

04.21. June, 2022

Hansen's SPA Test

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- Consider a decision made under conditions of uncertainty h periods ahead

- Let

$$\{\delta_{k,t-h}, k=0,1,\dots,M\}$$

be a finite set of decision rules.

- Decisions are evaluated with a real-valued loss function

$$L\left(\sum_t, \delta_{k,t-h}\right)$$

where \sum_t is a random variable that represents

the aspects of the problem that are unknown at the time the decision must be made.

- We evaluate forecasts/predictions in terms of their expected loss,

$$E \left[L \left(\frac{y}{x}_t, \delta_{k,t-h} \right) \right]$$

- We don't need to assume that any of the forecasts are made from a "correctly specified" population model.
 - Indeed, we don't have to believe in or reference any such thing
- Typically, the situation will require the estimation of parameters from a forecasting model as an indirect step in obtaining forecasts

$$\delta_{k,t-h} = \delta_{k,t-h}(\hat{\theta}_{k,t-h})$$

- These $\hat{\theta}_{k,t-h}$ are likely to influence expected loss — typically by increasing loss
- The first model $k=0$ plays a special role and is called the benchmark
- The decision rule can represent a point forecast, an interval forecast, $(\delta_{k,b-h})$ density forecast, trading rule, or other heuristic for decision making under uncertainty

Example (Trading Rule)

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- Let $\delta_{k,t-1}$ ($h=1$ period) be a binary "signal function"

that instructs a trader to take either a short ($\delta = -1$) or a long ($\delta = +1$) position in an asset at time $t-1$

- The k^{th} trading rule yields the profit

$$\pi_{k,t} = 1.0 + \delta_{k,t-1} r_t$$

where r_t is the return on the asset in period t

$$r_t = \ln P_t - \ln P_{t-1}$$

where P_t is the asset price, index level, or portfolio NAV at time t

- Say we have a forecasting model in the form of a simple linear regression (for simplicity's sake) that takes the form

~~the~~

$$\hat{r}_{k,t} = \hat{\alpha} + \hat{\beta} X_{t-1}$$

- We can generate the signal as

$$s_{k,t} = \text{sign}(\hat{r}_{k,t})$$

(6)

- Of course we generate many such models
- We wish to know if any of the models $k=1, \dots, m$ outperform the benchmark model $\delta_{0,t}$ in terms of expected loss
- So we set up a null hypothesis that the benchmark is NOT inferior to any of the alternatives
- Key to this analysis is the relative performance defined as

$$d_{k,t} = L\left(\frac{\xi}{\eta}_t, \delta_{0,t-h}\right) - L\left(\frac{\xi}{\eta}_t, \delta_{k,t-h}\right) \quad \text{for } k=1, \dots, m$$

— So $d_{k,t}$ denotes the performance of model k relative to the benchmark

— We are working with isoelastic utility, so

$$U(\pi_{k,t}) = \frac{(\pi_{k,t})^{1-\sigma}}{1-\sigma} \quad \text{for } \sigma=2,3,4,5$$

so

$$L\left(\frac{x}{x_t}, \delta_{k,t}\right) = -U(\pi_{k,t})$$

— Let's look at an example set of calculations for $\alpha=2.0$

— Suppose $r_t = -0.05$ at time t

— Let $\delta_{0,t} = +1$, that is the benchmark model is a constant "long-only" strategy

— Suppose that $\delta_{k,t} = -1$ for an arbitrary model k (i.e. the k^{th} model yields a "short" signal)

- Then we have the following results

$$L_{0,t} = \frac{- \left(1.0 + \overset{\substack{\downarrow g_{0,t} \\ \uparrow r_t}}{+1} (-0.05) \right)^{1-2}}{1-2} = 1.0526$$

$$L_{k,t} = \frac{- \left(1.0 + \overset{\substack{\downarrow g_{k,t} \\ \uparrow r_t}}{-1} (-0.05) \right)^{1-2}}{1-2} = 0.9524$$

$$d_{k,t} = \overset{\substack{\uparrow \\ L_{0,t}}}{1.0526} - \overset{\substack{\uparrow \\ L_{k,t}}}{0.9524} = \underbrace{0.1002}_{\text{positive loss differential}}$$

NB: Model k outperforms the benchmark

Loss is an "economic bad",
so a higher $d_{k,t}$ favors
model k more and more as
it increases!

- Hypothesis of Interest

- Stack the $d_{k,t}$ for $1, \dots, m$ and call it

$$\text{bold } \mathbf{d}_t = (d_{1,t}, d_{2,t}, \dots, d_{m,t})'$$

which is the vector of relative performances at time t

$$\text{bold } \mu = E[\mathbf{d}_t]$$

- We can formulate our null

$$H_0: \mu \leq 0$$

— We work under the assumption that model k is better than the benchmark iff $E(d_{k,t}) > 0$

— So, once the d_t have been calculated, we work exclusively from here on with these relative losses

— Step 1: calculate $\{d_{k,t}\}_{t=1}^T$ for $k=1, \dots, m$

— Step 2: move on to calculate $T_n^{RC} = \max(n^{1/2}\bar{d}_1, \dots, n^{1/2}\bar{d}_m)$

$$\text{where } \bar{d}_k = \frac{1}{n} \sum_{t=1}^n d_{k,t}$$

— The test statistic becomes

$$T_n^{RC} = \max(n^{1/2}\bar{d}_1, \dots, n^{1/2}\bar{d}_m)$$

— This makes sense b/c we're looking the best performing model relative to the benchmark model ($\delta_{0,t} = +1$)

— So far this identical to White's Reality Check (RC)

— Hansen's SPA alters the test statistic as the following

$$T_n^{SPA} = \max \left[\underbrace{\max_{k=1, \dots, m} \left(\frac{n^{1/2} \bar{d}_k}{\hat{\omega}_k} \right)}_{\substack{\text{the best performing} \\ \text{model} \\ * \text{ can still be} \\ \text{negative}}}, 0 \right]$$

None if no model j has $\bar{d}_j > 0$

— Hansen follows White by considering two methods for implementation:

1. Parametric Monte Carlo
2. Bootstrap

— We will only consider the bootstrap, as is general practice

— Hansen uses the Politis's $\hat{\gamma}$ Ramanuo stationary bootstrap

- The stationary bootstrap produces pseudo-time series

$$\{d_{b,t}^*\} \equiv \{d_{\tau_{b,t}}\} \quad b = 1, \dots, B$$

where $\{\tau_{b,1}, \dots, \tau_{b,n}\}$ is constructed

by combining blocks of $\{1, \dots, n\}$ of random lengths

- The typical case is with block length chose from a geometrically distributed parameter $q \in (0, 1]$
- B should be chose large enough so as to not be affected by the actual draws of $\tau_{b,t}$
- For us, there is no reason not to set $B \geq 10,000$

- From the pseudo-time series we calculate their sample averages

$$\bar{d}_b^* \equiv \frac{1}{n} \sum_{t=1}^n d_{b,t}^* \quad b = 1, \dots, B$$

- We seek the distribution of the test statistic under the null hypothesis, so we impose the null by recentering the bootstrap variables around $\hat{\mu}^l, \hat{\mu}^c, \hat{\mu}^u$

$$Z_{k,b,t}^* \equiv d_{k,b,t}^* - g_i(\bar{d}_k) \quad \text{for}$$

$$i = l, c, u$$

$$b = 1, \dots, B$$

$$t = 1, \dots, n$$

$$- g_l(x) = \max(0, x)$$

$$g_c(x) = x \cdot \mathbb{1}\{x \geq -\sqrt{(\hat{\omega}_k^2/n)} z \ln \ln n\}$$

$$g_u(x) = x$$

- The expected values of $Z_{k,b,t}^*$, $i = l, c, u$ conditional on (d_1, \dots, d_n) are given by $\hat{\mu}^l, \hat{\mu}^c, \hat{\mu}^u$

- ~~let $\hat{\mu} = \hat{\mu}^l, \hat{\mu}^c, \hat{\mu}^u$ then~~ (skip this)

- The test statistic becomes

$$T_{b,n}^{SPA*} = \max \left\{ 0, \max_{k=1, \dots, m} \left[\eta^{1/2} \bar{Z}_{k,b}^* / \hat{\omega}_k \right] \right\}$$

for $b = 1, \dots, B$

— where

$$\bar{Z}_{k,b}^* = \frac{1}{n} \sum_{t=1}^n Z_{k,b,t}^* \quad \text{for } k = 1, \dots, m$$

$\hat{\omega}_k$ = a variance estimate $\left(\begin{array}{l} \text{I'm really going into this calculation.} \\ \text{The SPA function will handle this for you!} \end{array} \right)$

— The Bootstrap p-value is given by

$$\hat{p}_{SPA} = \frac{\sum_{b=1}^B \mathbb{1} \{ T_{bn}^{SPA*} > T_n^{SPA} \}}{B}$$

— The null should be rejected for small p-values

— There will be three values for each of $i = l, c, u$

(The SPA test spits them out)

— See Table 1 of Hansen (JBES, 2005) to keep things
straight