1 Probability and Stochastic Process

1.1 Probability

$\operatorname{Var} X = \mathbb{E}[(X-\mathbb{E}X)^2] = \mathbb{E}[X^2] - (\mathbb{E}X)^2$. $\operatorname{Var}(aX+b) = a^2 \operatorname{Var} X$.

$\operatorname{Cov}(X,Y) = \mathbb{E}[(X-\mathbb{E}X)(Y-\mathbb{E}Y)] = \mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y]$. $\operatorname{Cov}(aX+b,Y) = a\operatorname{Cov}(X,Y)$.

$\operatorname{Var}(X+Y) = \operatorname{Var}(X) + \operatorname{Var}(Y) + 2\operatorname{Cov}(X,Y)$.

Cov Matrix for $X = (X_1,\dots,X_n)^T$: $\operatorname{Cov}(X) = (\operatorname{Cov}(X_i,X_j))_{i,j}$.

$\operatorname{Corr}(X,Y) = \dfrac{\operatorname{Cov}(X,Y)}{\sqrt{\operatorname{Var} X \operatorname{Var} Y}}$

矩母函数 Moment generating function: For rv X, MGF is $M_X(t) = \mathbb{E}[e^{tX}]$. For vec-valued rv $\mathbf{X}$, $M_X(\mathbf{t}) = \mathbb{E}[e^{\langle \mathbf{t},\mathbf{X}\rangle}]$. 可以生成$n$阶矩 $\mathbb{E}[X^n] = \dfrac{d^n}{dt^n} M_X\Big|_{t=0}$. 矩母函数相同说明分布相同.

特征函数 Ch.f.: For rv X, $\varphi_X(t) = \mathbb{E}[\exp(itX)]$. For vec-valued rv $\mathbf{X}$, $\varphi_X(\mathbf{t}) = \mathbb{E}[e^{i\langle \mathbf{t},\mathbf{X}\rangle}]$.

一些分布

- Binomial(p,n): $P_X(k) = C_n^k p^k (1-p)^{n-k}$. 期望$np$, Var $np(1-p)$.
- Poisson(λ): $P_X(k) = e^{-\lambda}\dfrac{\lambda^k}{k!}$. 期望$\lambda$, Var λ.
- Normal(μ,σ^2): $f_X(x) = \dfrac{1}{\sqrt{2\pi\sigma^2}}\exp(-\dfrac{(x-\mu)^2}{2\sigma^2})$. 偏度为0, 峰度为3. MGF: $\exp(\dfrac{1}{2}u^2 t)$.
- Exponential(λ): $f_X(x) = \lambda e^{-\lambda x}(x \geq 0)$. 期望$\dfrac{1}{\lambda}$, Var $\dfrac{1}{\lambda^2}$.

Multivariate Gaussian $\mathcal{N}(\mu,\Sigma)$

定义: Random vec X是d维Gaussian Vec 若对任意$t \in \mathbb{R}^d$, $\langle t, X\rangle$都是Gaussian.

Note that n个正态分布拼起来不一定是Gaussian vec, 但n个独立正态分布拼起来一定是.

给定vec μ和半正定对称阵Σ, 存在Gaussian Vector X with mean μ and Cov Σ. 如果Σ是满秩的, 则存在density $f(\mathbf{x}) = (2\pi)^{-d/2}\det(\boldsymbol{\Sigma})^{-1/2}\exp\left(-\dfrac{1}{2}(\mathbf{x}-\boldsymbol{\mu})^{\mathrm{T}}\boldsymbol{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu})\right)$,

MGF $\exp\left(\mu^T t + \dfrac{1}{2}t^T\Sigma t\right)$. ChF $\exp\left(i\mu^T t - \dfrac{1}{2}t^T\Sigma t\right)$.

条件概率: $\mathbb{P}(A|B) = \dfrac{\mathbb{P}(A\cap B)}{\mathbb{P}(B)}$. 贝叶斯公式: $\mathbb{P}(A|B) = \mathbb{P}(B|A)\dfrac{\mathbb{P}(A)}{\mathbb{P}(B)}$.

条件期望: $\mathbb{E}[X|\mathcal{F}]$是一个随机变量使得 (1)是$\mathcal{F}$可测的; (2)$\mathbb{E}[\mathbb{E}[X|\mathcal{F}]1_A] = \mathbb{E}[X1_A], \forall A \in \mathcal{F}$.

对两个rv X,Y, 有joint density $f_{X,Y}(x,y)$, 则Marginal density $f_X(x) = \int_{\mathbb{R}} f_{X,Y}(x,v)dv$. 条件密度 $f_{X|Y}(x|y) = \dfrac{f_{X,Y}(x,y)}{f_Y(y)}$, 条件期望 $\mathbb{E}[X|y] = \int_{\mathbb{R}} x f_{X|Y}(x|y)dx$. $\mathbb{E}[g(X)|Y] = h(Y)$ where $h(y) = \dfrac{\int g(x)f_{X,Y}(x,y)dx}{\int f_{X,Y}(x,y)dx}$.

独立性引理. 若X,Y独立, 则$\mathbb{E}[\varphi(X,Y)|Y] = h(Y)$ where $h(y) = \mathbb{E}[\varphi(X,y)]$. 更一般地, $X_1,\dots,X_k$是$\mathcal{G}$可测的, $Y_1,\dots,Y_l$独立于$\mathcal{G}$, 则$\mathbb{E}[f(X_1,\dots,X_k,Y_1,\dots,Y_l)|\mathcal{G}] = g(x_1,\dots,x_k)$ where $g(x_1,\dots,x_k) = \mathbb{E}[f(x_1,\dots,x_k,Y_1,\dots,Y_l)]$.

一些命题

- F递增+右连续+$[0,1]$,即可定义一个分布函数. 如果存在非负f使$F(t) = \int_{-\infty}^{t} f(x)dx$, 则分布有density.
- X有pdf f_X, $Y = g(X)$其中g可微且严格单调, 则$f_Y(y) = f_X(g^{-1}(y))\frac{d}{dy}g^{-1}(y)$.
- $X \sim \mathcal{N}(\mu, \sigma^2)$, 则$\mathbb{E}[|X|] = \mu\left[2\Phi\left(\frac{\mu}{\sigma}\right) - 1\right] + \frac{2\sigma}{\sqrt{2\pi}}\exp\left\{-\frac{\mu^2}{2\sigma^2}\right\}$. 其中$\Phi$为std norm CDF.
- 在$[0,1]$的均匀分布下取n个值, 最大值的期望是$\frac{n}{n+1}$.
- Distribution of $X+Y$ when $X \sim f, Y \sim g$ are independent: $\mathbb{P}(X+Y \leq z) = \int \mathbb{P}(x \leq z-y)g(y)f(y)dy$, density of $X+Y$ is $h(z) = \int f(z-y)g(y)dy$.
- 顺序统计量 kth order statistic: the kth smallest value in a sample of n from a random distribution. There is $\mathbb{P}(X_{(k)} \leq x) = \sum_{j=k}^{n} F(x)^j(1-F(x))^{n-j}$.

大数定律: $X_1, \ldots, X_n$ 是 iid rv 序列, 期望μ有限. 令 $S_n = X_1 + \cdots + X_n$, 则 (弱) $\frac{S_n}{n} \to \mu$ in probability i.e. $\lim_{n\to\infty}\mathbb{P}(|\frac{S_n}{n} - \mu| > \varepsilon) = 0$. (强) Almost surely $\lim_{n\to\infty}\frac{S_n}{n} = \mu$.

中心极限定理 Central Limit Theorem: $X_1, \ldots, X_n$ 是 iid rv 序列, 期望μ和方差σ^2有限, 令 $S_n = X_1 + \cdots + X_n$, 则 $Y_n = \frac{S_n - \mu n}{\sigma\sqrt{n}}$ converges in distribution to std norm.

1.2 Stochastic Process

鞅和停时

(X_n) or (X_t)是鞅, T是停时, 则$(X_{n\wedge T})$ or $(X_{t\wedge T})$是鞅.

[Optional Stopping Thm] (X_n) u.i. sub-mtg, $S \leq T$是停时, 则$\mathbb{E}[X_T|\mathcal{F}_S] \geq X_S$. (X_t) u.i. mtg, $S \leq T$是停时, 则$\mathbb{E}[X(T)|\mathcal{F}(S)] = X(S)$.

Rk. 一致可积u.i.即$\forall\varepsilon, \exists K$ s.t. $\mathbb{E}[|X_n|1_{|X_n|\geq K}] < \varepsilon(\forall n)$. 对离散sub-mtg, 一致可积$\Leftrightarrow$ convergence a.s. and in L^1 $\Leftrightarrow$ convergence in L^1. 对连续mtg, 一致可积$\Leftrightarrow$ convergence in L^1 $\Leftrightarrow$ $\exists Y \in L^1, X(t) = \mathbb{E}[Y|\mathcal{F}(t)]$.

Brownian Motion 性质

- Scaling invariance: $\frac{1}{a}B(a^2t)$是BM. 可得first passage time $T_a = a^2T_1$ in distr.
- Time inversion: $X(t) = tB(\frac{1}{t})(t>0), X(0) = 0$是BM. 可得 $\lim_{t\to\infty}\frac{B(t)}{t} = 0$ a.s.
- Reflection Principle: T是停时, $B_t1_{t\leq T} + (2B_T - B_t)1_{t>T}$是BM.
- $B(t), B(t)^2 - t$是鞅. 指数鞅 $X(t) = \exp(\lambda B(t) - \frac{1}{2}\lambda^2 t)$对$\lambda \in \mathbb{R}$.
- Arcsine law: $L = \sup\{t \in [0,1] : B(t) = 0\}$ is distributed as $\mathbb{P}(L \leq x) = \frac{2}{\pi}\arcsin\sqrt{x}$.

- Wald's Lemma: 停时T有$\mathbb{E}T < \infty$, 则$\mathbb{E}[B(T)] = 0$, $\mathbb{E}[B(T)^2] = \mathbb{E}T$.
- Law of the Iterated Logarithm: $\limsup_{t\to\infty} \dfrac{B(t)}{\sqrt{2t\log\log(t)}} = 1$ a.s.

Stochastic Calculus

二次变差 $[f,f](T) = \lim_{|\Pi|\to 0} \sum_{j=0}^{n-1} (f(t_{j+1}) - f(t_j))^2$. 有 $[W,W](t) = t$ a.s.

Ito Isometry: $\mathbb{E}\left[(\int_0^T X_t dW_t)(\int_0^T Y_t dW_t)\right] = \mathbb{E}\left[\int_0^T X_t Y_t dt\right]$.

$\mathbb{E}[W_t^2] = t, \mathbb{E}[W_t^4] = 3t^2$. $\int_0^t W_s ds \sim \mathcal{N}(0, \frac{1}{3}t^2)$, $\int_0^t f(s)dW_s \sim \mathcal{N}\left(0, \int_0^t f(s)^2 ds\right)$.

$\int_0^T W_t dW_t = \frac{1}{2}(W_T^2 - T)$ (apply Ito's lemma to W_t^2).

Ito过程: 由$dX(t) = \Delta(X(t),t)dW(t) + \Theta(X(t),t)dt$形式SDE决定的随机过程$X(t)$为Ito过程. 特别地, 若$\Delta$只关于$t$, 则有$[X,X](t) = \int_0^t \Delta(u)^2 du$.

Ito Lemma: 对Ito过程X_t, 有 $df(t,X_t) = f_t(t,X_t)dt + f_x(t,X_t)dX_t + \frac{1}{2}f_{xx}(t,X_t)dX_t dX_t$. 特别地, $df(W(t)) = f'(W_t)dW_t + \frac{1}{2}f''(W_t)dt$.

Stock Price S_t following log-normal Brownian motion: $dS_t = \alpha S_t dt + \sigma S_t dW_t$, $d\log S_t = (\alpha - \frac{1}{2}\sigma^2)dt + \sigma dW_t$.

Girsanov Thm. 定义$Z(t) = \exp\left(-\int_0^t \Theta(u)dW(u) - \frac{1}{2}\int_0^t \Theta(u)^2 d\right)$, $\widetilde{W}(t) = W(t) + \int_0^t \Theta(u)du$, 并假设$\Theta(u)Z(u)$平方可积. 令$Z = Z(T)$, 则$\mathbb{E}Z = 1$, 且$Z$作为Radon-Nikodym导数, 即$\widetilde{\mathbb{P}}(A) = \int_A Z(\omega)d\mathbb{P}(\omega)$定义的 $\widetilde{\mathbb{P}}$下, $\widetilde{W}(t)$是BM.

在$\Theta(t) = \dfrac{\alpha(t) - R(t)}{\sigma(t)}$定义的$\widetilde{\mathbb{P}}, \widetilde{W}$下, $dS(t) = R(t)S(t)dt + \sigma(t)S(t)d\widetilde{W}(t)$, 贴现后 $dS^*(t) = \sigma(t)S^*(t)d\widetilde{W}(t)$是鞅.

Martingale Representation Thm. $M(t)$是平方可积鞅, 则存在适应的平方可积过程$\theta(t)$使得$M(t)$ a.s.有积分表示 $M(t) = \mathbb{E}[M_0] + \int_0^t \theta(s)dW(s)$.

贴现后的 deriv value process $V^*(t)$ 是鞅, 由鞅表示定理有$\theta(t)$使 $V^*(T) = \widetilde{\mathbb{E}}V_0 + \int_0^T \theta(t)d\widetilde{W}(t)$ $= \widetilde{\mathbb{E}}V_0 + \int_0^T \dfrac{\theta(t)}{\sigma(t)S^*(t)}dS^*(t)$, 即为复制策略.

1.3 Stochastic Differential Equation

线性SDE求解 考虑$\begin{cases} dX(t) = (c(t) + d(t)X(t))dt + (e(t) + f(t)X(t))dW(t) \\ X(0) = X_0 \end{cases}$ 其中 c,d,e,f 非随机. 结论: 解为 $X_1(t)\cdot\left(X_0 + \int_0^t (c(s) - f(s)e(s))\,(X_1(s))^{-1}\,ds + \int_0^t e(s)\,(X_1(s))^{-1}\,dW(s)\right)$, 其中 $X_1(t) = \exp\left(\int_0^t f(s)dW(s) - \int_0^t (d(s) - \frac{1}{2}f(s^2))ds\right)$.

解法: Duhamel原理.

先得到 $\begin{cases} dX_1(t) = d(t)X_1(t)dt + f(t)X_1(t)dW(t) \\ X_1(0) = 1 \end{cases}$ 的解$X_1(t)$ (对$d(\ln X_1(t))$用Ito即可).

再分离变量, 设 $X(t) = X_1(t) \cdot X_2(t)$ 其中X_2满足 $\begin{cases} dX_2(t) = A(t)dt + B(t)dW(t) \\ X_2(0) = X_0 \end{cases}$ 是原方程的解, $A(t), B(t)$待定. 写开$dX(t)$代回原方程, 有 $\begin{cases} A(t) = (c(t) - f(t)e(t))(X_1(t))^{-1} \\ B(t) = e(t)(X_1(t))^{-1} \end{cases}$, 积分即得$X_2$. 从而有原方程解$X_1 \cdot X_2$.

Feynman Kac Theorem 考虑方程 $dX(u) = \beta(u, X(u))du + \gamma(u, X(u))dW(u)$, 记$g(t,x) = \mathbb{E}^{t,x}[h(X(T))]$, 其中$X$是初值$X(t) = x$下的解. 则$g_t + \beta g_x + \frac{1}{2}\gamma^2 g_{xx} = 0$.

2 OLS

$y = X\beta + \varepsilon$, G-M假设 $\mathrm{Cov}(e) = \sigma^2 I_n$.

估计$\hat{\beta} = (X^T X)^{-1} X^T y$. 满足$\mathbb{E}[\hat{\beta}] = \beta, \mathrm{Var}(\hat{\beta}) = \sigma^2 (X^T X)^{-1}$. 是BLUE最佳线性无偏估计.

X已知非随机, y已知随机, β未知非随机, $\hat{\beta}$随机, e未知随机(σ^2 未知). 每个y_i都有一个对应的总体$N(\beta^T x_i, \sigma^2)$

记$H = X(X^T X)^{-1} X^T$,有$\hat{y} = Hy$. H对称幂等,$HX = X$,迹为$k+1$.

$\mathbb{E}[\hat{y}] = y, \mathrm{Var}(\hat{y}) = \sigma^2 H$. 残差$e = y - \hat{y}$(注意区别于误差向量$\varepsilon$)有 $\mathbb{E}[e] = 0, \mathrm{Var}(e) = \sigma^2(I - H)$.

$SSR = \sum(\hat{y}_i - \bar{y})^2, SSE = \sum(\hat{y}_i - y_i)^2, SST = \sum(y_i - \bar{y})^2$. 有$SST = SSE + SSR$.定义$R^2 = 1 - SSR/SST$.

$\mathrm{Var}(\hat{\beta}_j) = \frac{\sigma^2}{SST_j(1 - R_j^2)}$, 其中$SST_j = \sum_i (x_{ij} - \bar{x_j})^2$, R_j^2为x_j关于其他自变量含截距回归的R^2.

MLE: $\hat{\sigma^2} = \frac{RSS}{n}$是有偏的, 无偏估计为$\hat{\sigma^2} = \frac{RSS}{n-k-1}$(或写为$se^2$).

$\hat{\beta}_j$标准误(标准化残差)$se(\hat{\beta}_j) = \frac{\hat{\sigma}}{(SST_j(1 - R_j^2))^{1/2}}$. $SE(\hat{\beta}_j)$是$Cov(\hat{\beta})$对应对角元的开根. T化残差为原始残差除以估计的标准差.

t检验统计量$t_{\hat{\beta}_j} = \hat{\beta}_j / se(\hat{\beta}_j)$. 整体回归F统计量$F = \frac{R^2/k}{(1 - R^2)/(n-k-1)}$.

衡量多重共线性$VIF_j = \frac{1}{1 - R_j^2}$, 大于10认为严重. 有$SE(\beta_j) = \frac{\sigma^2}{(n-1)\hat{Var}(X_j)} VIF_j$.

y对x做一元回归, 回归系数$\hat{\beta}_{yx} = \frac{Cov(x,y)}{Var(x)}$. 回归$R^2$的分布$\sim Beta(\frac{k-1}{2}, \frac{n-k}{2})$. $Beta(\alpha, \beta)$的期望为$\frac{1}{1 + \beta/\alpha}$.

3 Options

3.1 Pricing

Binomial Model. 风险中性概率 $\widetilde{p} = \frac{1+r-d}{u-d}$, $\widetilde{q} = \frac{u-1-r}{u-d}$. $V_n(\omega) = \frac{1}{1+r}[\widetilde{p}V_{n+1}(\omega H) + \widetilde{q}V_{n+1}(\omega T)]$. $\Delta_n(\omega) = \frac{V_{n+1}(\omega H) - V_{n+1}(\omega T)}{S_{n+1}(\omega H) - S_{n+1}(\omega T)}$.

Put option value wrt Strike price 应该是凸的.

当total variance $\sigma^2 T$较小, ATM put 价值有近似 $P_{ATM} \simeq 0.4\sigma S_0\sqrt{T}$. ATM Call 和 Put 都有$\Delta \simeq 0.5$.

Put-Call Parity $C(t) - P(t) = S(t) - Ke^{-r(T-t)}$.

BS equation: 假设股价符合几何布朗运动$dS = \mu S dt + \sigma S dW$, 即$S_t = S_0 \exp((r - \frac{1}{2}\sigma^2)t + \sigma W(t))$. $\frac{\partial V}{\partial t} + \frac{1}{2}\sigma^2 S^2 \frac{\partial^2 V}{\partial S^2} + rS\frac{\partial V}{\partial S} - rV = 0$ (推导: 对$e^{-rt}V(t, S(t))$用Ito).

BSM formula: $c = S_0 N(d_1) - K\mathrm{e}^{-rT} N(d_2)$, $p = K\mathrm{e}^{-rT} N(-d_2) - S_0 N(-d_1)$, 其中 $d_1 = \frac{\ln(S_0/K) + (r + \sigma^2/2)T}{\sigma\sqrt{T}}$, $d_2 = \frac{\ln(S_0/K) + (r - \sigma^2/2)T}{\sigma\sqrt{T}} = d_1 - \sigma\sqrt{T}$.

3.2 Greeks

Delta: 标的资产价格变化引起的期权价格变化. Gamma: 标的资产价格变化引起的Delta值变化. Vega: 隐含波动率变化引起的期权价格变化. Theta: 期权的时间价值随时间流逝损耗的速度.

Delta & Gamma

- Call的Delta是正的, Put的Delta是负的. Call和Put的Gamma都是正的.
- 对Call, 随着Vol下降, ITM Delta上升(范围从50到100), OTM Delta下降; 随着到期日临近, ITM Delta上升, OTM Delta下降. 波动率下降/到期日临近下,Delta-标的价格变化图像为Fig1左.
- 对Put, 随着波动率上升, OTM Delta下降(范围从0到-50), ITM Delta上升; 随着到期日临近, ITM Delta下降, OTM Delta上升.
- Gamma在ATM最大.ATM的Gamma与Strike负相关.
- 随波动率下降/到期日临近下, 期权的Gamma值变化图像为Fig1右.

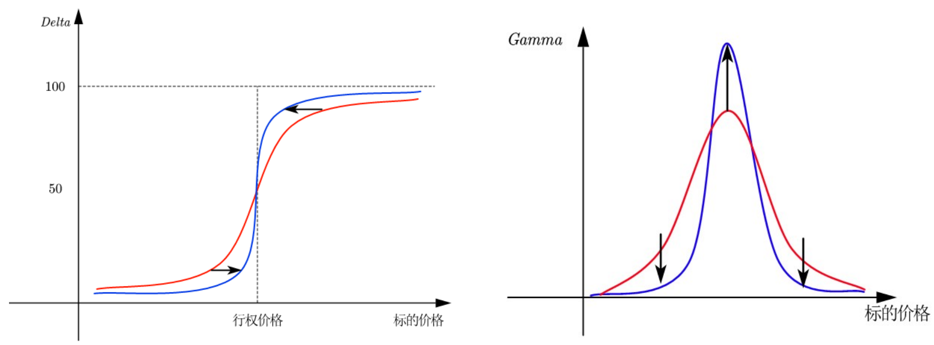

图 1: Fig1

Theta

- Theta通常是负的.
- Theta值在平值时绝对值最大, 深度实值或深度虚值时绝对值较小.
- 期权价值与—Theta—在临近到期时的变化见Fig2.

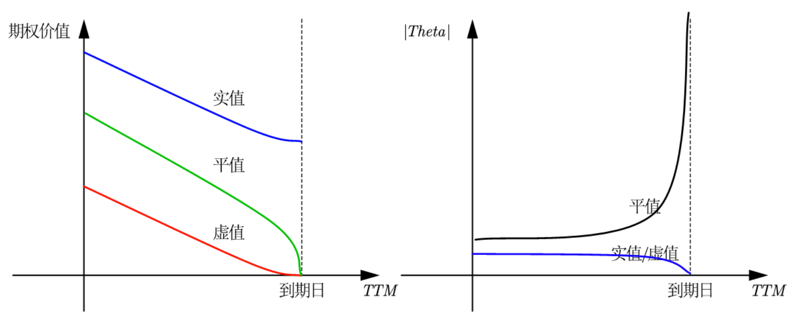

图 2: Fig2

- 平值期权的Theta与波动率成比例变化.

Vega

- Vega在平值时最大, 深度实值或深度虚值时较小.
- 期权价值与Vega在不同波动率下的情况见Fig3.

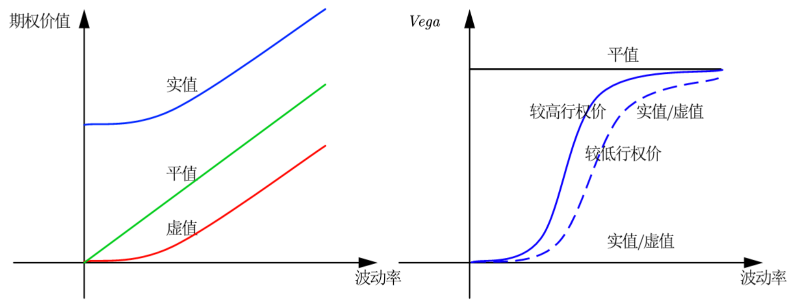

图 3: Fig3

- Vega值随到期日临近的变化见Fig4.

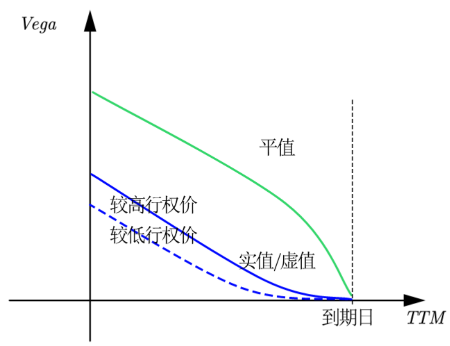

图 4: Fig4

3.3 Structure

对称策略

以下默认期权多头. 价指Strike Price.

跨式期权 Straddle: Long 同价的Call+Put. \/ 形. Neutral Delta, Long Gamma, Long Vega, Short Theta.

宽跨式期权 Strangle: Long 高价Call + 低价Put. _ / 形. Neutral Delta, Long Gamma, Long Vega, Short Theta.

蝶式期权 Fly: Long 低价Call + 高价Call, Short 2 中间价Call. _ / _ 形. Neutral Delta, Short Gamma, Short Vega, Long Theta.

鹰式期权 Iron Condor: Long 低价Call + 高价Call, Short 中低价Call+中高价Call. _ / - _ 形. Neutral Delta, Short Gamma, Short Vega, Long Theta.

时间价差

时间价差多头: 买入长期期权, 卖出短期期权.(因为长期期权通常更贵) 使用平值期权1:1构成Delta中性.

时间价差多头是Short Gamma的, 因为若标的价格不变, 随时间流逝, 短期期权价值减少是多于长期期权的.

时间价差多头是Long Vega的, 因为波动率变化(上升)对长期期权有更大影响(增加更多时间价值).

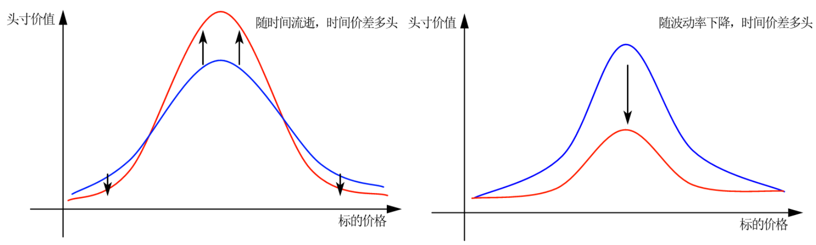

图 5: Fig5

策略选择: 如果隐含波动率低, 要 Long Vega. 当隐含波动率很低但被认为会升高时, 时间价差多头可能获利.

垂直价差

买入与卖出相同类型、同时到期、行权价格不同的期权. 牛市价差 Call Spread: 买低, 卖高. (Call:牛市看涨, Put:牛市看跌). 熊市价差 Put Spread: 卖低, 买高. (Call:熊市看涨, Put:熊市看跌).

买低卖高, 无论是Call还是Put都具有牛市特征, 即具有正的Delta值. 两个行权价之间差距越大, 牛市特征越明显(价差的Delta越大).

Call Spread Collar: CS + underwrite. Put Spread Collar: PS + overwrite.

Risk reversal: Buy downside put, partially funded by selling an upside call, or vice versa.

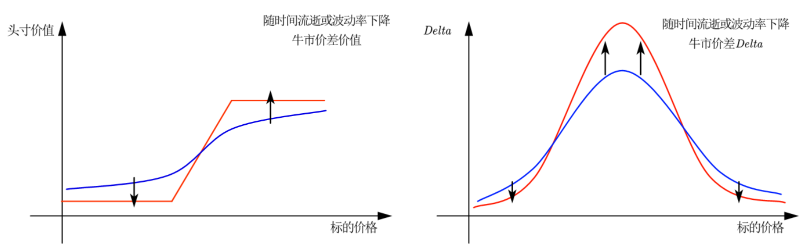

图 6: Fig5

3.4 其他

美式期权

看涨期权价值=内在+波动率+利率-股利. 因此美式看涨若提前行权, 只可能在股利支付前一天. 看跌期权价值=内在+波动率-利率+股利. 因此美式看跌若提前行权, 要距离除息日足够远, 且波动率价值较小. 无论看涨看跌, 越是实值, 美式与欧式价格差越大; 波动率越小, 美式与欧式价格差越大.

结构化

Down and out + Down and in = Vanilla Call.

Knock-in: Structure is activated after being knocked in (before that coupon is protected).

Knock-out: Immediate termination of structure.

雪球是什么: FCN-KI autocallable (fixed coupon note kick-in variant)

4 Linear Algebra

4.1 矩阵性质

- $|\boldsymbol{AB}| = |\boldsymbol{A}||\boldsymbol{B}|$, $|k\boldsymbol{A}| = k^n|\boldsymbol{A}|$
- $(k\boldsymbol{A})^{-1} = k^{-1}\boldsymbol{A}^{-1}$, $|\boldsymbol{A}^{-1}| = |\boldsymbol{A}|^{-1}$
- $\mathrm{tr}(\boldsymbol{AB}) = \mathrm{tr}(\boldsymbol{BA})$, $\mathrm{tr}\left(\boldsymbol{AA}'\right) \geq \mathrm{tr}\left(\boldsymbol{A}^2\right)$.
- 若 $\boldsymbol{A}$ 是 n 阶实矩阵, 则 $\mathrm{tr}\left(\boldsymbol{AA}'\right) \geq 0$, 等号成立$\Leftrightarrow$ $\boldsymbol{A} = \boldsymbol{O}$
- $r(\boldsymbol{AB}) \leq \min\{r(\boldsymbol{A}), r(\boldsymbol{B})\}$;
- $r(\boldsymbol{A}+\boldsymbol{B}) \leq r(\boldsymbol{A}) + r(\boldsymbol{B}), r(\boldsymbol{A}-\boldsymbol{B}) \leq r(\boldsymbol{A}) + r(\boldsymbol{B})$;
- Sylvester不等式. 设$\boldsymbol{A}$是$m\times n$矩阵,$\boldsymbol{B}$是$n\times t$矩阵,则 $r(\boldsymbol{AB}) \geq r(\boldsymbol{A}) + r(\boldsymbol{B}) - n$.
- 设$\boldsymbol{A}$是$m\times n$阶实矩阵,则 $r\left(\boldsymbol{A}'\boldsymbol{A}\right) = r\left(\boldsymbol{AA}'\right) = r(\boldsymbol{A})$
- 设$\boldsymbol{A}$是$m\times n$矩阵,则:

  (1)若$r(\boldsymbol{A}) = n$,即$\boldsymbol{A}$列满秩,则必存在秩等于n的 $n\times m$矩阵$\boldsymbol{B}$使$\boldsymbol{BA} = \boldsymbol{I}_n$;

  (2)若$r(\boldsymbol{A}) = m$,即$\boldsymbol{A}$行满秩,则必存在秩等于m的 $n\times m$矩阵$\boldsymbol{C}$使$\boldsymbol{AC} = \boldsymbol{I}_m$.
- 满秩分解. 设$\boldsymbol{A}$是秩为r的$m\times n$矩阵,则有满秩分解$\boldsymbol{A} = \boldsymbol{BC}$, 其中$\boldsymbol{B}$是秩为$r$的$m\times r$矩阵,$\boldsymbol{C}$是秩为$r$的$r\times n$矩阵.
- 设A是n阶幂等矩阵,则存在n阶非异阵$\boldsymbol{P}$,使得$\boldsymbol{P}^{-1}\boldsymbol{AP} = \begin{pmatrix} \boldsymbol{I}_r & \boldsymbol{O} \\ \boldsymbol{O} & \boldsymbol{O} \end{pmatrix}$, 其中$r = \mathrm{r}(\boldsymbol{A})$

4.2 特征值

- 任一复方阵必相似于一上三角阵,且主对角线上元素为特征值.
- Cayley-Hamilton Thm. $f(x)$为矩阵A的特征多项式, 则$f(A) = O$.
- 若A特征值为$\lambda_1, \cdots, \lambda_n$, 则$f(A)$的特征值为$f(\lambda_1), \cdots, f(\lambda_n)$. 若$A$适合多项式$g(x)$,则$A$的任意特征值适合$g(x)$.
- 特征值降阶公式. A, B是$m\times n$与$n\times m$矩阵, $m \geq n$.则 $|\lambda I_m - AB| = \lambda^{m-n}|\lambda I_n - BA|$.

- 可对角化判定方法

  充分条件: 有 n 个不同的特征值; 相似于实对称阵.

  充要条件: 有 n 个线性无关的特征向量; 极小多项式无重根; 初等因子都是一次多项式; Jordan块都是一阶矩阵; 有完全的特征向量系 (即m重特征值有m个线性无关特征向量).

- Jordan标准型求法

  $\lambda I - A$相抵于$\mathrm{diag}\{1,\ldots,1,d_1(\lambda),\ldots,d_k(\lambda)\}$, 对角元$d_i|d_{i+1}$. $d_1,\ldots,d_k$的准素因子全体(初等因子)对应Jordan块拼起来即为Jordan标准型.

- $J = J_r(\lambda)$为Jordan块.则$f(J)$主对角线上均为$f(\lambda)$, 上次对角线上均为$f'(\lambda)$, 距离主对角线j位的对角线上均为$\dfrac{1}{j!}f^{(j)}(\lambda)$. 对$\lambda \neq 0$, $J_r(\lambda)^m$的Jordan标准型为$J_r(\lambda^m)$.

- A^k求法: 先求出Jordan标准型J, 根据$AP = PJ$解方程得P, 求J^k再乘过渡矩阵即可.

4.3 二次型

- 设A为n阶实对称阵,则以下结论等价:

  (1)A正定 (2)A合同于I_n (3)存在非异实矩阵$C, A = C'C$ (4)A的主子式都大于0

  (5)A的顺序主子式都大于0 (6)A的特征值都大于0.

- $\boldsymbol{A} = (a_{ij})$是$n$阶半正定实对称矩阵,则$|\boldsymbol{A}| \leq a_{11}a_{22}\cdots a_{nn}$, 等号成立当且仅当 $\boldsymbol{A}$ 是对角矩阵或某个$a_{ii} = 0$.

- 设$\boldsymbol{A}$为n阶实对称矩阵, 则$\boldsymbol{A}$半正定或半负定$\Leftrightarrow$ 对任意$\boldsymbol{\alpha}$满足$\boldsymbol{\alpha}'\boldsymbol{A}\boldsymbol{\alpha} = 0$, 均有$\boldsymbol{A}\boldsymbol{\alpha} = \mathbf{0}$.

- 若实矩阵A满足$A' = A^{-1}$, 则称A为正交阵. A为正交阵/酉阵的充要条件为A的n个行向量构成一组标准正交基.

- 实对称阵与Hermite阵特征值全为实数,反对称阵特征值全为0或纯虚数.

- 实对称阵与Hermite阵合同于$\mathrm{diag}\{I_p, -I_q, 0\}$. 实对称阵(Hermite阵)正交相似(酉相似)于实对角阵.

- 复正规阵酉相似于复对角阵,对角元模长都为1.实反对称阵酉相似于复对角阵.

- Gram-Schmidt正交化方法. $\{u_1,\ldots,u_m\}$为一组线性无关的向量, 令

$$v_{k+1} = u_{k+1} - \sum_{i=1}^{k} \frac{(u_{k+1}, v_i)}{\|v_i\|^2} v_i$$

  则$\{v_1,\ldots,v_m\}$为一组正交向量.

4.4 一些分解

- QR分解

  设A为n阶实/复矩阵, 则$A = QR$, 其中Q为正交/酉阵, R为主对角元均≥ 0的上三角阵. 若A非异, 则分解唯一.

- Jordan-Chevalley分解

  设A为n阶复方阵, 则有分解$A = B + C$,满足:

  (1)B可对角化 (2)C为幂零阵 (3)$BC = CB$ (4)B, C可表示为A的多项式

  并且满足前三条的分解唯一.

- Cholesky分解

  设A为n阶实对称阵/Hermite阵, 若A正定, 则存在对角元均为正实数的下三角(或上三角)实矩阵L 使得$A = LL'/A = L\overline{L}'$, 并且分解唯一. 若$A$为半正定阵, 则对角元均为非负数, 且分解不一定唯一.

- 极分解

  $\varphi \in \mathcal{L}(V)$, 则$\varphi = \omega\psi$. 其中$\omega$保积,$\psi$半正定自伴随.若$\varphi$可逆,则分解唯一.

  $A \in M_n(R)$, 则$A = OS$, 其中O为正交阵, S为半正定实对称阵.

  $A \in M_n(C)$, 则$A = UH$, 其中U为酉阵, H为半正定Hermite阵.

- 奇异值分解

  $A \in M_{m\times n}(R)$,则$A = P\operatorname{diag}\{S, 0\}Q'$. 其中$P, Q$为$m, n$阶正交阵,$S = \operatorname{diag}\{\sigma_1, \cdots, \sigma_r\}$, $\sigma_1 \geq \cdots \geq \sigma_r > 0$为$A$的所有奇异值,即$\sigma_1^2, \cdots, \sigma_r^2$为$A'A$的非零特征值全体.

4.5 计算

初等变换法求逆阵: A是非异阵, 作$n \times 2n$矩阵(A, I_n), 实施初等行变换, 将左侧化为I_n, 此时右侧矩阵即为A^{-1}.

A是实对称阵, 求非异矩阵C使得$C'AC$是对角阵: 作$n \times 2n$矩阵(A, I_n), 实施初等行变换, 并对左侧矩阵实施对应初等列变换, 将左侧化为对角阵. 此时右侧矩阵的即为C'.

A是实对称阵, 求正交矩阵P使得$P'AP$是对角阵: 求特征值, 对每个特征值λ, 求解$(\lambda I - A)x = 0$得到基础解系. 若基础解系有多个向量, 进行正交化. 所有列向量单位化后拼接得到P.

5 Calculus

5.1 一元微积分

Please see 数分2 notes attached.

5.2 多元微分

Hessian matrix: f为$\mathbb{R}^n \to \mathbb{R}$函数, $H(f) = \left(\dfrac{\partial^2 f}{\partial x_i \partial x_j}\right)_{n\times n}$

Jacobi matrix: f为$\mathbb{R}^n \to \mathbb{R}^m$向量值函数, $J(f) = \left(\dfrac{\partial f_i}{\partial x_j}\right)_{m\times n}$

Prop. $H(f(x)) = J(\nabla f(x))^T$.

Hessian矩阵正定的极值点是极小值点, 负定是极大值点.

隐函数存在定理: 对多元函数$F(x_1,\ldots,x_n,y)=0$, 在周围闭矩形连续且有连续偏导, $F_y \neq 0$, 有$\dfrac{\partial y}{\partial x_i} = -\dfrac{F_{x_i}}{F_y}$. 多元向量值函数$F(x_0,y_0,u_0,v_0)=0, G(x_0,y_0,u_0,v_0)=0$, Jacobi行列式$\dfrac{\partial(F,G)}{\partial(u,v)} \neq 0$, 则有$\begin{pmatrix} u_x & u_y \\ v_x & v_y \end{pmatrix} = -\dfrac{\partial(F,G)}{\partial(u,v)}^{-1} \dfrac{\partial(F,G)}{\partial(x,y)}$.

几何应用

1.曲线$\Gamma: x=x(t), y=y(t), z=z(t)$, 在$P_0(x_0,y_0,z_0)$处切向量$\vec{\tau} = (x', y', z') \mid_{P_0}$, 法平面为$x'(x-x_0)+y'(y-y_0)+z'(z-z_0)=0$.

2.曲线$\Gamma: \begin{cases} F(x,y,z)=0 \\ G(x,y,z)=0 \end{cases}$, 在$P_0(x_0,y_0,z_0)$处切向量$\vec{\tau} = (\dfrac{\partial(F,G)}{\partial(y,z)}, \dfrac{\partial(F,G)}{\partial(z,x)}, \dfrac{\partial(F,G)}{\partial(x,y)}) \mid_{P_0}$,法平面为$\operatorname{grad} F(P_0), \operatorname{grad} G(P_0)$张成的平面.

3.曲面$F(x,y,z)=0$在$P_0(x_0,y_0,z_0)$处法向量$\vec{n} = (F_x, F_y, F_z) \mid_{P_0}$, 切平面为$\dfrac{x-x_0}{F_x(P_0)} = \dfrac{y-y_0}{F_y(P_0)} = \dfrac{z-z_0}{F_z(P_0)}$.

4.曲面$x=x(u,v), y=y(u,v), z=z(u,v)$,法向量$\vec{n} = (\dfrac{\partial(y,z)}{\partial(u,v)}, \dfrac{\partial(z,x)}{\partial(u,v)}, \dfrac{\partial(x,y)}{\partial(u,v)})$.

5.3 重积分

重积分变量代换: 映射$T: \begin{cases} x=x(u,v) \\ y=y(u,v) \end{cases}, D \to T(D)$ 有连续偏导且$\dfrac{\partial(x,y)}{\partial(u,v)} \neq 0$. $f(x,y)$在$T(D)$连续, 则 $\iint_{T(D)} f(x,y)\mathrm{d}x\mathrm{d}y = \iint_D f(x(u,v),y(u,v)) \left|\dfrac{\partial(x,y)}{\partial(u,v)}\right| \mathrm{d}u\mathrm{d}v$

常用变量代换:

极坐标变换$x=r\cos\theta, y=r\sin\theta$下$\mathrm{d}x\mathrm{d}y = r\mathrm{d}r\mathrm{d}\theta$.

柱坐标变换$x=r\cos\theta, y=r\sin\theta, z=z$下$\mathrm{d}x\mathrm{d}y\mathrm{d}z = r\mathrm{d}r\mathrm{d}\theta\mathrm{d}z$.

球坐标变换$x=r\sin\varphi\cos\theta, y=r\sin\varphi\sin\theta, z=r\cos\varphi, r\in[0,+\infty), \varphi\in[0,\pi], \theta\in[0,2\pi]$下$\mathrm{d}x\mathrm{d}y\mathrm{d}z = r^2\sin\varphi\mathrm{d}r\mathrm{d}\varphi\mathrm{d}\theta$.

广义球坐标变换$x=ar\sin\varphi\cos\theta, y=br\sin\varphi\sin\theta, z=cr\cos\varphi$下$\mathrm{d}x\mathrm{d}y\mathrm{d}z = abcr^2\sin\varphi\mathrm{d}r\mathrm{d}\varphi\mathrm{d}\theta$.

n重球坐标变换$x_1 = r\cos\varphi_1, x_2 = r\sin\varphi_1\cos\varphi_2, \cdots, x_{n-1} = r\sin\varphi_1\cdots\sin\varphi_{n-2}\cos\varphi_{n-1}, x_n = r\sin\varphi_1\cdots\sin\varphi_{n-1}, 0\le\varphi_1,\cdots,\varphi_{n-2}\le\pi, 0\le\varphi_{n-1}\le 2\pi$下$\dfrac{\partial(x_1,x_2,\cdots,x_n)}{\partial(r,\varphi_1,\cdots,\varphi_{n-1})} = r^{n-1}\sin^{n-2}\varphi_1 \sin^{n-3}\varphi_2\cdots\sin\varphi_{n-2}$.

5.4 曲线与曲面积分

Please see 数分3 notes attached.

6 常微

1. 分离变量

(1)齐次方程$\frac{dx}{dt}=f(\frac{x}{t})$. 令$\frac{x}{t}=u$,则$\frac{du}{dt}t=f(u)-u$.

(2)$\frac{dx}{dt}=f(at+bx+c)$. 令$y=at+bx+c$,则$\frac{dy}{dt}=a+bf(y)$.

2. 非齐次线性方程 $\frac{dx}{dt}=P(t)x+Q(t)$

常数变易,两边乘$e^{-\int P(t)dt}$. 常数变易公式$x=e^{\int P(t)dt}(\int e^{-\int P(t)dt}Q(t)dt+C)$.

3. 全微分方程 $M(t,x)dt+N(t,x)dx=0$

(1) $\frac{\partial M(t,x)}{\partial x}=\frac{\partial N(t,x)}{\partial t}$, 则存在$u(t,x)$使得$du(t,x)=M(t,x)dt+N(t,x)dx$

设$u(t,x)=\int M(t,x)dt+\varphi(x)$,由$N(t,x)=\frac{\partial}{\partial x}\int M(t,x)dt+\varphi'(x)$可求出$\varphi(x)$.

(2) $\frac{\partial M(t,x)}{\partial x}\neq\frac{\partial N(t,x)}{\partial t}$, 要找积分因子$\mu$使得$\frac{\partial \mu M}{\partial x}=\frac{\partial \mu N}{\partial t}$

可寻找特殊形式的$\mu(t,x)$,如取$\mu(x),\mu(t),\mu(xt),\ldots$,代入$\frac{\partial \mu M}{\partial x}=\frac{\partial \mu N}{\partial t}$ 求解.

4. 导数未解出的一阶方程

$x=f(t,\frac{dx}{dt})$或$t=f(x,\frac{dx}{dt})$, 引入$p=\frac{dx}{dt}$求解.

5. 高阶方程的降阶

(1)不含x,$F\left(t,x^{(k)},\cdots,x^{(n)}\right)=0$. 令$x^{(k)}=y$,则化为$F\left(t,y,\cdots,y^{(n-k)}\right)=0$.

(2)不含t,$F\left(x,\frac{dx}{dt},\cdots,\frac{d^nx}{dt^n}\right)=0$. 引入$y=\frac{dx}{dt}$,以$x$为新自变量.则$x^{(k)}$可用$y,\frac{dy}{dx},\cdots,\frac{d^{k-1}y}{dx^{k-1}}$表示.

6. 齐次常系数线性方程 $x^{(n)}+a_1x^{(n-1)}+\cdots+a_{n-1}x^{(1)}+a_nx=0$

特征方程$\lambda^n+a_1\lambda^{n-1}+\cdots+a_{n-1}\lambda+a_n=0$. $\lambda_1,\ldots,\lambda_s$为不同实根,重数$n_1,\ldots,n_s$, $\alpha_1\pm i\beta_1,\ldots,\alpha_p\pm i\beta_p$为共轭虚根,重数为$m_1,\ldots,m_p$. 则实值通解

$$x(t)=\sum_{i=1}^{s}P_i(t)e^{\lambda_i t}+\sum_{i=1}^{p}e^{\alpha_i t}(W_i(t)\cos\beta_i t+V_i(t)\sin\beta_i t)$$

其中$P_i(t)$为n_i-1次实系数多项式,$W_i(t),V_i(t)$为m_i-1次实系数多项式.

7. 非齐次常系数线性方程 $x^{(n)}+a_1x^{(n-1)}+\cdots+a_{n-1}x^{(1)}+a_nx=f(t)$

解为$x(t)=x_1(t)+x^*(t)$,其中$x_1(t)$为$x^{(n)}+a_1x^{(n-1)}+\cdots+a_{n-1}x^{(1)}+a_nx=0$的通解, $x^*(t)$为$x^{(n)}+a_1x^{(n-1)}+\cdots+a_{n-1}x^{(1)}+a_nx=f(t)$的特解.

$x^*(t)=\int_0^t K(t-s)f(s)ds$,其中$K(t)$为$x^{(n)}+a_1x^{(n-1)}+\cdots+a_{n-1}x^{(1)}+a_nx=0$ 在初值条件$K(0)=K'(0)=\cdots=K^{(n-1)}(0)=0,K^{(n)}(0)=1$下的解.

8. Euler方程 $t^nx^{(n)}+a_1t^{n-1}x^{(n-1)}+\cdots+a_{n-1}tx^{(1)}+a_nx=0$

引入$s=\ln|t|$,记$D_s=\dfrac{d}{ds}$,则$t^nx^{(n)}=D_s(D_s-1)\cdots(D_s-n+1)x$.

9. 齐次常系数线性微分方程组$\dfrac{d\vec{x}}{dt}=A\vec{x}$

若A可对角化,则$\vec{x}(t)=\sum_{i=1}^n c_ie^{\lambda_it}\vec{p_i}$,$\vec{p_i}$为$\lambda_i$的特征向量.

若A有复数特征值$\lambda=\alpha+i\beta$和$\bar{\lambda}=\alpha-i\beta$, 则方程组实值解形如$\vec{x}=e^{\alpha t}\{\vec{p}(t)\cos\beta t+\vec{q}(t)\sin\beta t\}$, 其中$\vec{p}(t)$和$\vec{q}(t)$是$t$的次数小于$\lambda$重数的实向量多项式,其向量系数由微分方程组确定.

对一般矩阵A,Jordan标准型为J,$P^{-1}AP=J$,则$\vec{x}(t)=Pe^{Jt}\vec{c}$, 其中对$\lambda_i$的Jordan块$J_i$,$e^{J_it}$第一行为$e^{\lambda_it},te^{\lambda_it},\ldots,\dfrac{t^{n_i-1}}{(n-1)!}e^{\lambda_it}$. 记$\vec{p_i}$为$P$的第$i$个列向量,则有

$$\vec{x}(t)=\sum_{i=1}^s\left\{c_{i_1}e^{\lambda_it}\vec{p}_{i_1}+c_{i_2}\left[te^{\lambda_it}\vec{p}_{i_1}+e^{\lambda_it}\vec{p_{i_2}}\right]+\cdots+c_{i_{n_i}}\left[\frac{t^{n_i-1}}{(n_i-1)!}e^{\lambda it}\vec{p_{i_1}}+\cdots+e^{\lambda_it}\vec{p}_{i_{n_i}}\right]\right\}.$$

$\forall\,\mathrm{Re}\{\lambda_i\}<0\Leftrightarrow\|\vec{x}(t)\|\le M$.

10. 非齐次常系数线性微分方程组$\dfrac{d\vec{x}}{dt}=A\vec{x}+\vec{f}(t)$

方程的解$\vec{x}(t)=Pe^{Jt}c(\vec{t})=Pe^{Jt}\vec{c}+\int_0^t e^{A(t-s)}\vec{f}(s)ds$

对初值问题$\vec{x}(t_0)=\vec{x_0}$,有$\vec{x}(t)=e^{A(t-t_0)}\vec{x_0}+\int_{t_0}^t e^{A(t-s)}\vec{f}(s)ds$.

7 Others

7.1 矩阵范数

Frobenius范数$\|A\|=\sqrt{\sum_{i,j}a_{ij}^2}$

由向量范数$\|\vec{x}\|_p=(\sum_i|x_i|^p)^{1/p}$诱导的矩阵范数$\|A\|_p=\sup_{\vec{x}\neq\vec{0}}\dfrac{\|A\vec{x}\|_p}{\|\vec{x}\|_p}$.

$\|A\|_1=\max\limits_{1\leqslant j\leqslant n}\left\{\sum_{i=1}^n|a_{ij}|\right\},\|A\|_2=\sqrt{\lambda_{\max}\left(A^TA\right)},\|A\|_\infty=\max\limits_{1\leqslant i\leqslant n}\left\{\sum_{j=1}^n|a_{ij}|\right\}$.

由向量范数诱导的矩阵范数有性质 (1)$\|A\vec{x}\|\leqslant\|A\|\cdot\|\vec{x}\|$ (2)$\|A\|=\sup\limits_{\|\vec{x}\|=1}\|A\vec{x}\|$ (3)$\|AB\|\leqslant$

$\|A\| \cdot \|B\| \quad (4) \left\| \int_\alpha^\beta A(s) ds \right\| \leqslant \left| \int_\alpha^\beta \|A(s)\| ds \right|$

矩阵指数函数: $(e^{At})^{-1} = e^{-At}$, $e^{A(t+s)} = e^{At} \cdot e^{As}$.

7.2 矩阵求导

关于t求导与积分:对矩阵每个元素求导与积分.

$\dfrac{d}{dt}[A(t)B(t)] = A'(t)B(t) + A(t)B'(t)$.

将矩阵$X_{m\times n}$按列堆栈向量化, $vec(X) = [x_{11}, \ldots, x_{m1}, \ldots, \ldots, x_{mn}]^T$. 将矩阵函数$F: m \times n \to p \times q$向量化, $vec(F(X)) = [f_{11}(X), \ldots, f_{p1}(X), \ldots, \ldots, f_{pq}(X)]^T$.

$D_X F(X) = \dfrac{\partial vec_{pq\times 1}(F(X))}{\partial vec_{mn\times 1}^T X} \in \mathbb{R}^{pq\times mn}$.

向量变元标量函数: $\dfrac{\partial a^T x}{\partial x} = a$, $\dfrac{\partial x^T A x}{\partial x} = Ax + A^T x$, $\dfrac{\partial a^T x x^T b}{\partial x} = ab^T x + ba^T x$.

矩阵变元标量函数 $\dfrac{\partial a^T X b}{\partial X} = ab^T$, $\dfrac{\partial a^T X X^T b}{\partial X} = ab^T X + ba^T X$.