Non-Stationary Processes

1) Cyclostationary 2) Orthogonal Increment

$X(t)$ w.s.s. $\Leftrightarrow E[X(t)] = m,\quad E[X(t)X(s)] = R_X(t-s)$

$R_X(t+T, s+T) = R_X(t,s),\ \forall T \in \mathbb{R}$ (w.s.s.) $\xrightarrow[\text{condition}]{\text{relax this}}$ $R_X(t+T, s+T) = R_X(t,s),\ \exists T \in \mathbb{R}$ Cyclo-Stationary

$R_X(t+mT, s+mT) = R_X(t,s),\ \forall m$

Relation between WSS & cyclostationary:

Randomization $\Theta \sim U(0,T)$, Θ, $X(t)$ indep.

$Y(t) = X(t+\Theta)$: $X(t)$ Cyclo $\Rightarrow Y(t)$ w.s.s.

$$R_Y(t,s) = E[Y(t)Y(s)] = E[X(t+\Theta)X(s+\Theta)] = E_\Theta\left[E_X[X(t+\theta)X(s+\theta) \mid \Theta=\theta]\right] = E_\Theta[R_X(t+\theta, s+\theta)]$$

$$\overset{\Theta \sim U(0,T)}{=\!=\!=} \frac{1}{T}\int_0^T R_X(t+\theta, s+\theta)\,d\theta$$

$$\forall T',\ R_Y(t+T', s+T') = \frac{1}{T}\int_0^T R_X(t+T'+\theta, s+T'+\theta)\,d\theta \overset{\theta'=T'+\theta}{=\!=\!=} \frac{1}{T}\int_{T'}^{T'+T} R_X(t+\theta', s+\theta')\,d\theta'$$

$$= \frac{1}{T}\int_0^T R_X(t+\theta', s+\theta')\,d\theta' = R_Y(t,s)$$

$\Rightarrow Y(t)$ w.s.s.

Constellation (Phase + Amp. $\rightarrow$ Symbol/Bitstream)

PAM (Pulse $\overset{\text{Complex}}{\text{Amplitude}}$ Modulation) BPSK, QPSK, QAM

30:00

$X(t) = \sum_{-\infty}^{+\infty} \alpha_k \phi(t-kT)$ $\quad\alpha_k$: r.v. Information Symbol

$\phi(t)$: Baseband Waveform.

$$R_X(t,s) = E[X(t)X(s)] = E\left[\sum_k\sum_n \alpha_k \alpha_n \phi(t-kT)\phi(s-nT)\right] = \sum_k\sum_n E[\alpha_k\alpha_n]\,\phi(t-kT)\phi(s-nT)$$

$\{\alpha_n\}$ WSS $\rightarrow R_\alpha(k-n) \Rightarrow \sum_k\sum_n R_\alpha(k-n)\cdot\phi(t-kT)\phi(s-nT)$

Generally : $R_X(t+T', s+T') \neq R_X(t,s)$

But when $T' = T$, $R_X(t+T, s+T) = \sum_k\sum_n R_\alpha(k,n)\,\phi(t+T-kT)\phi(s+T-nT) \xrightarrow[n'=n-1]{k'=k-1} \sum_{k',n'} R_\alpha(k'+1, n'+1)\,\phi(t-k'T)\,\phi(s-n'T)$

$R_\alpha(k'+1,n'+1) = R_\alpha(k'-n')$, and the sum $= R_X(t,s)$

$X(t)$: Cyclostationary Stochastic processes.

$$\bar{X}(t) = X(t+\Theta), \quad \Theta \sim U(0,T)$$

$$R_{\bar{X}}(t,s) = \frac{1}{T}\int_0^T R_X(t+\theta, s+\theta)d\theta = \frac{1}{T}\int_0^T \sum_k \sum_n R_\alpha(k-n)\phi(t-kT+\theta)\phi(s-nT+\theta)d\theta$$

$k' = k-n, \quad n' = n$

$$= \frac{1}{T}\int_0^T \sum_{k'}\sum_{n'} R_\alpha(k')\phi(t+\theta-(n'+k')T)\phi(s+\theta-n'T)d\theta$$

Let $\theta' = \theta - n'T$: $\frac{1}{T}\sum_{k'}\sum_{n'} R_\alpha(k')\int_{-n'T}^{-(n'-1)T}\phi(t+\theta'-k'T)\phi(s+\theta')d\theta'$

Time Correlation: $X(t)$ deterministic $R_X(\tau) = \int_{\mathbb{R}} X(t+\tau)X(t)dt$

$$= \frac{1}{T}\sum_{k'} R_\alpha(k') \cdot \sum_{n'=-\infty}^{+\infty}\int_{-n'T}^{-(n'-1)T}\phi(t+\theta'-k'T)\phi(s+\theta')d\theta' = \frac{1}{T}\sum_{k'} R_\alpha(k')\int_{\mathbb{R}}\phi(t+\theta'-k'T)\phi(s+\theta')d\theta' \qquad \theta'' = s+\theta'$$

$$= \frac{1}{T}\sum_{k'} R_\alpha(k')\int_{\mathbb{R}}\phi(t-k'T-s+\theta'')\phi(\theta'')d\theta''$$

$$= \frac{1}{T}\sum_{k'} R_\alpha(k') R_\phi(t-s-k'T) = R_{\bar{X}}(t-s)$$

$$S_{\bar{X}}(w) = \int_{-\infty}^{+\infty} R_{\bar{X}}(\tau)\exp(-jw\tau)d\tau = \frac{1}{T}\int_{-\infty}^{+\infty}\left[\sum_k R_\alpha(k)R_\phi(\tau-kT)\right]\exp(-jw\tau)d\tau = \frac{1}{T}\sum_k R_\alpha(k)\cdot\int_{\mathbb{R}} R_\phi(\tau-kT)\exp(-jw\tau)d\tau$$

$$= \frac{1}{T}\sum_k R_\alpha(k)\exp(-jwkT)\int_{\mathbb{R}} R_\phi(\tau')\exp(-jw\tau')d\tau'$$

$$= \frac{1}{T} S_\alpha(w)\cdot S_\phi(w) = \frac{1}{T}S_\alpha(w)\left|\Phi(w)\right|^2$$

$Z(t) = \sum_k \alpha_k \delta(t-kT) \qquad Z(t) \to \boxed{\phi(t)} \to ? \qquad Z(t) * \phi(t) = \sum \alpha_k \phi(t-kT)$

2) Orthogonal Increment

$X(t)$, $\forall t_1 < t_2 \le t_3 < t_4$, $X(t_4)-X(t_3) \perp X(t_2)-X(t_1)$: $E[(X(t_4)-X(t_3))(X(t_2)-X(t_1))] = E[4-3]E[2-1]$

$$R_X(t,s) = E[X(t)X(s)] \xrightarrow[X(0)=0]{s<t} E[(X(t)-X(s)+X(s)-X(0))(X(s)-X(0))] = E[X^2(s)]$$

$R_X(t,s) = E[X^2(\min(t,s))] = g(\min(t,s)) \to$ Characteristic Property of Orthogonal Increment.

i.e. if $R_X(t,s) = g(\min(t,s))$, $X(t)$ has Orthogonal Increment
$(\forall t,s)$

$$E[(X(t_4)-X(t_3))(X(t_2)-X(t_1))] = R_X(t_4,t_2) + R_X(t_3,t_1) - R_X(t_3,t_2) - R_X(t_4,t_1)$$

$t_4 > t_3 \ge t_2 > t_1$ if $R_X(t,s) = g(\min(t,s))$, then

$= g(t_2) + g(t_1) - g(t_2) - g(t_1) = 0$ $\therefore$ Orthogonal Increment

Example of Orthogonal Increment : Brownian Motion def. of Brownian Motion:

① $B(0)=0$ ② Orthogonal Increment ③ $B(t)-B(s)\sim N(0,\sigma^2(t-s))$

$R_B(t,s)=E(B^2(s))=\sigma^2 s=\sigma^2\min(t,s)$

$B(s)-B(0)\sim N(0,\sigma^2(s-0))=N(0,\sigma^2 s)$
$(B(s))$

$E(B(s))=0$, $E(B^2(s))=var(B(s))=\sigma^2 s$

$Y(t)=\frac{d}{dt}B(t)$ (Not Rigorous)

$R_Y(t,s)=E[Y(t)Y(s)]$
$=E\left[\frac{d}{dt}Y(t)\frac{d}{ds}Y(s)\right]$
$=\frac{\partial^2}{\partial t\partial s}E[Y(t)Y(s)]$

任何事都是有道理的，
区别是有没有必要知道它，
和有没有能力去知道它.

Everything in existence carries a purpose, the distinction lies in whether there is a necessity to comprehend it and a capacity to do so.

$=\frac{\partial^2}{\partial t\partial s}R_B(t,s)=\sigma^2\frac{\partial^2}{\partial t\partial s}\min(t,s)=\sigma^2\frac{\partial^2}{\partial t\partial s}\left(\frac{1}{2}(s+t-|s-t|)\right)$

$=-\frac{1}{2}\sigma^2\frac{\partial^2}{\partial t\partial s}|t-s|$

$R_Y(t,s)=-\frac{\sigma^2}{2}\frac{\partial^2}{\partial t\partial s}|t-s|$ $\left(\frac{d}{dx}|x|=\mathrm{sgn}(x)\right)$

$=-\frac{\sigma^2}{2}\frac{\partial}{\partial s}\left(\frac{\partial}{\partial t}|t-s|\right)$

$=-\frac{\sigma^2}{2}\frac{\partial}{\partial s}(\mathrm{sgn}(t-s))$ $\left(\frac{d}{dx}\mathrm{sgn}(x)=2\delta(x),\ U(x)=\begin{cases}1, & x\geq 0\\ 0, & x<0\end{cases},\ \frac{dU(x)}{dx}=\delta(x),\ \mathrm{sgn}(x)=U(x)-U(-x)\right)$

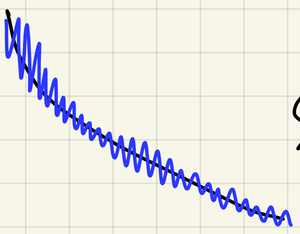
$=-\frac{\sigma^2}{2}[-2\delta(t-s)]$

$=\sigma^2\delta(t-s)$

derivative is $\delta(\cdot)$ function $\Rightarrow$ White Noise

(Brownian Motion)

Orthogonal Increment $\xrightarrow{\text{differential}}$ W.S.S.



Stationary lies in → ~~envelope~~ (Trend ⇒ Non-Stationary)
→ glitches (Brownian Motion $\xrightarrow[\text{High-Pass Filter}]{\text{Derivative}}$ W.S.S.)
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Isometry with Complex Exponentials (Oscillating)

∴ W.S.S. → High-Frequency

① $B(0)=0$ ② Orthogonal Increment ③ $B(t)-B(s)\sim N(0,\sigma^2(t-s))$

$B(t)\sim N(0,\sigma^2 t)$

$dB(t)\overset{?}{\sim}N(0,\sigma^2 dt)$

$B(t+dt)-B(t)\sim N(0,\sigma^2 dt)$

$\Rightarrow E[dB^2(t)]=\sigma^2 dt$

$(dB(t))^2\sim dt$

$dB(t)\sim(dt)^{1/2}$

∴ dB → has to go to 2^{nd} order.

Consider function $f(t,B(t))$. $df(t,B(t))\overset{?}{=}\frac{\partial f}{\partial t}dt+\frac{\partial f}{\partial B}dB(t)$

Not Quite Right.

$df(t,B(t))=\frac{\partial f}{\partial t}dt+\frac{\partial f}{\partial B}\underbrace{dB}_{\sqrt{dt}}+\frac{1}{2}\frac{\partial^2 f}{\partial B^2}\underbrace{(dB)^2}_{\simeq dt}$

$(dt \xrightarrow{?} df)$ $=\frac{\partial f}{\partial t}dt+\frac{\partial f}{\partial B}dB+\frac{1}{2}\frac{\partial^2 f}{\partial B^2}dt$ Ito Formula.

$\int_0^1 B(t)dB(t)\neq\int_0^1 d\left(\frac{1}{2}B^2(t)\right)$

$d\left(\frac{1}{2}B^2(t)\right)=B(t)dB(t)+\frac{1}{2}dt$

$\therefore\int_0^1 B(t)dB(t)=\int_0^1 d\left(\frac{1}{2}B^2(t)-\frac{1}{2}t\right)$

Stochastic Calculus ⇒ Option Pricing (期权定价)

$B(t)$ Brownian Motion → Stock Price Modelling

$B(t)$ may be less than 0 ⇒ Stock Price : $\exp(B(t))$
$\exp(\mu t+B(t))$

Option Pricing: Stock price: $\exp(\mu t + B(t))$ Geometric Brown Motion Samuelson (Economics)

$V(t, S(t)) \longrightarrow$ Portfolio (Heritage) Sell Stock for Option

Option

$V(t, S(t)) - \alpha S(t) = P(t)$ (Property)

$dP(t) \geq$ interest rate $\times$ $P(t) = rP(t)$ $\left(dP(t) = rP(t)dt \right)$

how to set proper V? $dP(t) = dV(t, S(t)) - \alpha dS(t)$ $\Big(S(t) = \exp(\mu t + B(t)),$

$$dP = \frac{\partial V}{\partial t}dt + \frac{\partial V}{\partial S}dS + \frac{1}{2}\frac{\partial^2 V}{\partial S^2}(dS)^2 - \alpha dS \longleftarrow \qquad dS = S\cdot\mu dt + S(t)dB(t) + \frac{1}{2}S\cdot dt \Big)$$

$S^2 dt$

$$= r(V - \alpha S)dt$$

$$\Rightarrow \left(\frac{\partial V}{\partial t} + \frac{1}{2}S^2\frac{\partial^2 V}{\partial S^2}\right)dt + \left(\frac{\partial V}{\partial S} - \alpha\right)dS = r(V - \alpha S)dt$$

Random Term.

$$\Rightarrow \begin{cases} \alpha = \frac{\partial V}{\partial S} \text{ (Heritage)} \\ \frac{\partial V}{\partial t} + \frac{1}{2}S^2\frac{\partial^2 V}{\partial S^2} = r\left(V - \frac{\partial V}{\partial S}\cdot S\right) \end{cases}$$

i.e. $\frac{\partial V}{\partial t} + \frac{1}{2}S^2\frac{\partial^2 V}{\partial S^2} + rS\frac{\partial V}{\partial S} - rV = 0$ Black-Scholes Equation.

2023 Spring Non-Stationary Processes

Strict-Sense Stationary: $\forall t$, $\forall t_1, \cdots, t_n$, $\forall T$ $\left(X(t_1), \cdots, X(t_n)\right)^T \overset{F}{\sim} \left(X(t_1+T), \cdots, X(t_n+T)\right)^T$

$\big($W.S.S.: $E[X(t)] = \mu$, $R_X(t,s) = g(t-s)\big)$

Conditional Expectation:

$E[g(Y)X|Y] = g(Y)E[X|Y]$

X. $EX = c$. $EX = \int x f_X(x)dx$, $X \sim f_X(x)$

X, Y, $E[X|Y] \Rightarrow$ r.v. $Y \rightarrow$ provisionally deterministic $E[X|Y]$

$$E_{X,Y}[g(X,Y)] = E_Y[E_X[g(X,Y)|Y]]$$

Conditional expectation is a r.v.

我們從來不曾懂得些什麼

我們只是不斷去習慣

$\{X_k\}$ i.i.d. N r.v.

$$E[X_1 + \cdots + X_N] = E[E[X_1 + \cdots + X_N | N]] = E[NE[X_k]] = E[X_k]\cdot E[N]$$

$X \to$ data, $Y \to$ target. $\min_g E|Y-g(X)|^2 \Rightarrow g(X) = \underbrace{E[Y|X]}_{\text{随机性在X上}}$ optimal choice.

$\forall g.\ E|Y-g(X)|^2 = E|Y-E[Y|X]+E[Y|X]-g(X)|^2$ Prove. this is 0

$= E[Y-E[Y|X]]^2 + E[E[Y|X]-g(X)]^2 + 2\underline{E[(Y-E[Y|X])(E[Y|X]-g(X))]}$

$E[(\underset{Y}{Y}-\underset{X}{E[Y|X]})(\underset{X}{E[Y|X]}-\underset{X}{g(X)})] = E[E[(Y-E[Y|X])(E[Y|X]-g(X))|X]] = E[(E[Y|X]-g(X))E[(Y-E[Y|X])|X]]$

$= E[(E[Y|X]-g(X))(\underbrace{E[Y|X]-E[Y|X]}_{=0})] = 0$

$\Rightarrow E[Y-g(X)]^2 = E[Y-E[Y|X]]^2 + E[g(X)-E[Y|X]]^2$

$\Rightarrow g(X) = E[Y|X]$

misleading

$E[Y|X]$ is also a r.v.

In textbooks, $E[g(X,Y)] = \int_{\mathbb{R}}\int_{\mathbb{R}} g(x,y) f_{XY}(x,y)\,dx\,dy = \int_{\mathbb{R}} \underbrace{\left(\int_{\mathbb{R}} g(x,y) f_{Y|X}(y|x)\,dy\right)}_{\text{随机性暂时被固定}} f_X(x)\,dx$

Randomized Phase on Cyclostationary:

$E[X(t+\Theta)X(s+\Theta)] = E_\Theta[E_X[X(t+\theta)X(s+\theta)|\Theta=\theta]] = E_\Theta[R_X(t+\Theta, s+\Theta)]$

$= \frac{1}{T}\int_0^T R_X(t+\theta, s+\theta)\,d\theta \Rightarrow$ W.S.S. (if $X(t)$ is cyclostationary)

$\forall \tau,\ E[X(t+\tau+\Theta)X(s+\tau+\Theta)] = \frac{1}{T}\int_0^T R_X(t+\tau+\theta, s+\tau+\theta)\,d\theta = \frac{1}{T}\int_\tau^{T+\tau} R_X(t+\theta', s+\theta')\,d\theta'$

$\because \exists T \in \mathbb{R},\ R_X(t+T, s+T) = R_X(t,s)$ $\therefore$ integrating over an period doesn't change the result.

(no matter where the range is exactly located)

Example on Cyclostationary: Pulse Signal.

$X(t) = \sum_{k=-\infty}^{+\infty} \alpha_k \phi_k(t) = \sum_{k=-\infty}^{+\infty} \alpha_k \phi(t-kT)$ ($\phi_k(t)$: Baseband Waveform, T: Symbol Length)

$E[\alpha_k \alpha_m^*] = R_\alpha(k-m) \Rightarrow$ Symbol Sequence W.S.S. (ISI?)

$R_X(t,s) = E[X(t)\overline{X(s)}] = E\left[\sum_{k=-\infty}^{+\infty} \alpha_k \phi(t-kT) \sum_{n=-\infty}^{+\infty} \alpha_n^* \phi^*(s-nT)\right]$

$= \sum_{k,n} E[\alpha_k \alpha_n^*]\phi(t-kT)\phi^*(s-nT) = \sum_{k,n} R_\alpha(k-n)\phi(t-kT)\phi^*(s-nT)$

Not W.S.S., But Cyclostationary $R_X(t+T, s+T) = R_X(t,s)$ + Randomized Phase

$Y(t)=X(t+\Theta)$, $\Theta\sim U(0,T)$,

$$R_Y(t,s)=\frac{1}{T}\sum_{k,n}R_\alpha(k-n)\int_0^T\phi(t+\theta-kT)\,\phi^*(s+\theta-nT)\,d\theta \Rightarrow \text{求和换元 Substitution.}\quad \begin{cases}k'=k-n\\ n'=n\end{cases}$$

$$=\frac{1}{T}\sum_{k'+n'=-\infty}^{+\infty}\sum_{n'=-\infty}^{+\infty}R_\alpha(k')\int_0^T\phi(t+\theta-(k'+n')T)\,\phi^*(s+\theta-n'T)\,d\theta=\frac{1}{T}\sum_{k'=-\infty}^{+\infty}\sum_{n'=-\infty}^{+\infty}R_\alpha(k')\int_0^T\phi(t+\theta-(k'+n')T)\,\phi^*(s+\theta-n'T)\,d\theta$$

Let $\theta'=\theta-n'T$
$$=\frac{1}{T}\sum_{k'=-\infty}^{+\infty}\sum_{n'=-\infty}^{+\infty}R_\alpha(k')\int_{-n'T}^{-(n'-1)T}\phi(t-k'T+\theta')\,\phi^*(s+\theta')\,d\theta'$$

$$=\frac{1}{T}\sum_{k'=-\infty}^{+\infty}R_\alpha(k')\left[\sum_{n'=-\infty}^{+\infty}\int_{-n'T}^{-(n'-1)T}\phi(t-k'T+\theta')\,\phi^*(s+\theta')\,d\theta'\right]=\frac{1}{T}\sum_{k'=-\infty}^{+\infty}R_\alpha(k')\int_{\mathbb{R}}\phi(t-k'T+\theta')\,\phi^*(s+\theta')\,d\theta'$$

$$=\frac{1}{T}\sum_{k'=-\infty}^{+\infty}R_\alpha(k')\,R_\phi(t-s-k'T)\rightarrow \text{Self-Correlation of Deterministic Signal}$$

$$R_\phi(\tau)=\int_{\mathbb{R}}\phi(\theta'+\tau)\,\phi(\theta')\,d\theta'$$

$$=\frac{1}{T}R_\alpha * R_\phi$$

$$\therefore R_Y=\frac{1}{T}R_\alpha * R_\phi$$

$$S_Y(w)=\int_{\mathbb{R}}R_Y(\tau)\exp(-jw\tau)\,d\tau=\frac{1}{T}\int_{\mathbb{R}}\sum_k R_\alpha(k)\,R_\phi(\tau-kT)\exp(-jw\tau)\,d\tau$$

$$=\frac{1}{T}\sum_k R_\alpha(k)\cdot\exp(-jwkT)\cdot\int_{\mathbb{R}}R_\phi(\tau-kT)\exp(-jw(\tau-kT))\,d\tau$$

$$=\frac{1}{T}S_\alpha(w)\cdot S_\phi(w)$$

Orthogonal Increment: $X(t)$, $X(0)=0$

$\forall t_1<t_2\le t_3<t_4$, $X(t_4)-X(t_3)\perp X(t_2)-X(t_1)$ $\big|$ $E[(X(t_4)-X(t_3))(X(t_2)-X(t_1))]=E[X(t_4)-X(t_3)]\,E[X(t_2)-X(t_1)]\big)$

$$R_X(t,s)=E[X(t)X(s)]\ (s<t)=E[(X(t)-X(s))(X(s)-X(0))]+E[(X(s)-X(0))^2]=E[X^2(s)]\ (s<t)$$

$$=E[X^2(\min(t,s))]\Rightarrow \text{not stationary.}$$

$$=g(\min(t,s))\quad \text{正交增量的特征性质?}$$

If Correlation is a function of $\min(s,t)$, Is the process orthogonal incremental?

$$E[(X(t_4)-X(t_3))(X(t_2)-X(t_1))]=R_X(t_4,t_2)+R_X(t_3,t_1)-R_X(t_4,t_1)-R_X(t_3,t_2)$$

$$=g(t_2)+g(t_1)-g(t_1)-g(t_2)=0\quad\Rightarrow \text{Orthogonal Increment}$$

$\Rightarrow$ Brownian Motion. (Example of Orthogonal Increment)

$B(0)=0$, Orthogonal Increment, $B(t)-B(s)\sim N(0,\sigma^2(t-s))\Rightarrow B(t)\sim N(0,\sigma^2 t)$

$R_B(t,s) = E[B^2(\min(t,s))] = \sigma^2 \min(t,s)$，处处连续不可导

$Y(t) = \frac{d}{dt}B(t) \Rightarrow$ W.S.S.

$R_Y(t,s) = E[Y(t)Y(s)] = E\left[\frac{d}{dt}X(t)\frac{d}{ds}X(s)\right] = \frac{\partial^2}{\partial t \partial s}E[X(t)X(s)] = \frac{\partial^2}{\partial t\partial s}\sigma^2\min(t,s) = \sigma^2\frac{\partial^2}{\partial t\partial s}\left[\frac{1}{2}(t+s-|t-s|)\right]$

$= \frac{\sigma^2}{2}\frac{\partial^2}{\partial t\partial s}(-|t-s|)$

$\mathrm{sgn}(x) = \frac{d}{dx}|x| = \begin{cases} 1, & x>0 \\ 0, & x=0 \\ -1, & x<0 \end{cases}$, $\frac{d}{dx}\mathrm{sgn}(x) = \frac{d}{dx}[u(x)-u(-x)] = \delta(x)+\delta(-x) = 2\delta(x)$

原式 $= -\frac{\sigma^2}{2}\frac{\partial}{\partial s}\mathrm{sgn}(t-s)$

$= \sigma^2\delta(t-s)$ White Noise

Non-Stationary $\xrightarrow{\text{Derivative}}$ Stationary

(BM) (White Noise)

$\Downarrow$

HPF

$\Downarrow$

gets high-frequency component (Glitch)

(Stationary/Oscillating)

Stationary ≠ Predictable

↓

Oscillating (Glitch)