

Martingales:

1 - Martingales: \rightarrow "Fair Game"

2 Conditional Expectation:

$$E(M(t) | \mathcal{F}_s) = M(s)$$

Take up to times.

3 Say X is a RV. (Ω, \mathcal{G}) .

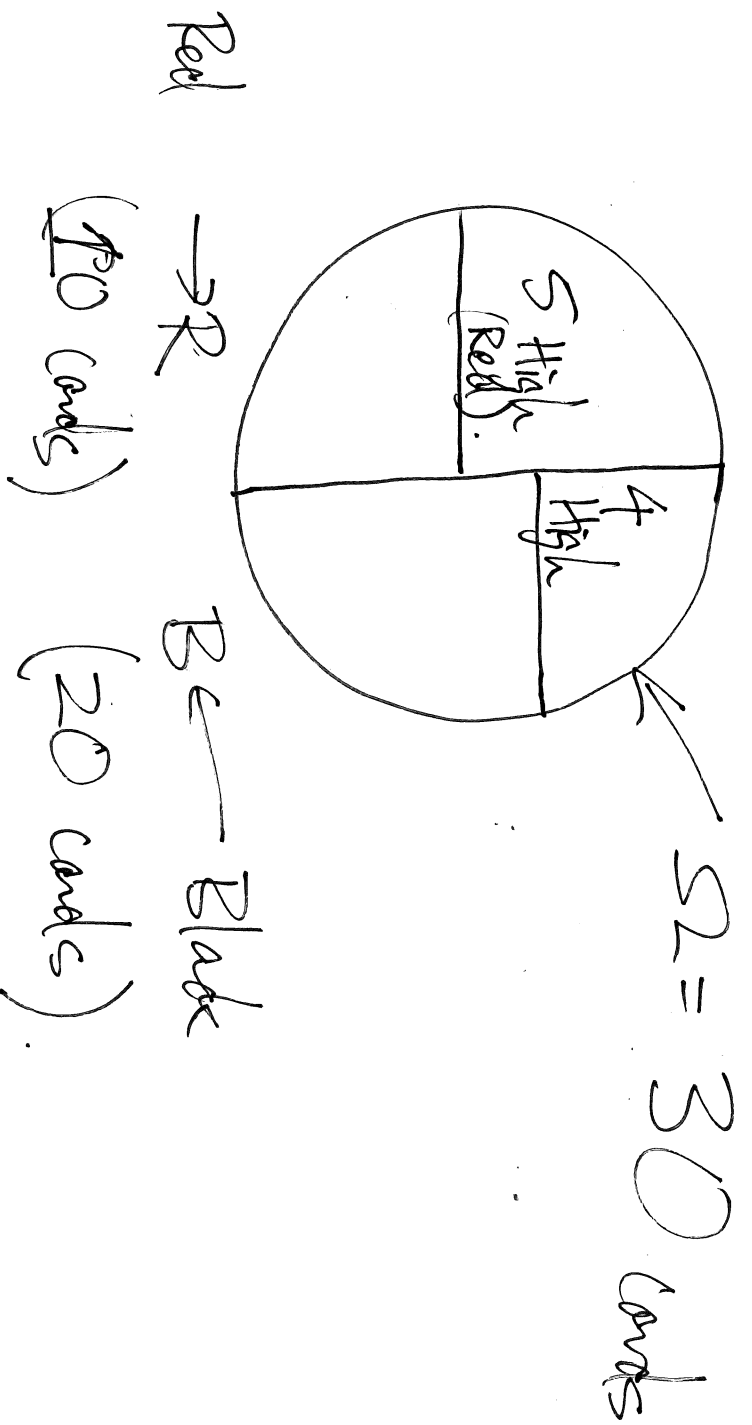
X is \mathcal{G} -measurable.

$$f \subseteq g \quad (\mathcal{F} \rightarrow \mathcal{T}\text{-alg}) \quad (\mathcal{T}\text{-sub-alg. of } \mathcal{G})$$

"Best approximation" of X using only the \mathcal{T} -alg \mathcal{F}

is called the conditional expectation

Example:



Game: High \rightarrow +1. } Plays through a Dealer.
Not High \rightarrow -1. }

Dealer: (1) Pays winnings.
(2) Tells you the COLOR.

$X \rightarrow$ outcome of game $\equiv \begin{matrix} 1 \\ H \end{matrix} - \begin{matrix} 1 \\ H^c \end{matrix}$

~~#~~ $Y = \mathcal{E}(S_2) \leftarrow$ all info.

$\mathcal{F} =$ info you get by talking to doctor.

$= \{\emptyset, R, B, S_2\}$.

X is NOT \mathcal{E} measurable.

$E(X | \mathcal{F}) =$ "Best approx of X only given \mathcal{E} "

$$\equiv \begin{matrix} 0 \\ R \end{matrix} + \left(\frac{1}{5} - \frac{4}{5}\right) \begin{matrix} 1 \\ B \end{matrix}$$

Def 0 $\mathcal{G} - \sigma$ alg. $\mathcal{F} \subseteq \mathcal{G}$ is a σ -alg.

$X \rightarrow$ RV $\text{ker } \mathcal{G}$ (X is \mathcal{G} -meas).

Define $E(X | \mathcal{F})$. To be a RV \mathcal{F} such that

① $E(X | \mathcal{F})$ is \mathcal{F} -measurable.

② (Partial Averaging): $\forall F \in \mathcal{F}, \int_F X dP = \int_F E(X | \mathcal{F}) dP$.

Remark: Existence \longrightarrow "RN theorem"

Remark: Uniqueness: If Y is any RV +

① Y is \mathcal{E} -meas.

② $\int Y dP = \int X dP \quad \forall F \in \mathcal{E}$ } $\Rightarrow Y = E(X|F)$.

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Eg 1: Say X is \mathcal{E} meas.

$$E(X|F) = X.$$

Fig 2: If X is independent of \mathcal{G}

then $E(X | \mathcal{G}) = EX$

Def: X is ind of \mathcal{G} if $\forall A \in \sigma(X), \forall B \in \mathcal{G}$
we have $P(A \cap B) = P(A)P(B)$.

Ex: Say $X = \sum a_i \mathbb{1}_{A_i}$, $\Rightarrow A_i \in \sigma(X)$.

Pick any

$$F \in \mathcal{G} \quad \int_X dP = \int_F \left(\sum a_i \mathbb{1}_{A_i} \right) dP$$

$$= \sum a_i P(A_i \cap F) = P(F) \underbrace{\sum a_i P(A_i)}_{EX} = \int_F EX dP$$

$$\Rightarrow EX = E(X | \mathcal{F}).$$

② If X is not simple \rightarrow approximate.

Properties: ① linearity: $E(X + \alpha Y | \mathcal{F}) = E(X | \mathcal{F}) + \alpha E(Y | \mathcal{F})$.

$(X, Y \rightarrow$ RV's, & $\alpha \in \mathbb{R})$.

② ~~If~~ If $X \leq Y$ a.s. then $E(X | \mathcal{F}) \leq E(Y | \mathcal{F})$ a.s.

③ Say $X \rightarrow \mathcal{F}$ -meas., $Y \rightarrow \mathcal{G}$ -meas.

$$E(XY | \mathcal{F}) = \cancel{X} E(X | \mathcal{F}) - X E(Y | \mathcal{F})$$

④ (Tower):

⊕ (Tower): $\mathcal{E} \subseteq \mathcal{F} \subseteq \mathcal{G}$ then

$$E(X | \mathcal{E}) = E(E(X | \mathcal{F}) | \mathcal{E}).$$

Filterations: X a stochastic process. $(X(t))$ is a RV.

Def: let $t \in [0, \infty)$. Define $\mathcal{F}_t^X = \sigma(\cup_{s \leq t} \sigma(X_s))$.
 $\mathcal{F}_t^X \approx$ all info observed up to time t .

Note: $\forall t, \mathcal{F}_t^X$ is a σ -alg. $\mathcal{F}_s^X \subseteq \mathcal{F}_t^X$ $s < t$.

Def: A filtration $\{\mathcal{F}_t\}$ is a family of σ -alg
+ ① V_t , \mathcal{F}_t is a σ -alg
② If $s < t \Rightarrow \mathcal{F}_s \subseteq \mathcal{F}_t$.

Def: \mathcal{F}_t^X is called the filtration generated by X .

Mostly: Wiener $\{\mathcal{F}_t\} = \{\mathcal{F}_t^W\}$ $W \rightarrow$ BM.

Def: Given a filtration $\{\mathcal{F}_t\}$. We say a process X
is adapted to $\{\mathcal{F}_t\}$ if $V_t, X(t)$ is \mathcal{F}_t -meas.

Martingale: We say a process M is a

Martingale w.r.t the filtration $\{\mathcal{F}_t\}$ if.

① M is adapted. ($M(t)$ is \mathcal{F}_t -meas).

② $E(M(t) | \mathcal{F}_s) = M(s)$. for $s \leq t$.

Sub M_g : $E(M(t) | \mathcal{F}_s) \geq M(s)$.

Super M_g : $E(M(t) | \mathcal{F}_s) \leq M(s)$.

Random Walks are M_g .

Prop: Brownian Motion is a Mg. (wrt the Brownian Filtration).

Pl: W a BM. $\{ \mathcal{F}_t \} = \{ \mathcal{F}_t^W \}$.

M_s NTS $E(W(t) | \mathcal{F}_s)$. for $s \leq t$.

Compute $E(W(t) | \mathcal{F}_s) = E(W(t) - W(s) + W(s) | \mathcal{F}_s)$.

$$= E(W(t) - W(s) | \mathcal{F}_s) + E(W(s) | \mathcal{F}_s) = W(s).$$

○

Since: ① $M(t) - M(s)$ is independent of \mathcal{F}_s .

$$\textcircled{2} E(M(t) - M(s) | \mathcal{F}_s) = E(M(t) - M(s)) = 0$$

QED.

Eg 2.6: Let $\mathcal{F}_\infty = \sigma(U_{\mathcal{F}_t})$. Let X be \mathcal{F}_∞ meas.

Define $M(t) = E(X | \mathcal{F}_t)$. Claim: M is a M_g .

Check:

$$E(M(t) | \mathcal{F}_s) = E(E(X | \mathcal{F}_t) | \mathcal{F}_s)$$

$$= E(X | \mathcal{F}_s) = M(s).$$

~~Theorem 6~~ $W \rightarrow$ Std BM. $W(0) = 0$

$$W(t) - W(s) \sim N(0, t-s).$$

$t \rightarrow$ Any fm. ~~$f(x) = x^3 + 4x$~~

compute : $E(f(W(t)) | \mathcal{F}_s) = E(f(W(t) - W(s) + W(s)) | \mathcal{F}_s)$

$$= \int_{-\infty}^{\infty} f(y + W(s)) \underbrace{G(t-s, y)}_{N(0, t-s)} dy$$

Ind of \mathcal{F}_s .

where $G(t-s, y) =$ Density of $N(0, t-s)$.

$$= \frac{1}{\sqrt{2\pi(t-s)}} e^{-\frac{y^2}{2(t-s)}}$$