

Portfolio Theory A1

MV Backtesting and Out-of-Sample Performance

Christopher Eason (ESNCHR001)

2025-09-11

Table of contents

1	Part I: Introduction to Strategy Backtesting	2
1.1	Question 1: Asymptotic distribution of the estimated annualized Sharpe Ratio	2
1.1.1	Definitions and Notation	2
1.1.2	Central Limit Theorem	2
1.1.3	Asymptotic Joint Distribution	3
1.1.4	Delta Method	4
1.1.5	Annualisation	5
1.2	Question 2: Question 2: Expected Maximum of a Sample of IID Normal Variables	6
1.2.1	Definition of the von Mises Function	6
1.2.2	Showing that the Normal Distribution is a von Mises Function . . .	7
1.2.3	Proposition 3.3.25: von Mises Functions and the Max-Domain of Attraction (MDA)	8
1.2.4	Linking the von Mises–MDA Proposition to the Standard Normal Distribution	9
1.2.5	Proposition 3.3.28: Closure Property of MDA under Tail Equivalence	9
1.2.6	Applying the closure proposition	9
1.2.7	Calculation d_N normalising constant	10
1.2.8	Calculation c_N normalising constant	11
1.2.9	Proposition (iii)	11
1.2.10	Combined	11
1.3	Question 3: Minimum Backtest Length to Avoid Overfitting	13
	References	14

Part I: Introduction to Strategy Backtesting

Question 1: Asymptotic distribution of the estimated annualized Sharpe Ratio

Show that the distribution of the estimated annualised Sharpe Ratio (SR) converges asymptotically as $y \rightarrow \infty$ to:

$$\hat{SR} \underset{y \rightarrow \infty}{\overset{a}{\sim}} N \left(SR, \frac{1 + \frac{SR^2}{2q}}{y} \right)$$

Definitions and Notation

- Let q be the number of return observations per year (e.g. $q = 12$ for monthly)
- Let y be the number of years of data.
- Let T be the total number of observations such that $T = qy$
- Let R_f be the risk-free rate
- Let R_t denote the one-period simple return of a portfolio or fund between the times $t - 1$ and t . Assume $R_t \sim N(\mu, \sigma^2)$.
- Let $\mu = E(R_t) - R_f$ be the mean of the excess returns and $\sigma^2 = Cov(R_t)$ be the variance of the excess returns.
- Let SR be the annualised Sharpe Ratio that is defined as

$$SR = \frac{\mu}{\sigma} \sqrt{q} \quad (1)$$

- Since μ and σ are the population movements of the distribution of R_t however they are unobservable and must be estimated using historical data. So given a sample of historical returns (R_1, R_2, \dots, R_T) , we let $\hat{\mu} = \frac{1}{T} \sum_{t=1}^T R_t$ and $\hat{\sigma}^2 = \frac{1}{T} \sum_{t=1}^T (R_t - \hat{\mu})^2$ be our estimates (Lo, 2002).
- Let \hat{SR} be the annualised estimate of the Sharpe Ratio that is defined as

$$\hat{SR} = \frac{\hat{\mu}}{\hat{\sigma}} \sqrt{q} \quad (2)$$

Central Limit Theorem

In order to derive the distribution of the estimated Sharpe ratio, we begin by assuming that the portfolio returns R_t are independently and identically distributed (IID). Practically, this means that the distribution of returns at one period is the same as at any other period and that returns are not correlated across time.

Under the IID assumption, and given that $R_t \sim N(\mu, \sigma^2)$, the sample mean $\hat{\mu}$ and sample variance $\hat{\sigma}^2$ of returns are sums of IID random variables. The Normality assumption is what allows us to use the properties of sums of independent Normal random variables and the χ^2 distribution to derive the variances of these estimates.

For the sample mean: $\hat{\mu} = \frac{1}{T} \sum_{t=1}^T R_t$ the variance of a sum of T independent random variables is $T\sigma^2$, and dividing by T^2 (because of the $1/T$ factor in the mean) gives

$$\text{Var}(\hat{\mu}) = \frac{\sigma^2}{T} \quad (3)$$

For the sample variance: $\hat{\sigma}^2 = \frac{1}{T} \sum_{t=1}^T (R_t - \hat{\mu})^2$ the CLT and the properties of the χ^2 distribution imply that

$$T \frac{\hat{\sigma}^2}{\sigma^2} \sim \chi_{T-1}^2.$$

The variance of a χ^2 with $T - 1 \approx T$ degrees of freedom is $2T$, so rescaling back to $\hat{\sigma}^2$ gives

$$\text{Var}(\hat{\sigma}^2) \approx \frac{2\sigma^4}{T} \quad (4)$$

Thus, taking Equation 3 and Equation 4 and considering the total number of observations $T = qy$, by the Central Limit Theorem, the distributions of $\hat{\mu}$ and $\hat{\sigma}^2$ converge asymptotically to Normal distributions. At this first stage, the CLT applies to sums of IID random variables, allowing us to get a joint asymptotic distribution for $\hat{\mu}$ and $\hat{\sigma}^2$ scaled by T .

$$\sqrt{T}(\hat{\mu} - \mu) \underset{T \rightarrow \infty}{\overset{a}{\rightsquigarrow}} N(0, \sigma^2), \quad \sqrt{T}(\hat{\sigma}^2 - \sigma^2) \underset{T \rightarrow \infty}{\overset{a}{\rightsquigarrow}} N(0, 2\sigma^4). \quad (5)$$

These asymptotic distributions allow us to approximate the estimation error of $\hat{\mu}$ and $\hat{\sigma}^2$, and note that as T increases, both variances shrink toward zero. This reflects the intuitive fact that the larger the dataset (i.e., the more periods per year q and/or the more years y), the smaller the uncertainty in our estimates.

Asymptotic Joint Distribution

We can take Equation 5 and for an asymptotic joint distribution of $\hat{\mu}$ and $\hat{\sigma}^2$.

$$\sqrt{T} \begin{bmatrix} \hat{\mu} - \mu \\ \hat{\sigma}^2 - \sigma^2 \end{bmatrix} \underset{T \rightarrow \infty}{\overset{a}{\rightsquigarrow}} \mathcal{N} \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma^2 & 0 \\ 0 & 2\sigma^4 \end{bmatrix} \right) \quad (6)$$

Delta Method

- Let $\hat{\boldsymbol{\theta}} = \begin{bmatrix} \hat{\mu} \\ \hat{\sigma}^2 \end{bmatrix}$ be a column vector
- Let $\boldsymbol{\theta} = \begin{bmatrix} \mu \\ \sigma^2 \end{bmatrix}$ be a column vector
- Let $\mathbf{V}_{\boldsymbol{\theta}} = \begin{bmatrix} \sigma^2 & 0 \\ 0 & 2\sigma^4 \end{bmatrix}$ be a matrix of joint covariance-variance matrix
- Let $g(\mu, \sigma^2) = SR$ be a function that takes μ and σ as parameters, and uses Equation 1. This means that $g(\hat{\mu}, \hat{\sigma}^2) = \hat{SR}$ be a function that takes $\hat{\mu}$ and $\hat{\sigma}$ as parameters, and uses Equation 2

We apply the delta method to propagate the uncertainty from the estimators μ and σ^2 through the nonlinear function $g(\mu, \sigma^2) = SR$. This allows us to derive the asymptotic distribution of the Sharpe ratio estimator \hat{SR} using the gradient of g and the covariance matrix of μ and σ^2 (Lo, 2002).

First, we can re-write Equation 6 as

$$\sqrt{T}(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}) \underset{T \rightarrow \infty}{\overset{a}{\rightsquigarrow}} \text{N}(0, \mathbf{V}_{\boldsymbol{\theta}})$$

Employing the delta method:

$$\sqrt{T}(g(\hat{\boldsymbol{\theta}}) - g(\boldsymbol{\theta})) \underset{T \rightarrow \infty}{\overset{a}{\rightsquigarrow}} \text{N}\left(0, \left(\frac{\partial g}{\partial \boldsymbol{\theta}}\right)' \mathbf{V}_{\boldsymbol{\theta}} \frac{\partial g}{\partial \boldsymbol{\theta}}\right) \quad (7)$$

Looking at just the variance term we can compute the gradient:

$$\frac{\partial g}{\partial \boldsymbol{\theta}} = \begin{bmatrix} \frac{\partial g}{\partial \mu} \\ \frac{\partial g}{\partial \sigma^2} \end{bmatrix} = \begin{bmatrix} \frac{\partial}{\partial \mu} \frac{\mu}{\sigma} \sqrt{q} \\ \frac{\partial}{\partial \sigma^2} \frac{\mu}{\sigma} \sqrt{q} \end{bmatrix} = \begin{bmatrix} \frac{\partial}{\partial \mu} \frac{\mu}{\sigma} \sqrt{q} \\ \frac{\partial}{\partial \sigma^2} \frac{\mu}{\sqrt{\sigma^2}} \sqrt{q} \end{bmatrix} = \begin{bmatrix} \frac{\sqrt{q}}{\sigma} \\ -2\mu(\sigma^2)^{-\frac{3}{2}} \sqrt{q} \end{bmatrix} = \begin{bmatrix} \frac{\sqrt{q}}{\sigma} \\ -\frac{\mu}{\sigma^3} \sqrt{q} \end{bmatrix}.$$

Taking this partial derivative and calculating the variance term for Equation 7.

$$\begin{aligned} \left(\frac{\partial g}{\partial \boldsymbol{\theta}}\right)' \mathbf{V}_{\boldsymbol{\theta}} \frac{\partial g}{\partial \boldsymbol{\theta}} &= \begin{bmatrix} \frac{\sqrt{q}}{\sigma} & -\frac{\mu}{2\sigma^3} \sqrt{q} \end{bmatrix} \begin{bmatrix} \sigma^2 & 0 \\ 0 & 2\sigma^4 \end{bmatrix} \begin{bmatrix} \frac{\sqrt{q}}{\sigma} \\ -\frac{\mu}{2\sigma^3} \sqrt{q} \end{bmatrix} = [\sqrt{q}\sigma \quad -\mu\sigma\sqrt{q}] \begin{bmatrix} \frac{\sqrt{q}}{\sigma} \\ -\frac{\mu}{2\sigma^3} \sqrt{q} \end{bmatrix} \\ \left(\frac{\partial g}{\partial \boldsymbol{\theta}}\right)' \mathbf{V}_{\boldsymbol{\theta}} \frac{\partial g}{\partial \boldsymbol{\theta}} &= q + \frac{q\mu^2}{2\sigma^2} = q + \frac{SR^2}{2} = q \left(1 + \frac{SR^2}{2q}\right) \end{aligned}$$

Using Equation 1 we see that $SR = \frac{\mu}{\sigma}\sqrt{q}$ so $SR^2 = \frac{\mu^2}{\sigma^2}q$. We can substitute this back into Equation 7 and find the distribution for \hat{SR} , remember that $g(\hat{\theta}) = \hat{SR}$ and $g(\theta) = SR$

$$\sqrt{T}(\hat{SR} - SR) \underset{T \rightarrow \infty}{\overset{a}{\rightsquigarrow}} N\left(0, q\left(1 + \frac{SR^2}{2q}\right)\right)$$

$$\hat{SR} \underset{T \rightarrow \infty}{\overset{a}{\rightsquigarrow}} N\left(SR, \frac{q\left(1 + \frac{SR^2}{2q}\right)}{T}\right)$$

Annualisation

Since $T = yq$, we express the asymptotic variance per year by switching the limiting argument from $T \rightarrow \infty$ to $y \rightarrow \infty$ to reflect the annualized Sharpe ratio. Writing the variance in terms of years makes it explicit that the uncertainty in the estimate decreases as the number of years of data grows, which is the meaningful timescale for investors.

$$\hat{SR} \underset{y \rightarrow \infty}{\overset{a}{\rightsquigarrow}} N\left(SR, \frac{q\left(1 + \frac{SR^2}{2q}\right)}{qy}\right)$$

$$\boxed{\hat{SR} \underset{y \rightarrow \infty}{\overset{a}{\rightsquigarrow}} N\left(SR, \frac{1 + \frac{SR^2}{2q}}{y}\right)}$$

The final asymptotic variance $\frac{1 + \frac{SR^2}{2q}}{y}$ shows two effects: (1) the variance shrinks with more years of data, and (2) higher Sharpe ratios increase estimation error slightly due to their dependence on both μ and σ^2 .

Question 2: Question 2: Expected Maximum of a Sample of IID Normal Variables

Motivate and justify the following approximation for large N :

Theorem 1.1. Given a sample of N IID Normal random variables X_n , $n = 1, 2, \dots, N$, where Z is the CDF of the standard normal distribution, the expected maximum of the sample is:

$$E[\max_N] := E[\max\{X_n\}].$$

The expected maximum can be approximated as:

$$E[\max_N] \approx (1 - \gamma)Z^{-1}\left(1 - \frac{1}{N}\right) + \gamma Z^{-1}\left(1 - \frac{1}{N}e^{-1}\right)$$

for some constant γ

To approximate the expected maximum of N i.i.d. Normal random variables, we proceed in three steps.

Step 1: Show the Normal is von Mises. Using Example 3.3.29 (Embrecchts et al., 1997), we first verify that the standard Normal distribution is a von Mises function with auxiliary function $a(x)$.

Step 2: Connect to the Gumbel MDA. By Proposition 3.3.25 (Embrecchts et al., 1997), any von Mises function belongs to the maximum domain of attraction of the Gumbel distribution ($\text{MDA}(\Lambda)$). Moreover, Proposition 3.3.28 (Embrecchts et al., 1997) shows that if two distributions are tail equivalent, they share the same MDA and norming constants. Together, these results guarantee that the maxima of a Normal sample, once properly normalized, converge in distribution to the Gumbel law, which is the Gumbel case of the Fisher–Tippett–Gnedenko theorem.

Step 3: Convergence of moments. We apply Resnick’s Proposition (iii) on moment convergence, we obtain that the expectation of the normalised maximum converges to the Euler–Mascheroni constant γ (Resnick, 1987). Together, these results yield the approximation $\mathbb{E}(x) \approx \alpha + \gamma\beta$ with α, β being norming constants derived from the Normal distribution.

Definition of the von Mises Function

Let F be a cumulative distribution function (CDF) with right endpoint x_F is the largest possible value that the random variable X can take (if it exists) or $+\infty$ if X is unbounded.

$$x_F = \sup\{x \in \mathbb{R} : F(x) < 1\} \in (-\infty, \infty]$$

We denote the survival function by

$$\bar{F}(x) = 1 - F(x)$$

We say F is a von Mises Function if there exists a scalar $z < x_F$ and functions $a(x)$, $c(x)$ satisfying the following conditions:

-
- $a : (z, x_f) \rightarrow (0, \infty)$ is a positive, absolutely continuous function (called the auxiliary function). It is a positive function that controls the rate of decay of the tail of F.
 - $c : (z, x_F) \rightarrow (0, \infty)$ is a positive function such that $\lim_{x \rightarrow x_f} c(x) = c > 0$ i.e. This means that as x gets arbitrarily close to x_F from below, the function $c(x)$ approaches a finite positive constant c . It serves as a normalizing factor to make the representation exact.

Then for all $x \in (z, x_F)$ the survival function admits the representation

$$\bar{F}(x) = c(x) \exp \left(- \int_z^x \frac{1}{a(t)} dt \right) \quad z < x < x_F \quad (8)$$

Showing that the Normal Distribution is a von Mises Function

Let $X \sim N(0, 1)$ with the cumulative distribution function $Z(x)$ and the probability density function $\phi(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$. Denote the survival function (tail) by

$$\bar{Z}(x) = 1 - Z(x)$$

We are going to check the von Mises conditions to show that $\bar{F}(x) = \bar{Z}(x)$.

- The standard normal is unbounded above, so $x_F = +\infty$. We can choose arbitrary $z = 0$ where $z < x_F$.
- We can define the auxiliary function as

$$a(x) = \frac{\bar{Z}(x)}{\phi(x)}$$

, where $\phi(x) > 0$ and $\bar{Z}(x) > 0$ for all x , so $a(x) > 0$.

- Defining the normalising factor $c(x)$:
 - Using the von Mises representation, it suggests we can find

$$c(x) = \bar{Z}(x) \exp \left(- \int_z^x \frac{1}{a(t)} dt \right)$$

- To obtain the asymptotic form of the standard normal tail we apply L'Hôpital's rule, this will give us Mills' Ratio. Firstly we check that the limits of the numerator and denominator of our proposed ratio

$$\lim_{x \rightarrow \infty} \frac{\bar{Z}(x)}{\phi(x)} \rightarrow 0$$

Secondly, we find the first derivatives for the numerator and the denominator

$$\begin{aligned} \lim_{x \rightarrow \infty} \frac{\bar{Z}(x)}{\frac{\phi(x)}{x}} &= \lim_{x \rightarrow \infty} \frac{\frac{d}{dx}(\bar{Z}(x))}{\frac{d}{dx} \frac{\phi(x)}{x}} = \lim_{x \rightarrow \infty} \frac{\frac{d}{dx}(1 - Z(x))}{\frac{\phi'(x)x - \phi(x)}{x^2}} = \lim_{x \rightarrow \infty} \frac{-Z'(x)}{\frac{-x\phi(x) \cdot x - \phi(x)}{x^2}} = \\ &= \lim_{x \rightarrow \infty} \frac{-\phi(x)}{-\phi(x) \left(1 + \frac{1}{x^2}\right)} = \lim_{x \rightarrow \infty} \frac{-\phi(x)}{-\phi(x)} = 1 \end{aligned}$$

Therefore, we can use the following rates of change form instead of the raw values (i.e. Mills' Ratio)

$$\bar{Z}(x) \sim \frac{\phi(x)}{x} \quad x \rightarrow \infty \quad (9)$$

- We can apply Mills' Ratio $\bar{Z}(x) \sim \frac{\phi(x)}{x}$ as $x \rightarrow \infty$ to our auxiliary function becomes

$$a(x) = \frac{\bar{Z}(x)}{\phi(x)} = \frac{\frac{\phi(x)}{x}}{\phi(x)} \sim \frac{1}{x} \quad (10)$$

- Therefore solving for $c(x)$

$$\begin{aligned} c(x) &= \bar{Z}(x) \exp \left(\int_z^x \frac{1}{a(t)} dt \right) = \bar{Z}(x) \exp \left(\int_z^x \frac{1}{\frac{1}{t}} dt \right) = \frac{\phi(x)}{x} \cdot \exp \left(\frac{x^2}{2} \right). \\ c(x) &= \frac{1}{\sqrt{2\pi}} \exp \left(-\frac{x^2}{2} \right) \frac{1}{x} \exp \left(\frac{x^2}{2} \right) = \frac{1}{x\sqrt{2\pi}} \end{aligned}$$

Note that $c(x) > 0$ as $x \rightarrow \infty$ for unbounded distributions like the normal, the slowly varying factor $c(x)$ may converge to zero as long as it varies slower than the exponential decay.

Therefore, with $a(x) \sim \frac{1}{x}$ and $c(x) \sim \frac{1}{x\sqrt{2\pi}}$, using Equation 8 we have

$$\bar{Z}(x) \sim c(x) \exp \left(- \int_z^x \frac{1}{a(t)} dt \right) = \frac{1}{x\sqrt{2\pi}} \exp \left(- \frac{x^2}{2} \right)$$

which is exactly the standard tail approximation (Mills' ratio) for the standard normal distribution. Since the standard normal distribution satisfies all the von Mises conditions we conclude that the standard normal distribution is a von Mises function.

Proposition 3.3.25: von Mises Functions and the Max-Domain of Attraction (MDA)

Suppose the distribution function F is a von Mises function with auxiliary function $a(x)$. Then F belongs to the max-domain of attraction (MDA) of the Gumbel distribution.

- Max-domain of attraction (MDA): This means that if X_1, X_2, \dots, X_N , where $n = 1, 2, \dots, N$, are IID random variables with distribution F , then the properly normalized

maximum

$$M_N := \max\{X_1, X_2, \dots, X_N\} \underset{N \rightarrow \infty}{\overset{a}{\sim}} G \quad (11)$$

Where G is the Gumbel distribution i.e. $F \in \text{MDA}(\Lambda)$

- A possible choice of norming constants for continuous and strictly increasing distribution function like the normal distribution is:

$$d_N := F^{-1}\left(1 - \frac{1}{N}\right) \quad c_N := a(d_N) \quad (12)$$

where $a(x)$ is the auxiliary function of F . Then the normalized maximum converges to

$$\frac{M_N - d_N}{c_N} \underset{n \rightarrow \infty}{\overset{d}{\rightarrow}} G \quad (13)$$

where G is the standard Gumbel distribution with cdf $G(x) = \exp(-e^{-x})$

Linking the von Mises–MDA Proposition to the Standard Normal Distribution

We now apply Proposition 3.3.25 to the standard normal distribution $X \sim N(0, 1)$. Since we have already shown from Equation 10 that $Z(x)$ is a von Mises function with auxiliary function $a(x) \sim \frac{1}{x}$ as $x \rightarrow \infty$, the standard normal belongs to the max-domain of attraction (MDA) of the Gumbel distribution i.e. $Z(x) \in \text{MDA}(\Lambda)$ Equation 11.

Proposition 3.3.28: Closure Property of MDA under Tail Equivalence

Let F and H be two distribution functions with the same right endpoint $x_F = x_H$. Suppose F belongs to the max-domain of attraction (MDA) $F \in \text{MDA}(\Lambda)$ with norming constants $(c_N > 0, d_N \in \mathbb{R})$.

Then G also belongs to the same MDA with the same norming constants (c_N, d_N) , i.e.

$$\lim_{n \rightarrow \infty} F^n(c_n x + d_n) = \Lambda(x) \quad x \in \mathbb{R}$$

then

$$\lim_{n \rightarrow \infty} H^n(c_n x + d_n) = \Lambda(x + b) \quad x \in \mathbb{R}$$

if and only if F and H are tail equivalent with

$$\lim_{x \rightarrow x_F} \frac{\bar{F}(x)}{\bar{H}(x)} = e^b \quad (14)$$

for some finite constant $b \in \mathbb{R}$

Applying the closure proposition

Now that we have established the standard normal belongs to the max-domain of attraction of the Gumbel Distribution, we need to compute the norming constants d_N and c_N to properly

normalise the maximum M_N i.e. Equation 13 establishing the Gumbel limiting distribution for the standard normal maximum.

First we acknowledge the usage of the L'Hôpital's rule to give us Equation 9 showing that $\bar{Z}(x) \sim \frac{\phi(x)}{x}$ as $x \rightarrow \infty$, we further use the Proposition 3.3.28 to establish our usage of Mills' Ratio as an easier distribution to work with compared to the more complicated Inverse CDF i.e. $\bar{Z}(x) = 1 - Z(x)$ of the standard normal distribution we would've worked with.

So taking $\bar{Z}(x) \sim \frac{\phi(x)}{x}$ as $x \rightarrow \infty$ and denoting $\bar{H}(x) := \frac{\phi(x)}{x}$, we can see that \bar{Z} and \bar{H} are tail equivalent with

$$\lim_{x \rightarrow \infty} \frac{\bar{Z}(x)}{\bar{H}(x)} = \lim_{x \rightarrow \infty} \frac{\frac{\phi(x)}{x}}{\frac{\phi(x)}{x}} = e^0 = 1$$

where $b = 0$, therefore showing Equation 14 and allowing us to use the norming constants computed for \bar{H} directly for \bar{Z} . This simplifies the calculation for d_N and c_N for the standard normal maximum and ensures that the asymptotic Gumbel approximation holds.

Calculation d_N normalising constant

From Equation 12, we choose $d_N = H^{-1} \left(1 - \frac{1}{N}\right)$. Intuitively, d_n represents the level such that the probability of exceeding it is $\frac{1}{N}$, i.e., the level of the expected maximum in a sample of size n . Equivalently, we can rewrite this in terms of the survival function:

$$\bar{H}(d_N) = \frac{1}{N} \quad \Rightarrow \quad -\ln \bar{H}(d_N) = \ln N$$

For the tail of the normal distribution, $\bar{H}(x) = \frac{\phi(x)}{x} \sim \frac{1}{\sqrt{2\pi}x} e^{-\frac{x^2}{2}}$, so taking the logarithm gives

$$-\ln \bar{H}(d_N) = -\ln \left(\frac{1}{\sqrt{2\pi}d_N} e^{-\frac{d_N^2}{2}} \right) = \frac{1}{2}d_N^2 + \ln(d_N) + \frac{1}{2}\ln 2\pi = \ln N$$

Now we can solve for d_N , but since this equation is non-linear, we'll find the asymptotic solution for large N using a Taylor expansion. The leading-order term

$$\frac{1}{2}d_N^2 \approx \ln N \quad \Rightarrow \quad d_N \sim \sqrt{2 \ln N}$$

Including the next-order correction from $\ln(d_N) + \frac{1}{2} \ln(2\pi)$, we expand and solve asymptotically:

$$d_N \approx \sqrt{2 \ln N} - \frac{\ln(\sqrt{2 \ln N}) + \frac{1}{2} \ln(2\pi)}{\sqrt{2 \ln N}}$$

Simplifying the logarithms yields the refined expansion:

$$d_N \approx \sqrt{2 \ln N} - \frac{\ln(\ln N) + \ln(4\pi)}{2\sqrt{2 \ln N}} + O((\ln N)^{-1/2}) \approx \sqrt{2 \ln N} - \frac{\ln(\ln N) + \ln(4\pi)}{2\sqrt{2 \ln N}} \quad (15)$$

Calculation c_N normalising constant

From Equation 12, we choose $c_N = a(d_N)$. Since $a(x) = \frac{1}{x}$ from Equation 10, we therefore get

$$c_N = a(d_N) = Z(d_N) \sim \frac{1}{\sqrt{2 \ln N}} = (2 \ln N)^{-\frac{1}{2}} \quad (16)$$

Proposition (iii)

Let $F = \Lambda$ and let H have right endpoint (x_F) . Define the norming constants

$$d_N = H^{-1} \left(1 - \frac{1}{N} \right), \quad c_N = a(d_N),$$

If for some integer $(k > 0)$

$$\int_{-\infty}^{x_H} |x|^k H(dx) < \infty,$$

then

$$\lim_{n \rightarrow \infty} \mathbb{E} \left[\left(\frac{M_N - d_N}{c_N} \right)^k \right] = \int_{-\infty}^{\infty} x^k \Lambda(dx) = (-1)^k \Gamma^{(k)}(1), \quad (17)$$

where $\Gamma^{(k)}(1) = \gamma \approx 0.5772$ is the k -th derivative of the Gamma function evaluated at $x = 1$ which is Euler–Mascheroni constant.

Combined

We can use Equation 13 and Equation 17 to show the approximation to the normalized maximum of the standard normal

$$\frac{M_N - d_N}{c_N} \xrightarrow[n \rightarrow \infty]{d} G$$

Using Proposition (iii) on moments Equation 17 to get the Gumbel limit where $k=1$

$$\lim_{N \rightarrow \infty} \mathbb{E} \left[\left(\frac{M_N - d_N}{c_N} \right)^1 \right] = \int_{-\infty}^{\infty} x^1 \Lambda(dx) = \Gamma^{(1)}(1) = \gamma$$

Solving for the $\mathbb{E}[M_N]$ we get the following

$$\lim_{N \rightarrow \infty} \mathbb{E} \left[\left(\frac{M_N - d_N}{c_N} \right)^1 \right] = \gamma \quad \Rightarrow \quad \mathbb{E}[M_N] \approx d_N + c_N \gamma = (1 - \gamma)d_N + \gamma(d_N + c_N)$$

Remembering that $d_N = H^{-1} \left(1 - \frac{1}{N} \right) = Z^{-1} \left(1 - \frac{1}{N} \right)$ and $c_N = a(d_N) = \frac{1}{Z^{-1} \left(1 - \frac{1}{N} \right)}$

$$\mathbb{E}[M_N] = (1 - \gamma)Z^{-1} \left(1 - \frac{1}{N} \right) + \gamma \left(Z^{-1} \left(1 - \frac{1}{N} \right) + \frac{1}{Z^{-1} \left(1 - \frac{1}{N} \right)} \right)$$

Equivalently,

$$\mathbb{E}[M_N] = (1 - \gamma)Z^{-1} \left(1 - \frac{1}{N} \right) + \gamma Z^{-1} \left(1 - \frac{1}{N} e^{-1} \right)$$

The left-hand term is equivalent to the result Equation 15 i.e. $Z^{-1} \left(1 - \frac{1}{N} \right) = d_N$, this tells us the size of the maximum. The right-hand term is equivalent to Equation 15 + Equation 16 i.e. $Z^{-1} \left(1 - \frac{1}{N} e^{-1} \right) = d_N + c_N$, this gives the appropriate scaling of the maximum so that when we normalize M_N it converges in distribution to a standard Gumbel.

Question 3: Minimum Backtest Length to Avoid Overfitting

References

- Embrechts, P., Klüppelberg, C., & Mikosch, T. (1997). *Modelling extremal events: For insurance and finance* (Vol. 33). Springer-Verlag. <https://doi.org/10.1007/978-3-642-33483-2>
- Lo, A. W. (2002). The statistics of sharpe ratios. *Financial Analysts Journal*, 58(4), 36–52. <https://doi.org/10.2469/faj.v58.n4.2453>
- Resnick, S. I. (1987). *Extreme values, regular variation and point processes*. Springer. <https://doi.org/10.1007/978-0-387-75953-1>