Geometry and Optimization of Relative Arbitrage

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Math Finance Colloquium, University of Southern California November 30, 2015

Introduction

Main themes

- Model-free and robust investment strategies
- Depend only on directly observable market quantities
- Stochastic portfolio theory (SPT), volatility pumping
- Connections with universal portfolio theory and other approaches

Set up

- ▶ *n* stocks, discrete time
- Market weight

$$\mu_i(t) = \frac{\text{market value of stock } i \text{ at time } t}{\text{total market value at time } t} \in (0, 1)$$

$$\mu(t) = (\mu_1(t), \dots, \mu_n(t)) \in \Delta_n \text{ (open unit simplex)}$$

$$\uparrow$$



Portfolio

► For each *t*, pick weights

$$\pi(t) = (\pi_1(t), \ldots, \pi_n(t)) \in \overline{\Delta}_n$$

Market portfolio: $\mu(t) = (\mu_1(t), \dots, \mu_n(t))$

• Relative value w.r.t. market portfolio μ :

$$V_{\pi}(t) = \frac{\text{growth of $1 of portfolio } \pi \text{ at time } t}{\text{growth of $1 of market portfolio } \mu \text{ at time } t}$$

• $V_{\pi}(0) = 1$ and

$$\frac{V_{\pi}(t+1)}{V_{\pi}(t)} = \sum_{i=1}^{n} \pi_i(t) \frac{\mu_i(t+1)}{\mu_i(t)}$$

Relative arbitrage

Definition

For $t_0 > 0$, a relative arbitrage over the horizon $[0, t_0]$ (w.r.t. μ) is a portfolio π such that $V_{\pi}(t_0) > 1$ for "all" possible realizations of $\{\mu(t)\}_{t=0}^{\infty}$.

Interpretations:

(i) (Probabilistic) If $\{\mu(t)\}_{t=0}^{\infty}$ is a stochastic process, we mean

$$\mathbb{P}\left(V_{\pi}(t_0) > 1\right) = 1.$$

(ii) (Pathwise) Let \mathcal{P} be a path property. We require $V_{\pi}(t_0) > 1$ for all sequences $\{\mu(t)\}_{t=0}^{\infty} \subset \Delta_n$ satisfying property \mathcal{P} .

Stochastic portfolio theory

- Relative arbitrage exists (for t₀ sufficiently large) under realistic conditions:
- ► Stability of capital distribution; diversity $\mu(t) \in K$



- Sufficient volatility
- Functionally generated portfolios (Fernholz)

e.g.
$$\pi_i(t) = \frac{-\mu_i(t)\log\mu_i(t)}{\sum_{j=1}^n -\mu_j(t)\log\mu_j(t)}$$
 (entropy-weighted portfolio)

Geometry

Geometry of relative arbitrage

Consider deterministic portfolios:

 $\pi(t) = \pi(\mu(t)),$

where $\pi : \Delta_n \to \overline{\Delta}_n$ is a portfolio map.

• Let $K \subset \Delta_n$ be open and convex:



Ask: If the portfolio map π : Δ_n → Δ̄_n is a relative arbitrage given the market is volatile and satisfies the generalized diversity condition μ(t) ∈ K, what does π look like?

Relative arbitrage as FGP

Theorem (Pal and W. (2014))

 $K \subset \Delta_n$ open convex, $\pi : \Delta_n \to \overline{\Delta}_n$ portfolio map. TFAE:

- (i) π is a pseudo-arbitrage over the market on K: there exists ε > 0 such that inf_{t≥0} V_π(t) ≥ ε for all sequences {μ(t)}[∞]_{t=0} ⊂ K, and there exists a sequence {μ(t)}[∞]_{t=0} ⊂ K along which lim_{t→∞} V_π(t) = ∞.
- (ii) π is functionally generated: there exists a non-affine, concave function $\Phi : \Delta_n \to (0, \infty)$ such that $\log \Phi$ is bounded below on *K* and

$$\sum_{i=1}^{n} \pi_i(p) \frac{q_i}{p_i} \ge \frac{\Phi(q)}{\Phi(p)}, \quad \text{for all } p, q \in K.$$

• The ratios π_i/μ_i are given by supergradients of the exponential concave function log Φ .

Examples



R package RelValAnalysis on CRAN

FGP leads to relative arbitrage

Recall

$$\frac{V_{\pi}(t+1)}{V_{\pi}(t)} = \sum_{i=1}^{n} \pi_i(\mu(t)) \frac{\mu_i(t+1)}{\mu_i(t)} \ge \frac{\Phi(\mu(t+1))}{\Phi(\mu(t))}$$

Write

$$\log \frac{V_{\pi}(t+1)}{V_{\pi}(t)} = \log \frac{\Phi(\mu(t+1))}{\Phi(\mu(t))} + T\left(\mu(t+1) \mid \mu(t)\right)$$

where

$$T\left(\mu(t+1) \mid \mu(t)\right) \ge 0$$

is a measure of volatility

FGP leads to relative arbitrage



Relative arbitrage as optimal transport maps

- \mathcal{X}, \mathcal{Y} : Polish spaces
- ► *c*: cost function
- \mathcal{P} : Borel probability measure on \mathcal{X}
- Q: Borel probability measure on Y
- Coupling: \mathcal{R} p.m. on $\mathcal{X} \times \mathcal{Y}$ with marginals \mathcal{P} and \mathcal{Q}
- Monge-Kantorovich optimal transport problem:



Optimal transport and FGP

Take

$$\mathcal{X} = \overline{\Delta}_n, \mathcal{Y} = [-\infty, \infty)^n$$

$$\mathcal{C} \text{ost:}$$

$$c(\mu, h) = \log\left(\sum_{i=1}^n e^{h_i} \mu_i\right)$$

• Portfolio at μ given h:

$$\pi_i(\mu) = \frac{\mu_i e^{h_i}}{\sum_{j=1}^n \mu_j e^{h_j}}$$
(1)

Theorem (Pal and W. (2014))

Let \mathcal{P} be any Borel probability measure on Δ_n , and let π be an FGP. Define $h = h(\mu)$ via (1), and let \mathcal{Q} be the law of h when $\mu \sim \mathcal{P}$. Then the coupling (μ, h) minimizes $\mathbb{E}_{\mathcal{R}}[c(\mu, h)]$ where \mathcal{R} has marginals \mathcal{P} and \mathcal{Q} .

Optimization

- ► Assume $\frac{1}{M} \le \frac{\mu_i(t+1)}{\mu_i(t)} \le M$ (*M* is unknown to the investor)
- $\mathcal{FG} := \{\pi : \Delta_n \to \overline{\Delta}_n \mid \text{functionally generated}\}$

• For $\pi \in \mathcal{FG}$,

$$\log \frac{V_{\pi}(t+1)}{V_{\pi}(t)} = \log \left(\sum_{i=1}^{n} \pi_i(\mu(t)) \frac{\mu_i(t+1)}{\mu_i(t)} \right)$$

=: $\ell_{\pi}(\mu(t), \mu(t+1))$

Logarithmic growth rate:

$$\frac{1}{t}\log V_{\pi}(t) = \int_{\Delta_n \times \Delta_n} \ell_{\pi} d\mathbb{P}_t$$

where

$$\mathbb{P}_t := \frac{1}{t} \sum_{s=0}^{t-1} \delta_{(\mu(s), \mu(s+1))}$$

is the empirical measure

▶ P: Borel probability measure on

$$\mathcal{S} := \left\{ (p,q) \in \Delta_n imes \Delta_n : rac{1}{M} \leq rac{q_i}{p_i} \leq M
ight\}$$

► Given P, consider

$$\sup_{\pi\in\mathcal{FG}}\int_{\mathcal{S}}\ell_{\pi}d\mathbb{P}$$

Solution $\widehat{\pi}$ is analogous to MLE

► Nonparametric MLE: given a random sample $X_1, ..., X_N \sim f_0$ in \mathbb{R}^d , consider

$$\sup_{f\in\mathcal{F}}\sum_{k=1}^N\log f(X_k)$$

where \mathcal{F} is a class of densities

Theorem (W. 2015)

Under suitable regularity conditions on \mathbb{P} :

- (Solvability) The problem has an optimal solution which is a.e. unique.
- (Consistency) If $\widehat{\pi}^{(N)}$ is optimal for \mathbb{P}_N , $\mathbb{P}_N \to \mathbb{P}$ weakly, and $\widehat{\pi}$ is optimal for \mathbb{P} , then

 $\widehat{\pi}^{(N)} \to \widehat{\pi} \quad a.e.$

Theorem (continued)

• (Finite-dimensional reduction) Suppose \mathbb{P} is discrete:

$$\mathbb{P} = \frac{1}{N} \sum_{j=1}^{N} \delta_{(p(j),q(j))}.$$

Then the optimal solution $(\widehat{\pi}, \widehat{\Phi})$ can be chosen such that $\widehat{\Phi}$ is polyhedral over the data points. In particular, $\widehat{\Phi}$ is piecewise affine over a triangulation of the data points.

• Aim: achieve the asymptotic growth rate of

$$V^*(t) = \sup_{\pi \in \mathcal{FG}} V_{\pi}(t)$$

- Cover (1991): wealth-weighted average (for constant-weighted portfolios)
- We will construct a "market portfolio" π̂ whose basic assets are the portfolios in FG

Wealth distribution

- Equip \mathcal{FG} with topology of uniform convergence
- ▶ ν_0 : Borel probability measure on \mathcal{FG} (initial distribution)
- At time 0, distribute $\nu_0(d\pi)$ wealth to $\pi \in \mathcal{FG}$
- ► Total wealth at time *t* is

$$\widehat{V}(t) := \int_{\mathcal{FG}} V_{\pi}(t) d
u_0(\pi)$$

• Wealth distribution at time *t*:

$$u_t(B) := rac{1}{\widehat{V}(t)} \int_B V_\pi(t) d
u_0(\pi), \quad B \subset \mathcal{FG}$$

Bayesian interpretation:

$$\nu_0$$
: prior, $V_{\pi}(t)$: likelihood, ν_t : posterior

Example

Wealth density for a family of constant-weighted portfolios:



In this context, define Cover's portfolio by the posterior mean

$$\widehat{\pi}(t) := \int_{\mathcal{FG}} \pi(\mu(t)) d\nu_t(\pi)$$

Then

$$V_{\widehat{\pi}}(t) \equiv \widehat{V}(t)$$

Suppose an asymptotically optimal portfolio π^* exists. Hope:

- Posterior ν_t concentrates around π^*
- $\widehat{V}(t)$ is "close" to $V^*(t)$

Theorem (W. (2015))

Let $\{\mu(t)\}_{t=0}^{\infty}$ be a sequence in Δ_n such that the empirical measure $\mathbb{P}_t = \frac{1}{t} \sum_{s=0}^{t-1} \delta_{(\mu(s),\mu(s+1))}$ converges weakly to an absolutely continuous Borel probability measure on S. Here, the asymptotic growth rate $W(\pi) := \lim_{t \to \infty} \frac{1}{t} \log V_{\pi}(t)$ exists for all $\pi \in \mathcal{FG}$.

(i) For any initial distribution ν_0 , the sequence $\{\nu_t\}_{t=0}^{\infty}$ of wealth distributions satisfies the large deviation principle (LDP) with rate

$$I(\pi) = \begin{cases} W^* - W(\pi) & \text{if } \pi \in \text{supp}(\nu_0), \\ \infty & \text{otherwise}, \end{cases}$$

where $W^* := \sup_{\pi \in \operatorname{supp}(\nu_0)} W(\pi)$.

Wealth distribution of \mathcal{FG} satisfies LDP:



Theorem (Continued)

 (ii) There exists an initial distribution ν₀ on FG such that W^{*} = sup_{π∈FG} W(π) for any absolutely continuous P. For this initial distribution, Cover's portfolio satisfies the asymptotic universality property

$$\lim_{t\to\infty}\frac{1}{t}\log\frac{\widehat{V}(t)}{V^*(t)}=0.$$

- Connections between SPT, universal portfolio theory and online portfolio selection (statistical learning)
- Risk-adjusted universal portfolios
- Relative arbitrage under price impacts and transaction costs
- Economic models inspired by SPT

References

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 S. Pal and T.-K. L. Wong. MAFE (2015)
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