SUPPLEMENTARY NOTE

Session 1: Risk and Return	
$FV = PV \times (1+r)^t$	$FV = P * e^{rt}$
$E(R) = \sum_{i=1}^{n} p_i R_i$	$\sigma^2 = \sum_{i=1}^{n} p_i (R_i - E(R))^2$
Sharpe Ratio = $\dfrac{\text{Risk premium}}{\text{SD of excess returns}}$	$E(r) = \sum_{s=1}^{n} p(s) r(s) = \frac{1}{n} \sum_{s=1}^{n} r(s)$
$g = TV_n^{1/n} - 1$ $TV_n = (1+r_1)(1+r_2)...(1+r_n)$	$\hat{\sigma}^2 = \frac{1}{n} \sum_{s=1}^{n} [r(s) - \bar{r}]^2$
$\hat{\sigma} = \sqrt{\frac{1}{n-1} \sum_{j=1}^{n} [r(s) - \bar{r}]^2}$	$\sigma_{R_i, R_j} = \sum_{i=1}^{n} P(R_i)[R_i - E(R_i)][R_j - E(R_j)]$
$\rho_{X,Y} = \dfrac{\sigma_{X,Y}}{\sigma_X \sigma_Y}$	$E(R_P) = \sum_{j=1}^{m} w_j E(R_j)$
$\text{Portfolio Variance} = x_1^2 \sigma_1^2 + x_2^2 \sigma_2^2 + 2(x_1 x_2 \rho_{12} \sigma_1 \sigma_2)$	
$Skew = Average \left[\dfrac{(R - \bar{R})^3}{\hat{\sigma}^3} \right]$	$Kurtosis = Average \left[\dfrac{(R - \bar{R})^4}{\hat{\sigma}^4} \right] - 3$
$\Pr(\$Loss > \$VaR) = p$	

Session 2: Basic Matrices	
$(AB)^{-1} = B^{-1} A^{-1}$ $(A^{-1})^{-1} = A$ $(A^T)^{-1} = (A^{-1})^T$ $(kA)^{-1} = \frac{1}{k} A^{-1}$	1. $(\mathbf{A}+\mathbf{B})^T = \mathbf{A}^T + \mathbf{B}^T$ 2. $(\mathbf{AB})^T = \mathbf{B}^T \mathbf{A}^T$ 3. $(k\mathbf{A})^T = k\mathbf{A}^T$ 4. $(\mathbf{A}^T)^T = \mathbf{A}$
$adjA = C^T$	$C_{ij} = (-1)^{i+j} m_{ij}$
Given $A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix},$	$A^{-1} = \dfrac{adjA}{\lvert A \rvert}$

Session 2: Basic Matrices	
then: $m_{11} = \begin{vmatrix} a_{22} & a_{23} \\ a_{32} & a_{33} \end{vmatrix}$	
$\lvert A \rvert = \det A = a_{11}c_{11} + a_{12}c_{12} + \ldots + a_{1n}c_{1n}$	

Session 3: Regression Analysis	
$y = \beta_0 + \beta_1 x_1 + \epsilon$	
$b_2 = \frac{n\sum X_iY_i - \sum X_i \sum Y_i}{n\sum X_i^2 - (\sum X_i)^2} = \frac{\sum (X_i - \bar{X})(Y_i - \bar{Y})}{\sum (X_i - \bar{X})^2} = \frac{\sum x_i y_i}{\sum x_i^2} = \frac{\sum x_i Y_i}{\sum X_i^2 - n\bar{X}^2} = \frac{\sum X_i y_i}{\sum X_i^2 - n\bar{X}^2}$	$b_1 = \frac{\sum X_i^2 \sum Y_i - \sum X_i \sum X_i Y_i}{n\sum X_i^2 - (\sum X_i)^2} = \bar{Y} - b_2 \bar{X}$
$\hat{\sigma}^2 = \frac{\sum_{i=1}^{n} [Y_i - (\hat{\beta}_1 + \hat{\beta}_2 X_i)]^2}{n-2}$	$\mathrm{var}(b_2) = \frac{\sigma^2}{\sum x_i^2}$ $se(b_2) = \frac{\sigma}{\sqrt{\sum x_i^2}}$ $\mathrm{var}(b_1) = \frac{\sum X_i^2}{n\sum x_i^2}\sigma^2$ $se(b_1) = \sqrt{\frac{\sum X_i^2}{n\sum x_i^2}\sigma^2}$
$r^2 = \frac{ESS}{TSS} = \frac{\sum (\hat{Y}_i - \bar{Y})^2}{\sum (Y_i - \bar{Y})^2}$	$\sum y_i^2 = \sum \hat{y}_i^2 + \sum e_i^2 = 2b_2^2 \sum X_i^2 + \sum e_i^2$
$R_i(t) = \alpha_i + \beta_i R_{S\&P500}(t) + e_i(t)$	$\sigma_i^2 = \beta_i^2 \sigma_M^2 + \sigma^2(e_i)$

Session 4: Optimization	
$slope = \lim_{\Delta x \to 0} \left[\frac{f(x+\Delta x) - f(x)}{\Delta x} \right] = f'(x)$	
$\max_{x,y} f(x,y)$ $subject\ to \quad g(x,y) \geq 0$	$\ell = f(x,y) + \lambda g(x,y)$