

Mitigating Estimation Error in Optimization

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Background in 1 Slide

- For the purpose of construction, value is measured by a single number, portfolio utility, which typically is return penalized for risk
- Optimizers find the portfolio weights that maximize this utility
- Alas, inputs into utility are only estimates
- Optimized portfolios perform worse than their forecasted utility and may look funny

Purpose of Talk

- Disabuse the false precision of portfolio utility and optimal portfolio weights
- Describe the fundamental mechanism that causes dissatisfaction with optimization and how to avoid it
- Briefly introduce two recent estimation error adjustment features in Northfield Optimizer

An [Easy-to-Graph] Example

- Recall familiar Markowitz utility function

$$\text{Utility} = \text{return} - \lambda \times \text{variance}$$

- Allocate money across 2 stocks

- Forecast returns

- $r_1 = 9\% \pm 1\%$

- $r_2 = 10\% \pm 1\%$

- Forecast correlation $\rho = 0.4 \pm 0.2$

- (For simplicity) Std deviations are known to be 30%

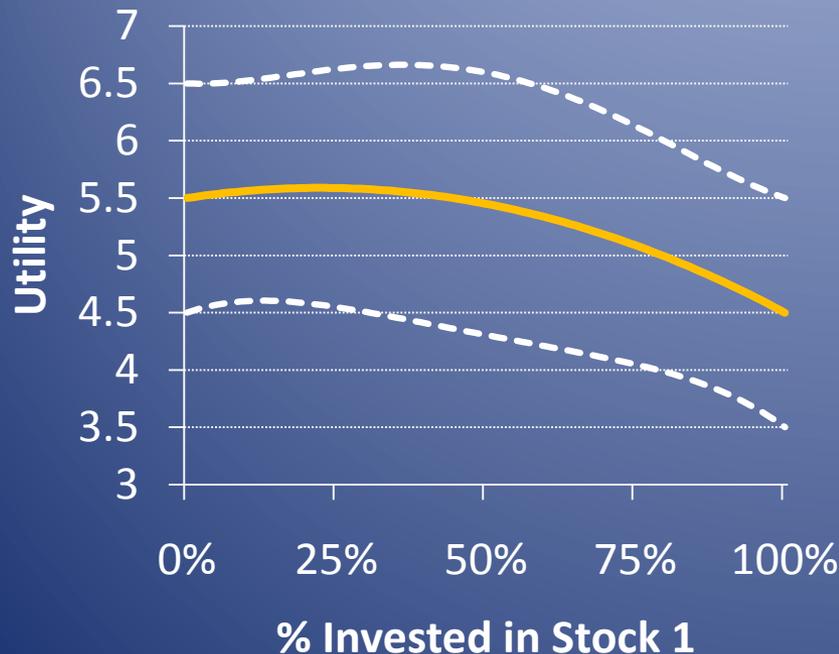
- User's risk aversion $\lambda = 1\%/200\%^2$

Reference: Propagation of Errors

- Suppose f is a function of variables known with uncertainty
 - $f = f(\mathbf{x}) = f(x^1, \dots, x^n)$
- Linearly approximate f in the area of interest, around the point \mathbf{x}_0
 - $f(\mathbf{x}) \approx f(\mathbf{x}_0) + \nabla f(\mathbf{x}_0) (\mathbf{x} - \mathbf{x}_0)$
- To approximate the error in f , take the variance
 - $\text{var}[f(\mathbf{x})] \approx \nabla f(\mathbf{x}_0) \text{var}(\mathbf{x}) \nabla^T f(\mathbf{x}_0)$
- An aside: this is the idea behind linear factor risk models

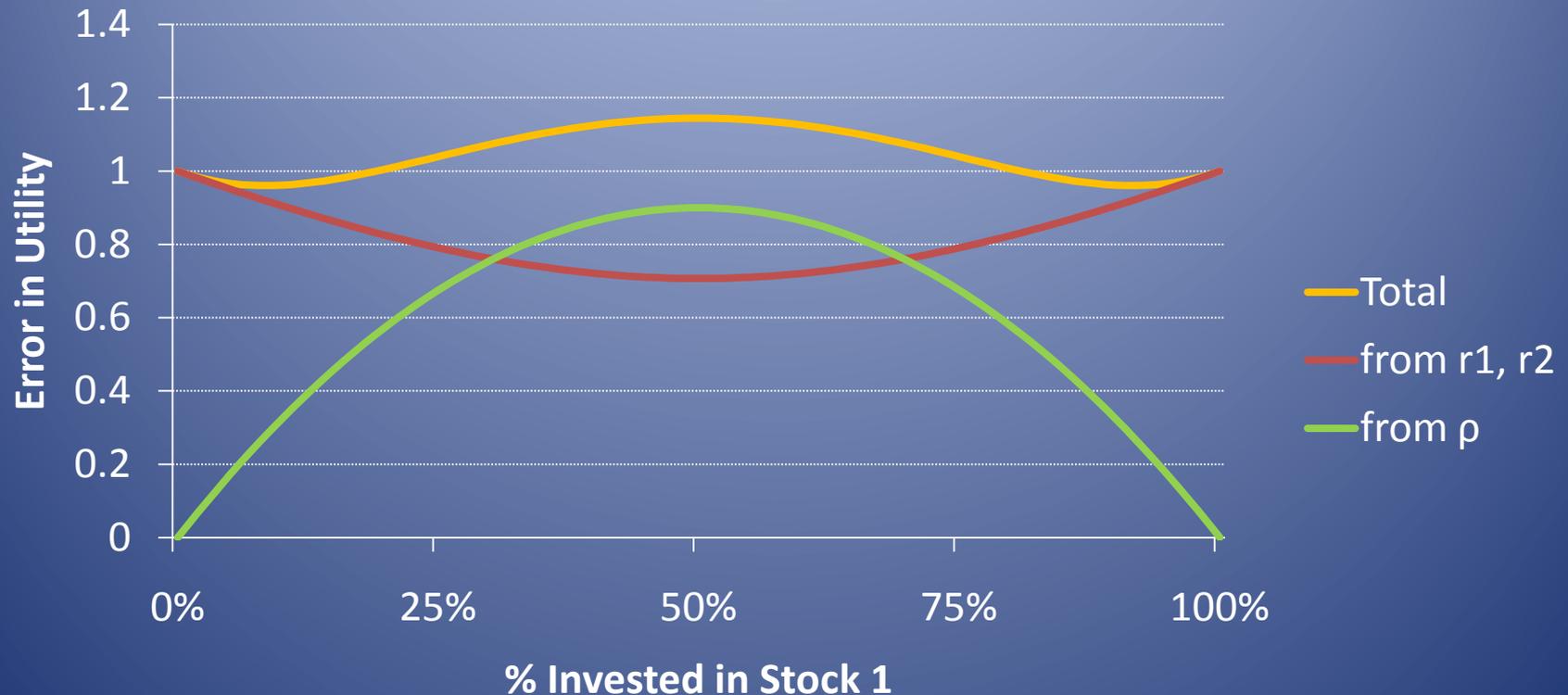
Utility

$$r_1 = 10 \pm 1 \quad r_2 = 9 \pm 1 \quad \rho = 0.4 \pm 0.2 \quad \sigma = 30 \quad \lambda = 1/200$$



- Utility ranges from 4.5 – 5.6
- Error is $\sim 1 \pm 0.1$
- Differences in utility are on par with the error
- Many combinations are indistinguishably good
- No single “Optimal Portfolio”

Bonus Slide: Sources of the Error



$$r_1 = 10 \pm 1 \quad r_2 = 9 \pm 1 \quad \rho = 0.4 \pm 0.2$$

Two Bowls of Baked Beans



Wise monkey says, “They are nearly the same; the second has a bit more onion”



Confused monkey says, “They’re entirely different; they don’t share a single bean in common”

- Many papers on estimation error in portfolio optimization are written by confused monkeys
 - Mistakenly focus on differences in holdings rather than the difference in portfolio utility

No Single Optimal Portfolio

Many, of Vastly Different Composition

- A. Markowitz utility function uses only 2 features – return & covariance
- B. Securities are similar, particularly in their forecasts
- C. Of course the optimal portfolio's composition is sensitive to the inputs, but its utility isn't



After changing a return forecast, confused monkey screams, "Optimization is too sensitive to the inputs!"

- Anthropomorphizes software and calls it an 'evil-doer'
- Kicks computer



Wise monkey understands that the sensitivity reflects reality: many combinations achieve similar utility. Using this to his advantage, he finds a point in the optimal region that minimizes his trading costs

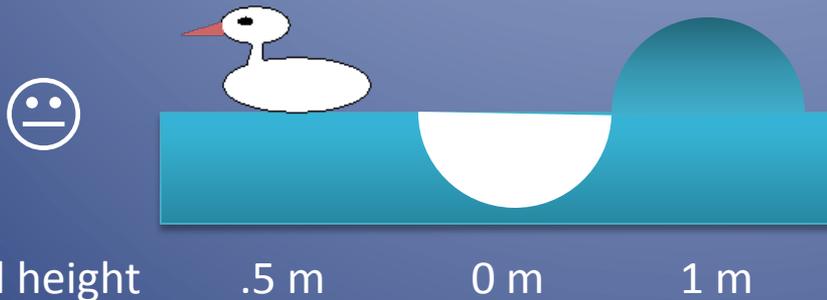
- Optimal utility can be achieved by portfolios of vastly different composition, so it is senseless to fret that 'the optimal portfolio' changes with the inputs

Recall Definition of Unbiased Estimator

- \hat{g} is an unbiased estimator of g if $E[\hat{g}] = g$
 - i.e. if I run the experiment many times, the average of my estimates ($\hat{g}_1, \hat{g}_2, \dots$) will be the true value, g
 - The error of each estimate can be huge
 - Investment managers generally have too few estimates to reach accuracy through averaging
- $\hat{g} = E[g | \text{information}]$ is a different statement, which has nothing to do with bias
 - Moreover, talking about $E[g]$ is gibberish until the context becomes Bayesian

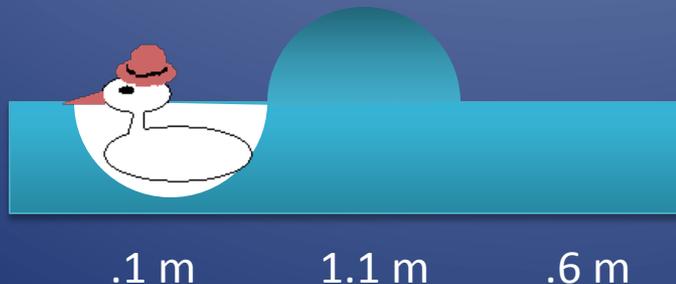
Unbiased Estimator: Height of Duck (Excluding Legs)

- Duck is sitting on ocean
- We are on land, eyes at sea level



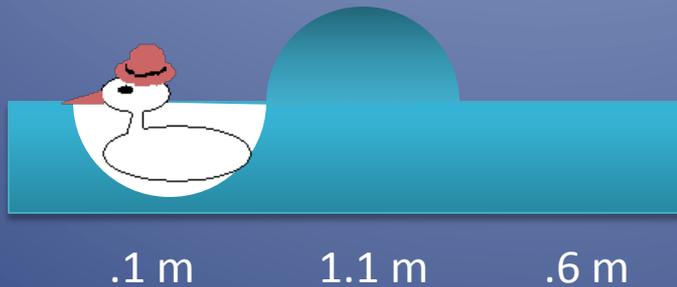
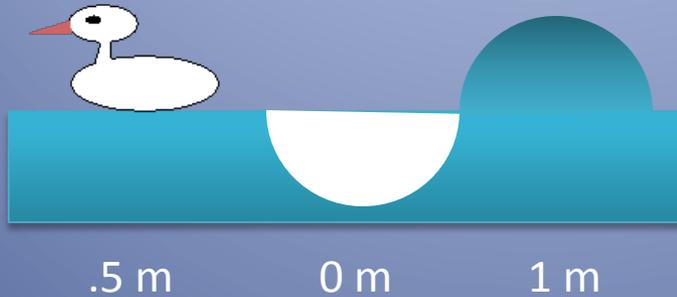
Average of the estimates is .5 m, the duck's true height

Add 2nd duck:



Average of the estimates is .6 m, the duck's true height

New Question: Height of Taller Duck?



Winner:



Average of estimate of taller duck is 0.87 meters!

The taller duck is only .6m

The estimate is biased

Straightforward Implications of *Unbiased* Estimates

- Markowitz utility

$$U(w,r,C) = \text{return} - \lambda \times \text{variance} = w^T r - \lambda w^T C w$$

To simplify notation, write as $U(w,G)$

w = security weights

G = parameters (returns, covariance) that are estimated

\hat{G} = an unbiased estimate of G

$w^*(\hat{G})$ = the value of w that maximizes $U(w,\hat{G})$

1) Good news: For a fixed portfolio, estimated utility is unbiased

Why?

– $U(w,G)$ is affine in G

– $E[U(w,\hat{G})] = U(w, E[\hat{G}]) = U(w,G)$

Implications of Unbiased Estimates (2)

2) Bad news: For an optimized portfolio, estimated utility on average **exaggerates true utility**

Why?

- For any fixed portfolio w ,
- $U(w^*(\hat{G}), \hat{G}) > U(w, \hat{G})$ since $w^*(\hat{G})$ maximizes $U(w, \hat{G})$
- $E[U(w^*(\hat{G}), \hat{G})] > E[U(w, \hat{G})] = U(w, G)$
- let $w = w^*(\hat{G})$

3) Worse news: **Not only is the optimized portfolio not optimal, but its estimated utility is on average greater than the maximum achievable utility**

Why?

- Same as above. let $w = w^*(G)$

Illustrating the Point by a False Paradox

- Fix a portfolio P
 - Estimated utility is some number, say 4
 - Estimate is unbiased
- Let O be the (estimated) maximum utility portfolio. Optimize to find it
 - Suppose O turns out to be P
- Is the estimation procedure for P now biased?
 - No
- Is the estimation procedure for O biased?
 - Yes
- But O and P are the same. How is O's estimate biased and P's not?
 - The estimated composition of O, the optimal portfolio, depends on the estimate. Although O happens to be P this time around, when estimates change, O changes with them while P doesn't

Real Life Effect of Optimizing with Unbiased Estimates

- What happens when utility is exaggerated?
 - Markowitz utility has 2 parts, risk and return
 - Return is on average less than estimated
 - and/or Risk is on average greater than estimated
 - **Portfolio is more aggressive** than preference used in the utility function
 - And (barring a fluke) not optimal at that risk tolerance
- Effect is a mathematical truth
- Easy solution: **For optimization, avoid unbiased estimates**

Recap of the 3 Major Points

- 1) Uncertainty in the inputs means **there is no single “optimal portfolio”**
 - What is optimal is a set of portfolios of indistinguishably different utility

- 2) Securities are alike, so **portfolios comprising no securities in common can have essentially the same utility**
 - Measuring distance from the “true optimal portfolio” in terms of difference in positions is senseless
 - Utility is the correct measure

- 3) **Optimization biases estimates**
 - Unbiased estimates are unsuitable for use in optimization
 - Quantities should instead be estimated with the goal of minimizing error

Bayesian Inference To Limit Errors

- Classical (also called frequentist) statistics vs. Bayesian
 - Frequentist uses only observations
 - Bayesian has prior beliefs about the likelihood of events. To infer reality, Bayesian combines observations with beliefs
- Oversized hairy biped spotted in the yard
 - Frequentist yells, “Sasquatch!”
 - Bayesian, believing bigfoot sighting nearly impossible, thinks, “Mother-in-law has stopped by”

Tool: Bayes Adjust Alphas

- Idea is described in paper by Black & Litterman (1992) but predates the Kalman Filter (1960)
 - Black, F. & Litterman, R. “Global Portfolio Optimization,” Financial Analysts Journal, 1992, v48(5,Sept/Oct), 22-43
- Imagine tracking a collection of sailboats crossing the Atlantic
- **The frequentist way of inferring the boats’ locations**
 - Receive unreliable report – “Boat X is at position Y”
 - Source sometimes overshoots, sometimes undershoots. Take report at face value and estimate boat is at position Y
- **A Bayesian way**
 - Know the boats’ courses, hence where they intend to be today [center of prior]
 - Currents and wind affect all boats [covariance of prior]
 - Receive unreliable report of their locations [observations with error]
 - The best guess of location combines the observations and the prior belief

Bayes Adjust Alphas (2)

- **Prior on mean returns**
 - $m \sim N(m_0, \Sigma/\tau)$
 $m_0 = 0$ if forecasting benchmark relative returns
 Σ = covariance of benchmark relative returns
 τ = intensity of prior
- **Forecasts impart new information but are noisy observations of reality**
 - $\hat{g} = m + \varepsilon \quad \varepsilon \sim N(0, \Omega)$
 - With each forecast, user provides standard deviation of the error
 - Users likely don't have opinions about the covariance of the errors, so Northfield assumes the errors are uncorrelated.
- **A Bayes forecast combines the prior and the error**
 - Most likely returns = $m_0 + \Sigma [\tau\Omega + \Sigma]^{-1} (\hat{g} - m_0)$

Tool: Blend Covariance

- Idea comes from a series of papers by Ledoit & Wolf
 - “Improved Estimation of the Covariance Matrix of Stock Returns with an Application to Portfolio Selection,” *Journal of Empirical Finance*, Dec v10(5):603–621
- To soften extremes, blend original covariance matrix with duller (less differentiated) versions of itself
 - Single Index
 - Constant Correlation
 - Constant Covariance
- Fortunately, each of these can be represented as a one factor model

Blend Covariance (2)

1) Single Index

Reduce the multifactor risk model to CAPM

$$- r_s = \beta_s r_m + \varepsilon_s$$

$$- \beta_s = \text{cov}(r_m, r_s) / \text{var}(r_m)$$

$$- \text{var}(\varepsilon_s) = \text{var}(r_s) - \beta_s^2 \text{var}(r_m)$$

– Reference market portfolio contains all stocks in the optimization (excluding cash) weighted by cap

Blend Covariance (3)

2) Constant Correlation

More restrictive than CAPM - all stocks have the same pairwise correlation, ρ , but different variances

$$- r_s = (\rho^{1/2} \sigma_s / \sigma_f) r_f + \varepsilon_s \quad \text{var}(\varepsilon_s) = (1-\rho) \sigma_s^2$$

where r_f is an artificial factor

- ρ is backed out from variance of reference portfolio

$$\sigma_m^2 = \sum_i (w_i \sigma_i)^2 + 2 \sum_{i < k} (w_i w_k \rho \sigma_i \sigma_k)$$

$$\rightarrow \rho = [\sigma_m^2 - \sigma_{m0}^2] / [\sigma_{m1}^2 - \sigma_{m0}^2]$$

where

$$\sigma_{m0}^2 = \sum_i (w_i \sigma_i)^2 = \text{var of reference if uncorrelated}$$

$$\sigma_{m1}^2 = (\sum_i w_i \sigma_i)^2 = \text{var of reference if perfectly correlated}$$

Blend Covariance (4)

3) Constant Covariance

Least differentiated of the three – all stocks have the same pairwise correlation, ρ , and the same variance, σ^2

$$- r_s = (\rho^{1/2} \sigma / \sigma_f) r_f + \varepsilon_s \quad \text{var}(\varepsilon_s) = (1-\rho) \sigma^2$$

where r_f is an artificial factor

– σ and ρ are backed out from variance of reference portfolio

$$\sigma_m^2 = \sum_i (w_i \sigma)^2 + 2 \sum_{i < k} (w_i w_k \rho \sigma^2)$$

ρ = as in constant correlation

$$\rightarrow \sigma^2 = \sigma_m^2 / [\rho + (1 - \rho) \sum_i w_i^2]$$

Summary

- Estimation error is an issue in optimization, but not so nefarious as many believe
- The mechanism, as illustrated by the ducks, is straightforward to understand
- The remedy is to use estimation procedures that limit error in place of procedures that are accurate on average
- The Northfield Portfolio Optimizer has tools to do so
- *For thought, but beyond the scope of this presentation:*
With uncertain inputs, utility becomes a random variable
 - One can redefine utility as a functional on its distribution
 - For example, people rebalancing once every 5 years would be more concerned with variance of utility than people rebalancing daily