mathcal{N}(\frac{y\mu}{\sigma}; 0, 1)}{\Phi(\frac{y\mu}{\sigma})} = y\mu + \sigma \Psi\left(\frac{y\mu}{\sigma}\right)$$

where we use  $\mathcal{N}(y\mu; 0, \sigma^2) = \sigma^{-1} \mathcal{N}(\frac{y\mu}{\sigma}; 0, 1)$  and define  $\Psi(z) = \frac{\mathcal{N}(z; 0, 1)}{\Phi(z)}$ .

# Moments of a truncated Gaussian density (3)

**Second moment.** We take the second derivative of  $Z_t$  wrt.  $\mu$ :

$$\begin{aligned}\frac{\partial^2 Z_t}{\partial \mu^2} &= \frac{\partial}{\partial \mu} \int_0^{+\infty} y \sigma^{-2} (t - y\mu) \mathcal{N}(t; y\mu, \sigma^2) dt \\ &= \Phi\left(\frac{y\mu}{\sigma}\right) \langle -\sigma^{-2} + \sigma^{-4} (t - y\mu)^2 \rangle_{p(t)}\end{aligned}$$

We can also write

$$\frac{\partial^2 Z_t}{\partial \mu^2} = \frac{\partial}{\partial \mu} y \mathcal{N}(y\mu; 0, \sigma^2) = -\sigma^{-2} y \mu \mathcal{N}(y\mu; 0, \sigma^2)$$

Combining both we obtain

$$\mathbb{V}[t] = \sigma^2 \left(1 - \Lambda\left(\frac{y\mu}{\sigma}\right)\right)$$

where we define  $\Lambda(z) = \Psi(z)(\Psi(z) + z)$ .