

Linear Programming Formulation of Portfolio Management

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last edited: 2017-10-18

Overview

This document presents portfolio management, as used by the Gravity simulation engine, as a linear programming problem in standard form. It also discusses implementation details using the [scipy.optimize.linprog](#) Python module.

Data

- [Ideal_portfolio.2010-01-01.csv](#)

CSV headers:

name	type	description
tradingitemid	integer	Internal equity ID.
ind_long	boolean	Indicates long position (proba_long > 0.5).
ind_short	boolean	Indicates short position (proba_short > 0.5).
proba_long	float	Probability long equity (i.e. value will increase).
proba_short	float	Probability short equity (i.e. value will decrease).
marketcap	float	Marketcap (MM).
volume	integer	Weekly trade volume.
beta	float	12 month average volatility relative to S&P 500.
borrowcost	float	Actual annualized cost to borrow.
borrowavailability	integer	Outstanding volume available for borrow.

Mathematical Formulation

Ideal Portfolio

Consider probability vectors \mathbf{P}^L and \mathbf{P}^S generated by a binary classification model, defined such that the elements

$$\begin{aligned} p_i^L &\equiv \text{probability long} \\ p_i^S &\equiv \text{probability short} \\ i &\in [0..N-1] \end{aligned}$$

For both longs and shorts, we neglect any position with a probability < 0.5 .

We apply an exponential weighting function to \mathbf{P}^L and \mathbf{P}^S to generate a set of position weight vectors $\hat{\mathbf{w}}^L$ and $\hat{\mathbf{w}}^S$, respectively. These vectors should be normalized such that

$$\begin{aligned} \sum_i \hat{w}_i^L &= M_L \quad (\hat{w}_i^L > 0) \\ \sum_i \hat{w}_i^S &= M_S \quad (\hat{w}_i^S < 0) \\ M_L &\equiv \text{normalized long exposure} \\ M_S &\equiv \text{normalized short exposure} \end{aligned}$$

For example, an unlevered dollar-neutral portfolio would have $M_L = 1.0$, $M_S = -1.0$.

Objective Function

Given an ideal portfolio, \hat{P}

$$\hat{P} = [\hat{\mathbf{w}}^L, \hat{\mathbf{w}}^S]$$

we seek to minimize the error between it and our optimal portfolio, P

$$P = [\mathbf{w}^L, \mathbf{w}^S]$$

objective function:

$$\min \sum_{\substack{i \in [0..N-1] \\ j \in (L, S)}} |w_i^j - \hat{w}_i^j|$$

Optimization Constraint Bounds (Optimization Hyperparameters)

This table contains constraints definitions and default values for portfolio optimization. The goal is make these constraint bounds parameterizable inputs to our portfolio management algorithm.

$$\begin{aligned} w_{max}^L &\equiv \text{maximum long position weight} \quad (\text{default} = 0.05) \\ w_{min}^S &\equiv \text{maximum long position weight} \quad (\text{default} = -0.03) \\ M_L &\equiv \text{normalized long exposure} \quad (\text{default} = 1.00) \\ M_S &\equiv \text{normalized short exposure} \quad (\text{default} = -1.00) \\ \delta_L^M &\equiv \text{long exposure buffer} \quad (\text{default} = 0.1) \\ \delta_S^M &\equiv \text{short exposure buffer} \quad (\text{default} = 0.1) \\ \delta_L^\beta &\equiv \text{long portfolio beta buffer} \quad (\text{default} = 0.1) \\ \delta_S^\beta &\equiv \text{short portfolio beta buffer} \quad (\text{default} = 0.1) \end{aligned}$$

Constraints

Here, we itemize the list of constraints.

1. Bounds on individual weightings

$$\begin{aligned} 0 &< w_i^L \leq w_{max}^L \\ w_{min}^S &\geq w_i^S < 0 \end{aligned}$$

2. Bounds on exposure

$$\begin{aligned} 1 - \delta_L^M &\leq \frac{1}{M_L} \sum_i w_i^L \leq 1 + \delta_L^M \\ 1 - \delta_S^M &\leq \frac{1}{M_S} \sum_i w_i^S \leq 1 + \delta_S^M \end{aligned}$$

- 3. Bounds on relative volatility (“beta”). We will eventually revisit this constraint to enforce near-beta-neutrality.**

$$1 - \delta_L^\beta \leq \sum_i \beta_i^L w_i^L \leq 1 + \delta_L^\beta$$
$$-(1 - \delta_S^\beta) \leq \sum_i \beta_i^S w_i^S \leq -(1 + \delta_S^\beta)$$

- 4. Constraints on liquidity (to be completed)**

We should have something here to that say 50% of entire portfolio can be liquidated completely in 2 weeks at 20% of volume cap. Potential hyperparams:

1. percent of portfolio required to be liquid (default = 50%)
2. time period of liquidity (default = 2 weeks)
3. max volume percent (default = 20%)

- 5. Constraints on short availability (to be completed)**

This is a tricky one because you need to define this constraint as the new position (e.g. $\text{PositionSizeIdeal} - \text{PositionSizeToday} = \text{order size} \leq \text{short avail quantity}$). I think this is ok to use though since position size today is known.

Linearizing the Above Problem (Long Only)

Θ_i^j - new variables to linearize the problems

New Objective function: $Min \sum_{i,j} \Theta_i^j$

New Constraints added:

$$w_i^j - \hat{w}_i^j \leq \Theta_i^j, i = 1, \dots, N$$

$$w_i^j - \hat{w}_i^j \geq -\Theta_i^j, i = 1, \dots, N$$

Scipy Implementation

To be completed.