

# Information Theory and Networks

## Lecture 18: Information Theory and the Stock Market

Paul Tune

`<paul.tune@adelaide.edu.au>`

`http://www.maths.adelaide.edu.au/matthew.roughan/  
Lecture\_notes/InformationTheory/`

School of Mathematical Sciences,  
University of Adelaide

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# Part I

## The Stock Market

Put all your eggs in one basket and then watch that basket.  
*Mark Twain, Pudd'nhead Wilson and Other Tales*

# Section 1

## Basics of the Stock Market

# Stock Market

- “Market” referred to is really the *secondary market*
  - ▶ *primary market* deals with the issuance of stock
- Consider  $m$  assets
  - ▶ one asset has the *risk-free rate*: theoretical zero risk
  - ▶ our goal: construct a portfolio i.e. allocation of assets with exponential wealth growth
- We assume no
  - ▶ Short selling
  - ▶ Leveraging

# Some Definitions

- We look at day-to-day fluctuations of the stock prices
- Stock market  $\mathbf{X} = (X_1, X_2, \dots, X_m)$ ,  $X_i \geq 0$ 
  - ▶ our universe of stocks is  $m$
  - ▶  $X_i$  price relative: (price at start of day)/(price at end of day)
  - ▶  $F(\mathbf{x})$ : underlying distribution of  $X_i$ s
- The portfolio  $\mathbf{b} = (b_1, b_2, \dots, b_m)$ ,  $b_i \geq 0$ ,  $\sum_{i=1}^m b_i = 1$
- The wealth relative  $S = \mathbf{b}^T \mathbf{X}$
- Investment period  $n$  days results in  $S_n = \prod_{i=1}^n \mathbf{b}_i^T \mathbf{X}_i$

## Section 2

# Log-Optimal Portfolios

# Optimising Growth Rate

- Want to maximise  $W(\mathbf{b}, F) := E[\log S]$ 
  - ▶  $W^*(F) := \max_{\mathbf{b}} W(\mathbf{b}, F)$
  - ▶ portfolio  $\mathbf{b}^*$  achieving  $W^*(F)$  is the *log-optimal portfolio*
- Suppose price relatives are i.i.d. according to  $f(\mathbf{x})$ . Assume constant rebalancing with allocation  $\mathbf{b}^*$ , so  $S_n^* = \prod_{i=1}^n \mathbf{b}^{*T} \mathbf{X}_i$ . Then,

$$\frac{1}{n} \log S_n^* \rightarrow W^* \text{ with probability 1.}$$

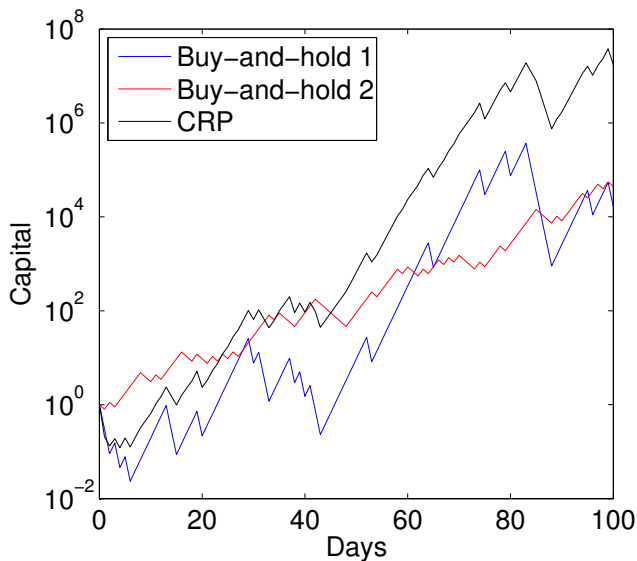
- **Implication:** regardless of current wealth, keep allocations between assets constant!
- Can we justify constant rebalancing portfolios beyond i.i.d.? Yes, for stationary markets, conditional allocation



# Shannon's Volatility Pumping

- Constant rebalancing portfolio (CRP): suggested by Shannon in a lecture at MIT in the 1960s
- Shannon used geometric Wiener to model the price relatives
- CRPs essentially exploit volatility of the price relatives
  - ▶ the higher the price volatility between assets, the higher the excess returns

# CRP vs. Buy and Hold



# Karush-Kuhn-Tucker Characterisation

- Observe the admissible portfolios form an  $m$ -simplex  $\mathcal{B}$
- Karush-Kuhn-Tucker (KKT) conditions yield:

$$E \left[ \frac{X_i}{\mathbf{b}^{*T} \mathbf{X}} \right] = \begin{cases} 1 & \text{if } b_i^* > 0 \\ 0 & \text{if } b_i^* = 0 \end{cases}$$

- **Implication:** portfolio at least as good as best stock return on average
- KKT conditions also imply:

$$E \left[ \log \frac{S}{S^*} \right] \leq 0 \text{ for all } S \text{ iff } E \left[ \frac{S}{S^*} \right] \leq 1 \text{ for all } S.$$

- Also,  $E \left[ \frac{b_i^* X_i}{\mathbf{b}^{*T} \mathbf{X}} \right] = b_i^* E \left[ \frac{X_i}{\mathbf{b}^{*T} \mathbf{X}} \right] = b_i^*$  (c.f. Kelly criterion)

# Wrong Belief

- In horse racing, side information improves wealth growth rate
- Suppose investor believes underlying distribution is  $G(\mathbf{x})$  instead of  $F(\mathbf{x})$ : what is the impact?
  - ▶ end up using allocation  $\mathbf{b}_G$  instead of  $\mathbf{b}_F$
  - ▶ characterise *increase in growth rate*

$$\Delta W = W(\mathbf{b}_F, F) - W(\mathbf{b}_G, G)$$

- Turns out  $\Delta W \leq D(F \parallel G)$  (proof: Jensen's inequality and KKT condition)

## Side Information

- Result can be used to show  $\Delta W \leq I(\mathbf{X}; Y)$ , equality holds if it is the horse race i.e. return due to win or loss
- In real life: private insider trading can significantly increase wealth
  - ▶ e.g. buying stock before press release of profit upgrades or sensitive announcement
  - ▶ practice is banned in most developed countries
  - ▶ insider trading must be declared in public records
- Information asymmetry lead to significant (dis)advantages, not just wealth-wise

# Causality

- Nothing said about causal strategies: in real life, not possible to invest in hindsight
- *Nonanticipating* or *causal* portfolio: sequence of mappings  $b_i : \mathbb{R}^{m(i-1)} \rightarrow \mathcal{B}$ , with the interpretation  $b_i(\mathbf{x}_1, \dots, \mathbf{x}_{i-1})$  used on day  $i$
- Suppose  $\mathbf{X}_i$  drawn i.i.d. from  $F(\mathbf{x})$ ,  $S_n$  is wealth relative from any causal strategy,

$$\limsup_{n \rightarrow \infty} \frac{1}{n} \log \frac{S_n}{S_n^*} \leq 0 \text{ with probability 1.}$$

- **Caveat:** theorem does not say for a fixed  $n$ , log-optimal portfolio does better than any strategy

# Part II

## Universal Portfolios

# Background

- Previous discussions assume  $F$  is known
- What's the best we can do, if  $F$  is not known?
  - ▶ use best CRP based on hindsight as benchmark
  - ▶ think of something (clever) to approach this benchmark
- Needs to be (somewhat) practical
  - ▶ causal strategy
  - ▶ universal: distribution free strategy
- **Solution:** adaptive strategy



# Finite Horizon

- Assume  $n$  is known in advance,  $\mathbf{x}^n = (\mathbf{x}_1, \dots, \mathbf{x}_n)$  is the stock market sequence
- **Theorem:** For any causal strategy  $\hat{\mathbf{b}}_i(\cdot)$ ,

$$\max_{\hat{\mathbf{b}}_i(\cdot)} \min_{\mathbf{x}_1, \dots, \mathbf{x}_n} \frac{\hat{S}_n(\mathbf{x}^n)}{S_n^*(\mathbf{x}^n)} = V_n$$

- $V_n$  is the normalisation factor, for reasons clearer later on
- Nothing said about the underlying distribution: distribution free!

# Finite Horizon: Big Picture

- **Big Picture:** look at all the outcomes length  $n$ , allocate wealth in hindsight, then construct best causal strategy from the optimal
- Has to perform close to optimal under “adversarial” outcomes
  - ▶ if  $m = 2$ , outcomes are  $((1, 0)^T, (1, 0)^T, \dots, (1, 0)^T)$ , clearly best hindsight strategy is to allocate only to stock 1
  - ▶ without hindsight, might want to “spread” allocation to maximise return, minimise loss
  - ▶  $\hat{b} = (1/2, 1/2)$  but will be  $2^n$  away from best strategy, need some form of adaptation

# Finite Horizon: Construction

- By optimality of CRPs, only need to compare the best CRP to the causal strategies
- Consider the case  $m = 2$ , can generalise from this case
- **Key idea:** convert  $S_n(\mathbf{x}^n) = \prod_{i=1}^n \mathbf{b}^T \mathbf{X}_i$  to

$$S_n(\mathbf{x}^n) = \sum_{j^n \in \{1,2\}^n} \prod_{i=1}^n b_{i,j_i} \prod_{i=1}^n x_{i,j_i} = \sum_{j^n \in \{1,2\}^n} w(j^n) x(j^n)$$

- Now, problem is about determining allocation  $w(j^n)$  to  $2^n$  stocks

## Finite Horizon: Construction II

- With 2 stocks,  $w(j^n) = \prod_{i=1}^n b^k (1-b)^{n-k}$ ,  $k$  number of times stock 1 price > stock 2 price
  - ▶ what is the optimal allocation  $b^*$  for this?
- $\sum_{j^n} w^*(j^n) > 1$  because best CRP has benefit of hindsight: can allocate more to the best sequences
  - ▶ causal strategy does not have this hindsight
  - ▶ make  $\hat{w}(j^n)$  proportional to  $w^*(j^n)$  by normalisation (using  $V_n$ )
- Then, find the optimal allocation for adversarial sequences
  - ▶ what is the best allocation, if at each time step in a sequence, exactly one stock yields non-zero return?
- Putting these two together can show

$$V_n \leq \max_{\mathbf{b}_i(\cdot)} \min_{\mathbf{x}_1, \dots, \mathbf{x}_n} \frac{\hat{S}_n(\mathbf{x}^n)}{S_n^*(\mathbf{x}^n)} \leq V_n$$

## Finite Horizon: Sequential

- Finally, need to convert back to the causal portfolio mapping
- For allocation to stock 1 at day  $i$ , sum over all sequences with 1 in position  $i$

$$\hat{\mathbf{b}}_{i,1}(\mathbf{x}^{i-1}) = \frac{\sum_{j^{i-1} \in m^{i-1}} \hat{w}(j^{i-1}) x(j^{i-1})}{\sum_{j^i \in m^i} \hat{w}(j^i) x(j^{i-1})}$$

- Algorithm enumerates over all  $m^n$  sequences: computationally prohibitive
- Asymptotics yield, for  $m = 2$  and all  $n$ ,  $\frac{1}{2\sqrt{n+1}} \leq V_n \leq \frac{2}{\sqrt{n+1}}$
- Observe:

$$\lim_{n \rightarrow \infty} \frac{1}{n} \log \frac{\hat{S}_n(\mathbf{x}^n)}{S_n^*(\mathbf{x}^n)} = \lim_{n \rightarrow \infty} \frac{1}{n} \log V_n = 0$$

for any  $\mathbf{x}^n$

# Horizon-Free

- Two tier process: think of all CRPs with various  $\mathbf{b}$  as mutual funds
- Now, we allocate our wealth according to a distribution  $\mu(\mathbf{b})$  to all these funds
  - ▶ each fund gets  $d\mu(\mathbf{b})$  of wealth
  - ▶ some will perform better than others, one is the best CRP in hindsight
- What kind of distribution should one choose? (Hint: think adversarial)

## Horizon-Free

- **Idea:** Choose a distribution  $\mu(\mathbf{b})$  that spreads over all CRPs to maximise

$$\hat{S}_n(\mathbf{x}^n) = \int_{\mathcal{B}} S_n(\mathbf{b}, \mathbf{x}^n) d\mu(\mathbf{b})$$

- Choose allocation  $\hat{\mathbf{b}}_{i+1}(\mathbf{x}^i) = \frac{\int_{\mathcal{B}} \mathbf{b} S_i(\mathbf{b}, \mathbf{x}^i) d\mu(\mathbf{b})}{\int_{\mathcal{B}} S_i(\mathbf{b}, \mathbf{x}^i) d\mu(\mathbf{b})}$ 
  - ▶ interpretation: numerator is weighted performance of the fund, denominator is total wealth
  - ▶ best performing CRP dominates overall, especially as  $n \rightarrow \infty$
- Allocation results in

$$\frac{\hat{S}_n(\mathbf{x}^n)}{S_n^*(\mathbf{x}^n)} \geq \min_{j^n} \frac{\int_{\mathcal{B}} \prod_{i=1}^n b_{j_i} d\mu(\mathbf{b})}{\prod_{i=1}^n b_{j_i}^*}$$

- With the right distribution, for e.g. the Dirichlet( $\frac{1}{2}, \frac{1}{2}$ ) for  $m = 2$ ,

$$\lim_{n \rightarrow \infty} \frac{1}{n} \log \frac{\hat{S}_n(\mathbf{x}^n)}{S_n^*(\mathbf{x}^n)} = 0$$

# Caveats

- There is no assumption on brokerage fees
  - ▶ in real life, a commission is charged by the broker for any trade
  - ▶ CRP relies on daily(!) rebalancing for best performance
- Optimal for a long enough investment horizon
- Relies on the volatility between stocks
  - ▶ simulations show that it performs poorly otherwise
  - ▶ need the daily rebalancing to exploit volatility
  - ▶ longer horizons such as a month or year less volatile (in general)
- Computationally impractical
  - ▶ finite horizon: need to evaluate over all possible  $m^i$  sequences on day  $i$ , combinatorial explosion
  - ▶ horizon free: need to work out the integral of returns over the simplex  $\mathcal{B}$



# Further reading I



Thomas M. Cover and Joy A. Thomas, *Elements of information theory*, John Wiley and Sons, 1991.