Portfolio Selection with Genetic Algorithms

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Outline

- The problem
- Markowitz Model
- Genetic Algorithm implementation
- GA versus traditional Markowitz
- GA versus the market
- Conclusions

The Problem: Portfolio Selection

Objective: Find mix of investments which

- Does not exceed target risk
- Maximizes expected return
- Involves both short and long positions

Investment mix Percentage of portfolio allocated to each stock

Expected return Evaluated over some fixed time interval

Risk Variance in expected return

Long positions Investment at current market prices

Short position Sale of borrowed shares

Markowitz Model

- Risk is sum of co-variances on expected returns

- Find mix $(x_0, x_1 \ldots x_n)$ such that
  - x_i is allocation to stock i
  - x_i is positive (negative) for long (short) position

- Meet the following constraints:
  - Sum of x_is is one
  - Total expected return meets given target
  - Risk is minimized

Can be solved exactly as a system of simultaneous linear equations. Software is available to do this.

GA Solution

- Explore several mixes in parallel
- Enforce lower bound on target return
- Minimize risk

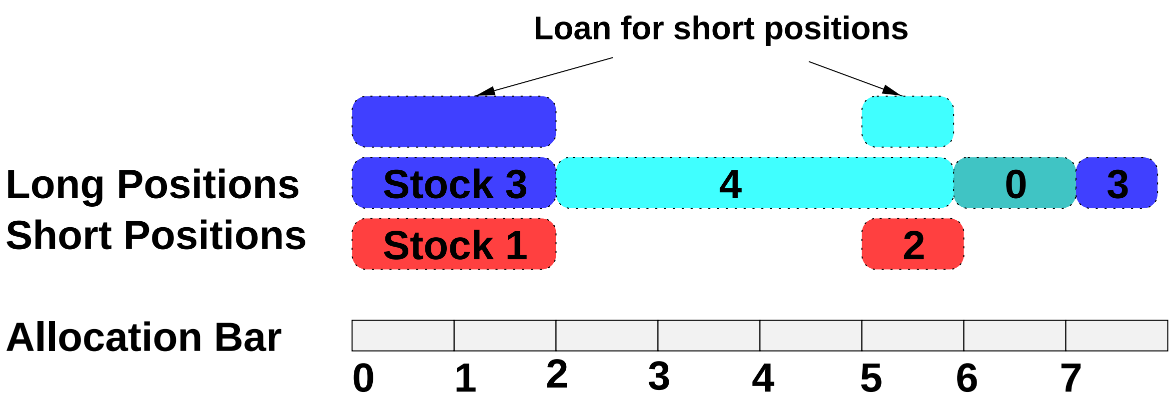
To do this, we developed a representation strategy for mixes which accounts for both long and short positions, and evaluated this mix using user-specified risk tolerance

GA Representation

Chromosome: one field per stock, one bit for position (long/short), offset into an “allocation bar”

Stock 0		Stock 1		Stock 2		Stock 3		Stock 4	
L/S	Off	L/S	Off	L/S	Off	L/S	Off	L/S	Off
1	110	0	000	0	101	1	111	1	010
L	6	S	0	S	5	L	7	L	2

“Allocation Bar” indicates mix ratio x_i, short positions are borrowed from preceding long position



Stock	*Position*	*Offset*	*Mix Ratio*
Stock 1	Short	0	-0.25
Stock 4	Long	2	0.625
Stock 2	Short	5	-0.125
Stock 0	Long	6	0.125
Stock 3	Long	7	0.625

GA Fitness Evaluation

The fitness of a chromosome is

$$\left(\frac{\gamma}{V}\right)^{\alpha} (E - T)^{\delta}$$

Parm	*Description*
V	Variance of this mix
E	Expected return of this mix
T	Minimum target return
α	Risk aversion factor
δ	Return bias
γ	For scaling fitness

Rewards smaller risk, penalizes unacceptable return, scales exponentially to fit user biases

GA Versus Traditional Markowitz

Method

Compute co-variances, expected rate of return with 5 weeks of weighted moving averages of historical data on 23 stocks (10/3/94—9/11/95); choose 5 stocks; compute optimal mix with Markowitz model at target return **1.5**. Compare to average over five GA runs.

Results

Method	*Risk*	*Return*
Markowitz	.455	1.5
GA	.384	.52
Difference	.071	1.02

Have Figure 8, GA performance, ready

GA Versus the Market

Method

Compute statistics as above; choose 12 stocks; purchase stocks according to GA solution; count your dough

GA portfolio: expected return 0.65, standard deviation 0.434, risk 0.188

Results

Months Held	*Return (annualized)*	*Fit*
1	0.349	< 1 Std. Dev.
13	0.042	< 2 Std. Dev.

Discussion

Need more current data, and more stocks to evaluate. Time period was too short.

Have ready: Figure 11, GA performance; Figure 12, Stock returns.

Conclusions

GA advantages over traditional Markowitz model

- Compares many solutions in parallel
- Potentially identifies similar risk with higher return
- Adjustable for investor's risk tolerance

Future Work

- Evaluate GA on larger datasets

- Evaluate for longer time frames

- Enable GA to detect and track trends

- Compare to other portfolio selection techniques