# Portfolio Managment: Homework 3

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*April 11, 2017*

## A.1. Questions on Treasury Inflation-Protected Securities (TIPS).

### a)

Regular bonds pay a fixed coupon throughout their life and return their pre-established face value at maturity. TIPS adjust to inflation – the principal value is pinned to the CPI, and coupon amounts are calculated based on their pre-established interest rate and the adjusted principal value.

### b)

If we expect inflation to rise we can short treasuries and use the proceeds to purchase TIPS, profiting on the difference between the treasury rate and the TIPS rate on the inflation-adjusted principal amount.

## A.2. Questions on HMC's portfolio.

### a)

### b)

## B.1. Relative performance of stocks and T-bills.

### a)

Considering that an unskilled investor could choose a stock only strategy and be 'correct' (that is, select the higher return) 68.1% of the time, Claire's "skill" is unconvincing. Claire is 8% less skilled than an investor who simply chooses a stock only strategy.

```
length(which(data$stocks > data$tbills)) / NROW(data) * 100
```

```
[1] 68.1
```

### b)

```
cumreturn <- (data + 1)
kable(t(apply(cumreturn, 2, prod)), digits = 6) # in dollars
```

| tbills | stocks |
|---|---|
| 20.5 | 4598 |

## B.2. Perfect vs. random market timing.

### a)

Naturally, the omniscient strategy performs better as it selects the highest return for each given year.

| cumreturn_perfect | mean_perfect | sr_perfect | mean_market | sr_market |
|---|---|---|---|---|
| 648122 | 0.166 | 0.964 | 0.117 | 0.405 |

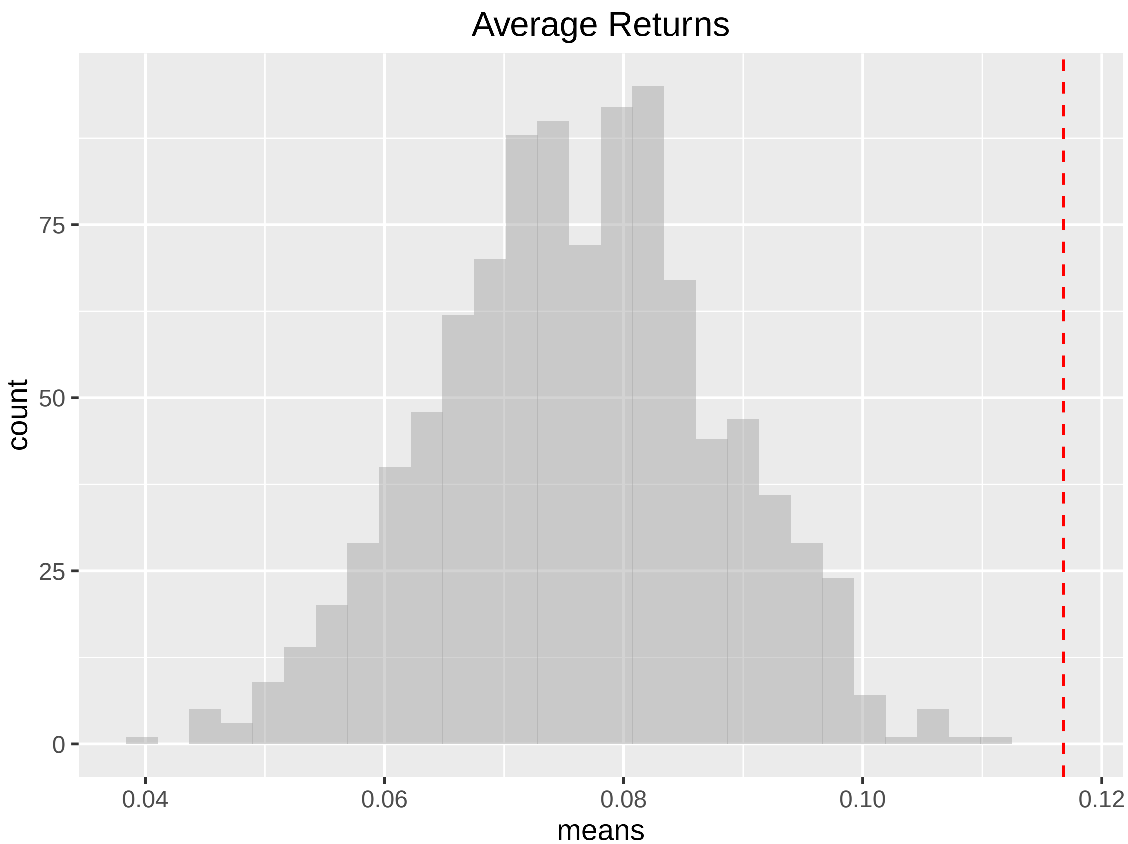
### b)

We write the function '`randomTiming`' that randomly selects between the treasury bill and market.

```
randomTiming <- function() as.matrix(apply(data, 1, function(x) sample(x, 1)))
# run 1000 simulations of random timing
simulations <- replicate(1000, randomTiming(), simplify = FALSE)

sim_means <- unlist(lapply(simulations, mean))
sim_sharperatios <- unlist(lapply(simulations,
                           function(x) mean(x - data$tbills) / sd(x - data$tbills)))
```

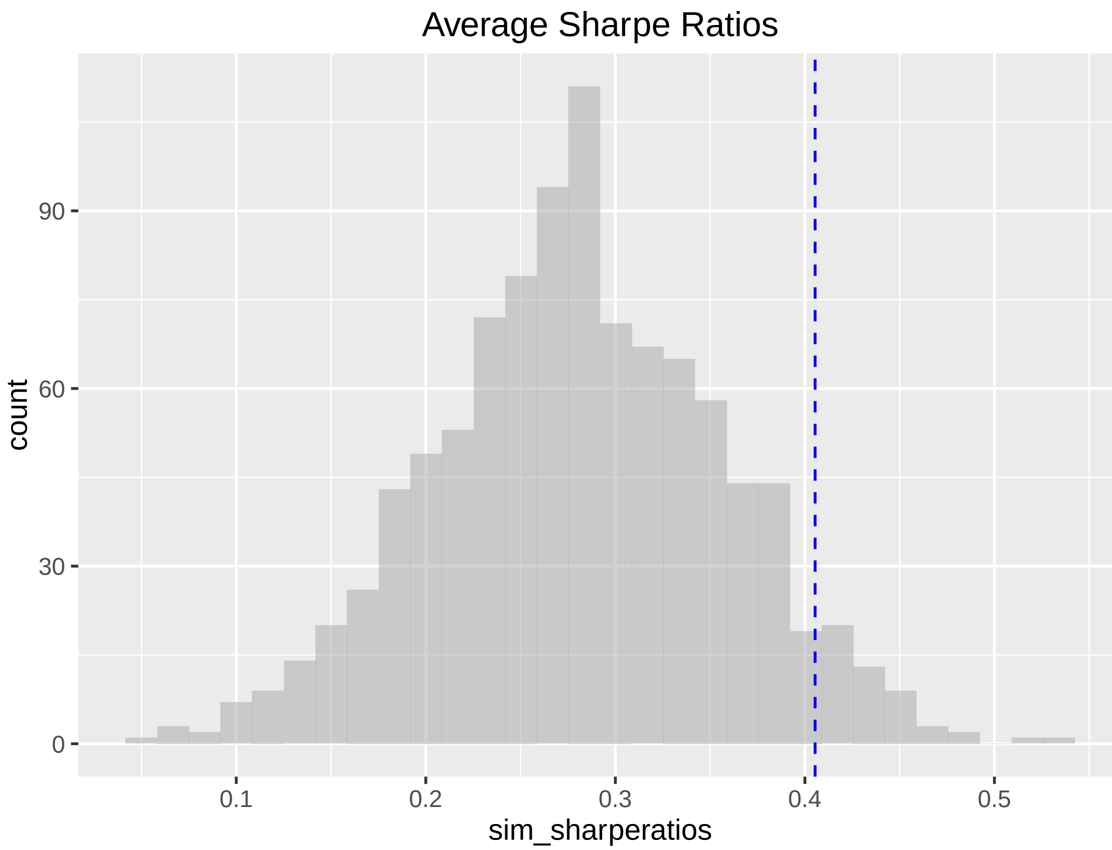
The expected return of Claire's random strategy is 7.62%. The average return of the stock only portfolio is shown in red.

```
[1] 0.0762
```




The expected Sharpe Ratio of Claire's random strategy is 0.28. The Sharpe Ratio of the stock only portfolio is shown in blue.

```
[1] 0.281
```




## B.3. Benefits of imperfect market timing.

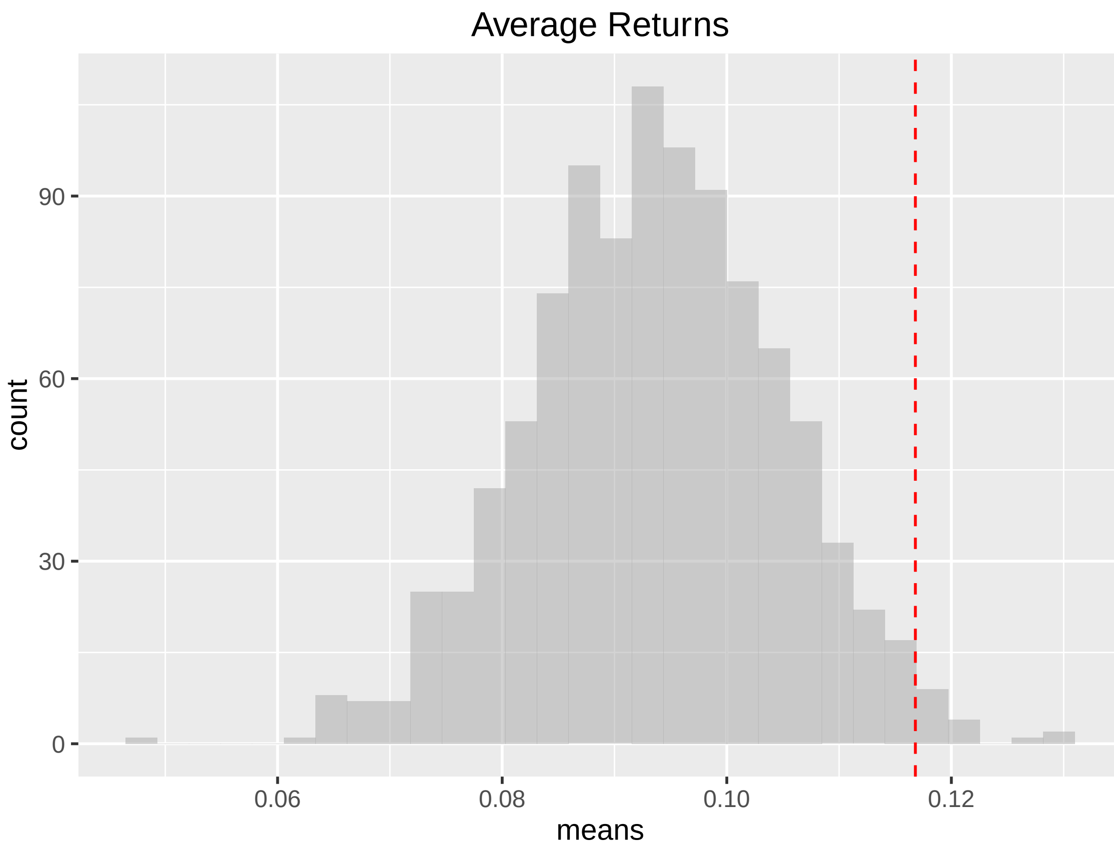
### a)

We write the function '`skillTiming`' that selects the 'correct' secruity 60% of the time.

```
skillTiming <- function() as.matrix(apply(data, 1,
               function(x) sample(c(max(x), min(x)),
                                  prob = c(0.60, 0.40), 1)))
              # get the 'correct', aka max 60% of time
simulations <- replicate(1000, skillTiming(), simplify = FALSE)
# run 1000 simulations of random timing

sim_means <- unlist(lapply(simulations, mean))
sim_sharperatios <- unlist(lapply(simulations,
                           function(x) mean(x - data$tbills) / sd(x - data$tbills)))
```

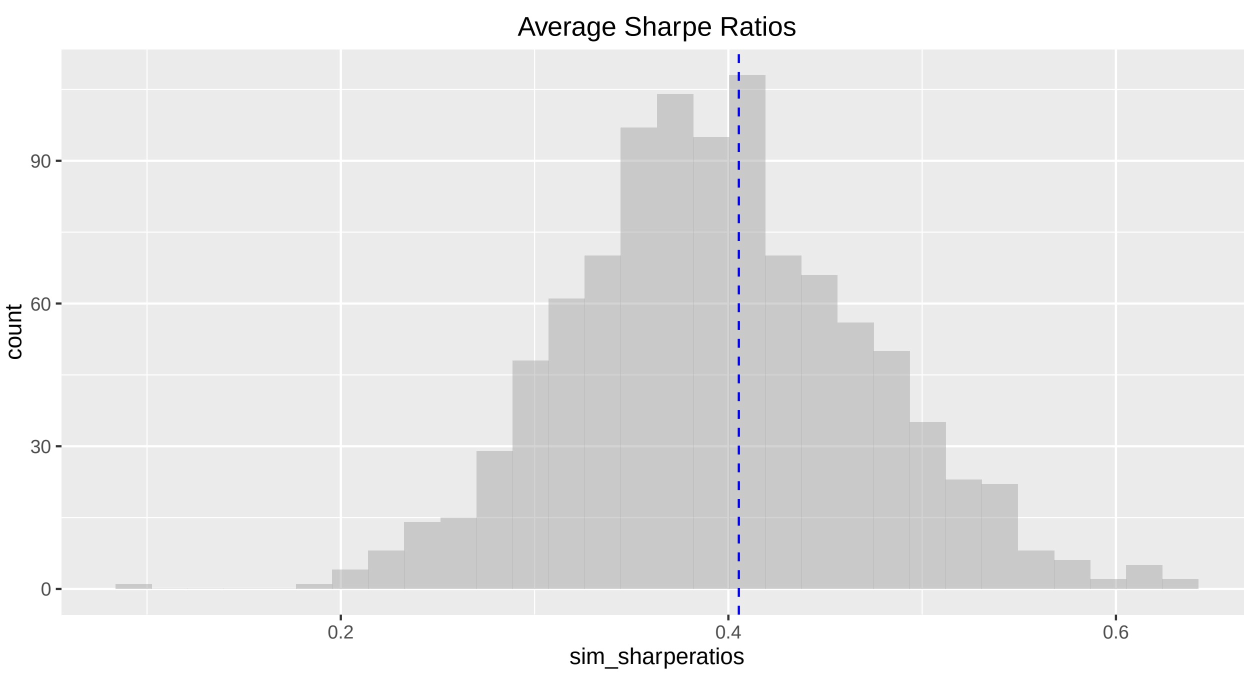
Claire's skill strategy yields an average return of 9.35%. Naturally, the skill strategy improves upon the random strategy but is still inferior to the market only portfolio.

```
[1] 0.0935
```




Equally, the 60% skill strategy yields an improved average Sharpe Ratio of 0.394.

```
[1] 0.394
```



### b)

With 2% fees, Claire's skill strategy yields a 7.35% average return and 0.261 Sharpe Ratio. As this is no better than randomly selecting between stocks and treasury bills, and worse yet than selecting a market only portfolio, we would not hire Claire based upon this fee arrangement.

```
[1] 0.0735
```

```
[1] 0.261
```

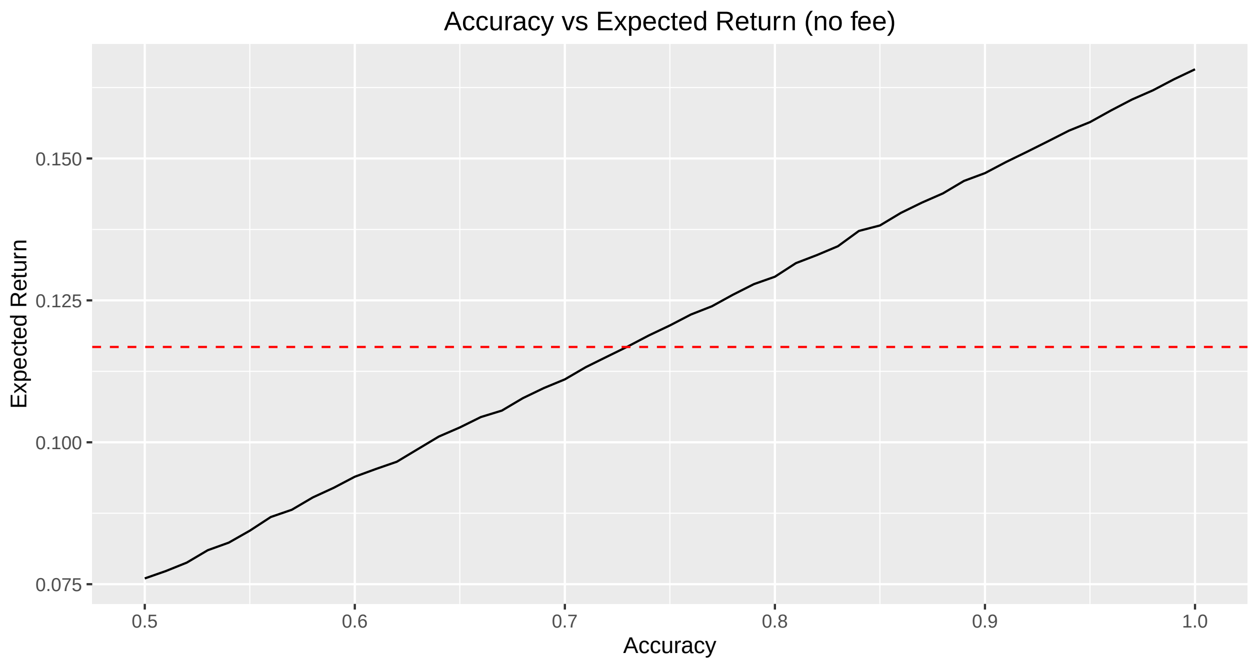
## B.4. Imperfect market timing with different forecasting accuracies.

We write the function '`skillTimingn`' that selects the 'correct' secruity n% of the time. Next, we simulate 1000 trails at an accuracy of [0.50 - 1.00], and parallize the operation over multiple cores.

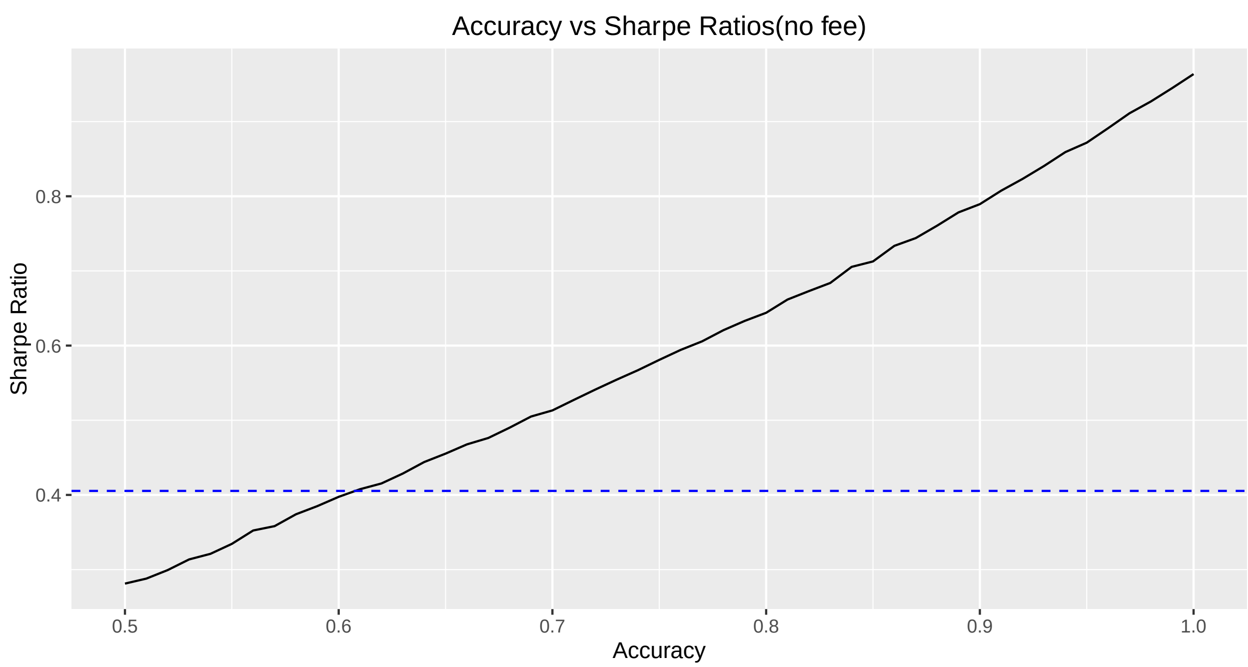
```
ns <- rep(50:100) / 100
skillTiming_n <- function(n) as.matrix(apply(data, 1,
                 function(x) sample(c(max(x), min(x)), prob = c(n, 1 - n), 1)))
# all(skillTiming_n(1.00) == perfect) # sanity check

registerDoMC(detectCores() - 1)
simulations <- foreach(i = ns) %dopar% {
  replicate(1000, skillTiming_n(i), simplify = FALSE)
  } # for each n, run a simulation

sim_means_ns <- unlist(lapply(simulations,
                      function(x) mean(unlist(lapply(x, mean)))))
sim_sharperatios <- unlist(lapply(simulations,
                      function(y) mean(unlist(lapply(y,
                      function(x) mean(x - data$tbills) / sd(x - data$tbills))))))
frame <- cbind.data.frame(ns, sim_means_ns, sim_sharperatios)
```

We plot the two cases: one without fees, and one with 2% management fees. To beat the stock-only strategy's expected return (11.68%), Claire requires a minimum accuracy of 73%. To exceed the market's Sharpe ratio (0.4054) requires an accuracy level of 61%. To beat the stock-only strategy's expected return (11.68%), Claire requires a minimum accuracy of 84%. To exceed the market's Sharpe ratio (0.4054) requires an accuracy level of 72%.

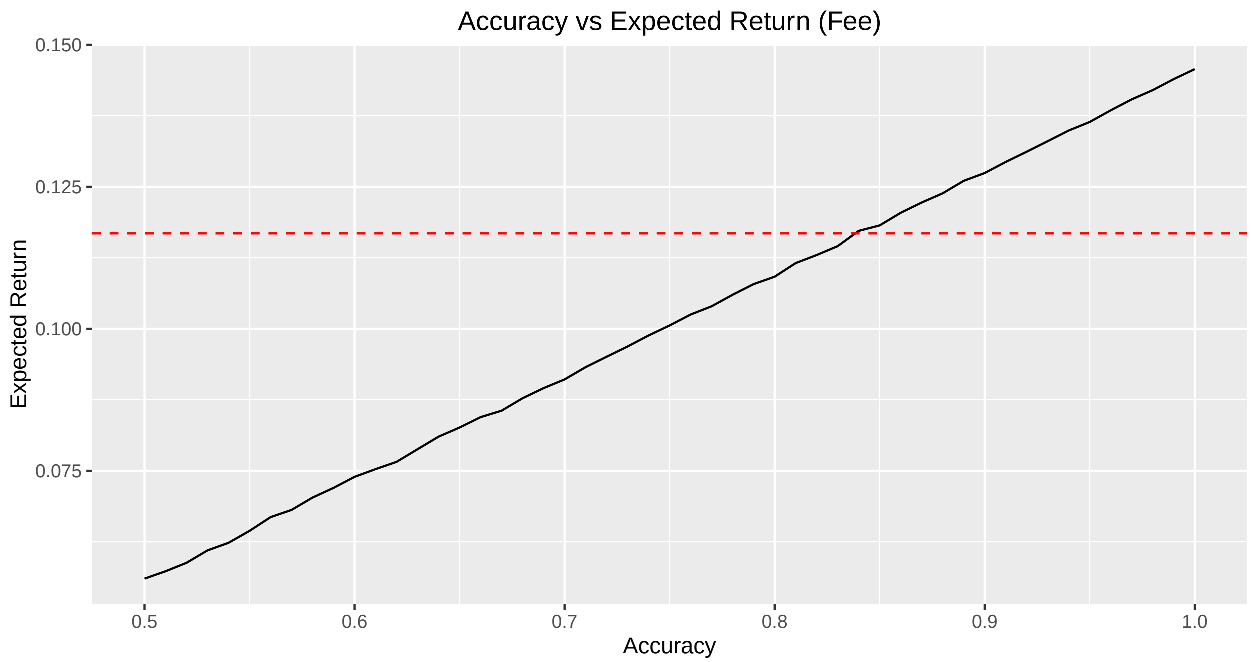
```
[1] 0.73
```


Accuracy vs Expected Return (no fee)
Expected Return
0.150
0.125
0.100
0.075
0.5
0.6
0.7
0.8
0.9
1.0
Accuracy

```
[1] 0.61
```

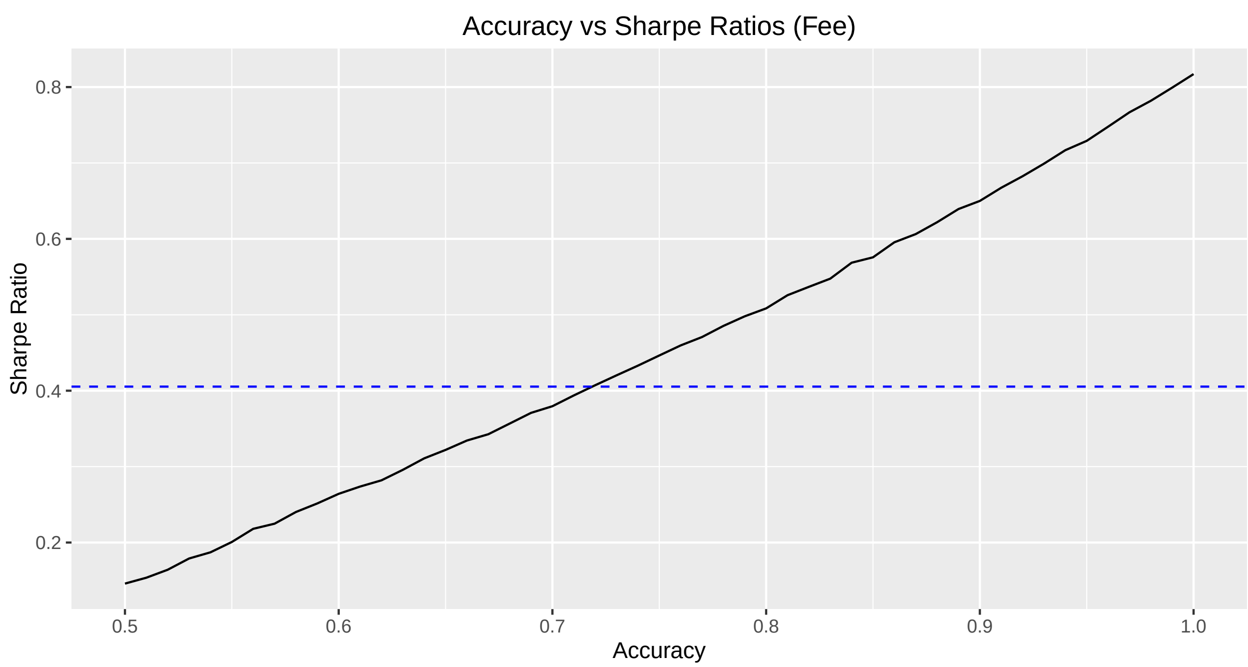

Accuracy vs Sharpe Ratios(no fee)
Sharpe Ratio
0.8
0.6
0.4
0.5
0.6
0.7
0.8
0.9
1.0
Accuracy

```
[1] 0.84
```



Accuracy vs Expected Return (Fee)
0.150
0.125
0.100
0.075
Expected Return
0.5
0.6
0.7
0.8
0.9
1.0
Accuracy


```
[1] 0.72
```



Accuracy vs Sharpe Ratios (Fee)
0.8
0.6
0.4
0.2
Sharpe Ratio
0.5
0.6
0.7
0.8
0.9
1.0
Accuracy

## C.1.

### a)

Given four possible states of the world and no market timing ability on part of the money manager, we calculate the expected return and standard deviation of the portfolio as follows:

| Prob | Rs | Rc | Ws | Ra |
|---|---|---|---|---|
| 0.25 | 0.05 | 0.01 | 0.7 | 0.038 |
| 0.25 | 0.05 | 0.01 | 0.3 | 0.022 |
| 0.25 | -0.02 | 0.01 | 0.7 | -0.011 |
| 0.25 | -0.02 | 0.01 | 0.3 | 0.001 |

Thus,

$E_A$ = 0.25(0.038 + 0.022 - 0.011 + 0.001) = 1.25%

$\sigma_A = \sqrt{0.25[(0.038 - 0.0125)^2 + (0.022 - 0.0125)^2 + (-0.011 - 0.0125)^2 + (0.001 - 0.0125)^2]^2} = 1.89\%$

### b)

– WRONG –

In english, stocks return -2% or 5% with equal probability, so on expectation our portfolio yields 1.5% with a standard deviation of 3.5%.

$E_s = \mathbb{E}[R_s]$ = 0.50(-0.02) + 0.50(0.05) = 1.5%

$\sigma_s = \text{Std}(R_s) = \sqrt{[(0.05 - 0.015)^2 + (-0.02 - 0.015)^2]/2} = 3.5\%$

Our goal is to construct a portfolio with a standard deviation equal to 1.89%. Thus, we find the optimal weights such that variance of our goal portfolio is satisfied.

$\sigma_P = \text{Std}(R_P)$ = w(0.035) + 1-w(0) = 0.0189

w = 0.54

Instead of trying to time the market, we construct a passive portfolio with constant weights:

$E_P = \mathbb{E}(R_P)$ = 0.70(0.015) + 0.30(0.01) = 1.35%

$\sigma_P = \text{Std}(R_P)$ = 0.50(0.035) + 0.50(0)

We hold a 70/30 stock/cash mix, thus we expect to yield a 1.35% return while maintaining

## C.2.

### a)

1 - Prob(z < $\sqrt{10}(\frac{0.10-0.04}{0.20})$)

= 0.171

### b)

Using the put-call parity:

2 * pnorm($\frac{0.20\sqrt{10}}{2}$) - 1

= 0.248

### c)

Naturally, as T grows the probability goes to zero.

1 - Prob(z < $\sqrt{20}(\frac{0.10-0.04}{0.20})$)

= 0.09

And the cost of insurance increases with T.

2 * pnorm($\frac{0.20\sqrt{20}}{2}$) - 1

= 0.346

### d)

In regards to the probability of underperformance when T = 10

1 - Prob(z < $\frac{0.10-0.04}{\sqrt{0.03^2+\frac{0.20^2}{10}}}$)

= 0.196

Likewise, the probability of underperformance when T = 20

1 - Prob(z < $\frac{0.10-0.04}{\sqrt{0.03^2+\frac{0.20^2}{20}}}$)

= 0.133

Natuarlly, the greater uncertainty increased the probability of underperformance. However, the effect of $\mu$ on the cost of shortfall insurance is zero. That is, the value of the option does not depend on $\mu$, so there is no change when T is either 10 or 20.

## C.3.

The authors speak to time diversification. The idea being that risk associated with high-expected-return portfolios (and thus high variance) can be reduced over longer periods of time. For this to properly work, however, the critical assumption is that returns must not be perfectly correlated over time. The returns—as the article alludes to, must be i.i.d.

## C.4.

Though the authors give a convincing argument for a behaviorist's irrational exuberance. We don't know which way the causation goes. While the Harvard MBA indicator may be significant, we can't say whether the influx of Harvard MBAs into the finance industry causes a financial crisis, or, perhaps more likely, an unseen omitted variable(s) actually causes the financial crisis. Either way, it certainly appears to be correlated, and at the least serves as an indicator. Given that Booth and Harvard MBAs are largely from the same socioeconomic circles, I would expect a similar result to hold–if not more so, given Booth's finance reputation.