

$X_t \in \mathbb{R}^d$  is gaussian if  $\forall t$

\*  $(X_{t_1}, X_{t_2}, \dots, X_{t_n}) \in \mathbb{R}^{dn}$  is Gaussian distributed

equivalently if  $\forall n, \gamma_i \in \mathbb{R}^d$

$\sum_{i=1}^n \langle X_{t_i}, \gamma_i \rangle$  is Gaussian:

$$\text{for } n=1, \quad \langle B_t, \gamma \rangle = \sum_{i=1}^d B_t^{(i)} \gamma^{(i)}$$

We know that  $B_t - B_0$  is normally distributed  
 $N(0, tI)$  distributed

this means that  $B_t^{(i)}$  is  $N(0, t)$  distributed

and independent of  $B_t^{(k)}$ ,  $i \neq k$

then  $\gamma^{(i)} B_t^{(i)} = B_{\frac{t}{(\gamma^{(i)})^2}}^{(i)}$  is  $N(0, \frac{t}{(\gamma^{(i)})^2})$  distributed

so and independent of the others

$$\text{So } \sum_{i=1}^d B_t^{(i)} \gamma^{(i)} \sim N(0, t \sum \frac{1}{(\gamma^{(i)})^2})$$

this is true so

$\langle r_k, X_k \rangle$  is normally distributed

thus  $(\langle r_1, X_{t_1} \rangle, \dots, \langle r_n, X_{t_n} \rangle)$  is normally distributed.

thus  $\sum \langle r_k, X_{t_k} \rangle$  is normally distributed

---

$$\sum_{k=1}^n \langle r_k, X_{t_k} \rangle = \sum_{k=1}^n \sum_{i=1}^d r_k^{(i)} X_{t_k}^{(i)} = \sum_{i=1}^d \sum_{k=1}^n r_k^{(i)} X_{t_k}^{(i)}$$

$$\sum_{k=1}^n r_k^{(i)} X_{t_k}^{(i)} = \sum_{k=1}^n r_k^{(i)} X_{t_k / r_k^{(i)^2}}$$

we can order these  $t_k / r_k^{(i)^2}$  increasingly

$$\text{as } 0 \leq \tilde{t}_1 \leq \tilde{t}_2 \leq \dots \leq \tilde{t}_n$$

$$\text{so } \sum_{k=1}^n X_{t_k / r_k^{(i)^2}} = \sum_{k=1}^n X_{\tilde{t}_k} \quad \text{the variables}$$

$$\tilde{X}_{t_k} = \begin{cases} X_{\tilde{t}_k}, & k=1 \\ X_{\tilde{t}_k} - X_{\tilde{t}_{k-1}}, & k=2, \dots, n \end{cases} \quad \text{are gaussian distributed and independent}$$

so  $(\tilde{X}_{t_1}, \tilde{X}_{t_2}, \dots, \tilde{X}_{t_n})$  is gaussian

$$X_{t_k} = \tilde{X}_{t_k} + \tilde{X}_{t_{k-1}} + \dots + \tilde{X}_{t_1} =$$

so

$$\begin{pmatrix} X_{t_n} \\ \vdots \\ X_{t_1} \end{pmatrix} = \begin{pmatrix} 1 & 1 & 1 & \dots & 1 \\ & 1 & 1 & \dots & 1 \\ & & 1 & \dots & 1 \\ & & & \ddots & 1 \\ 0 & 0 & 0 & \dots & 1 \end{pmatrix} \begin{pmatrix} \tilde{X}_{t_n} \\ \vdots \\ \tilde{X}_{t_1} \end{pmatrix} \text{ is gaussian}$$

thus  $\sum_{k=1}^n \cancel{X_{t_k}^{(i)}} \cancel{\gamma_k^{(i)2}}$  is gaussian these

are independent for each  $i$  so  $\sum_{k=1}^n \langle \gamma_k, X_{t_k} \rangle$  is gaussian

a smarter way

suppose  $\sum_{k=1}^n \langle \gamma_k, X_{t_k} \rangle$  is gaussian for some

$n$ , what about  $\sum_{k=1}^{n+1} \langle \gamma_k, X_{t_k} \rangle$

$$\begin{aligned} \langle \gamma_n, X_{t_n} \rangle + \langle \gamma_{n+1}, X_{t_{n+1}} \rangle &= \langle \gamma_n + \gamma_{n+1} - \gamma_{n-1}, X_{t_n} \rangle + \langle \gamma_{n+1}, X_{t_{n+1}} \rangle \\ &= \langle \tilde{\gamma}_n, X_{t_n} \rangle + \langle \gamma_{n+1}, X_{t_{n+1}} - X_{t_n} \rangle \end{aligned}$$

$$\langle \gamma, B_t \rangle = \langle \gamma, B_t - B_0 \rangle$$

$$\langle \gamma, B_t - B_0 \rangle$$

$$\sum \gamma_i B_t^{(i)}$$

$$2 \begin{pmatrix} \gamma_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \gamma_n \end{pmatrix} \begin{pmatrix} B_t \\ \vdots \\ B_t \end{pmatrix}$$

$$B_t$$

$$(B_t) \text{ d-altern}$$

$$(B_{t_1}, B_{t_2})$$

$$\langle 1, \gamma B_t \rangle$$

$$B_t^{(i)}$$