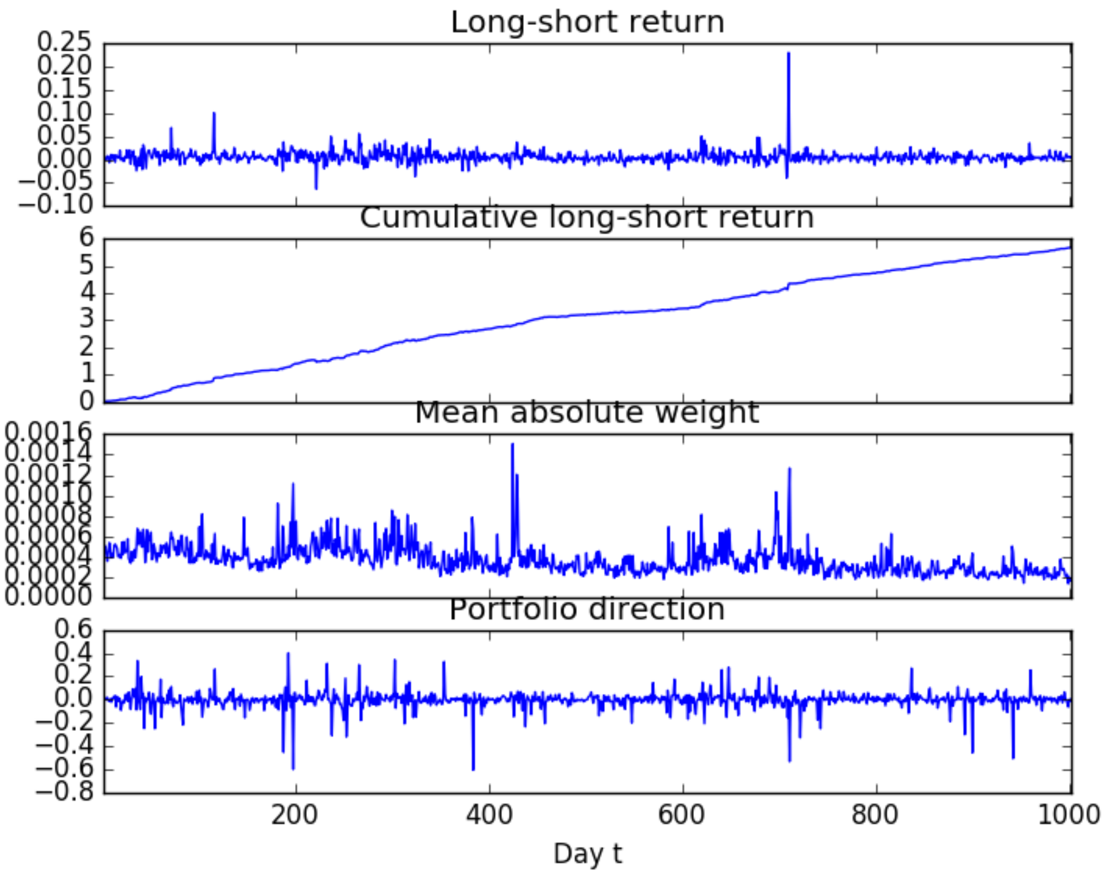

Average Daily Log Returns:	**0.00567383199315**
Standard Dev. Daily Log Returns:	**0.0126189200237**
Annualized Sharpe Ratio	**6.9963789661**
Skewness	**5.58448554934**
Kurtosis	**89.0234959108**
Max Drawdown Duration (days)	**6**
Max Drawdown Loss (% from peak)	**-4.20960993532%**
Equal-Weight Long Portfolio Correlation	**0.0121560966988**

Strategy performance is significantly improved from the first one here. An annualized Sharpe Ratio of 6.99 is great, but probably overestimate by some over-fitting of the parameters. This is likely to be the case simply from the fact that we have 12 dimensions so our optimizer function is likely to be modeling the noise of our data excessively. Nonetheless, the consistent upward steady trend in our cumulative returns is a very positive sign that these parameters are working well all throughout the data history and therefore likely to be reproduced in another sample outside the data. The maximum drawdown is solid and not concerning. Our results are right-skewed and we have high kurtosis but this is not really an issue since the mean returns are high.

This strategy is based on the idea of mean reversion for stocks, combined with a multitude of other metrics such as volatility and volume. The parameter values that we are using are as follows, for {a1, … , a12} respectively:

[-0.118, -3.057, 3.798, -2.059, 0.391, 3.857, -4.329, -3.933, -0.468, -2.175, 2.487, 2.485]

To obtain these results, we noticed that it was basically impossible to randomly generate starting initial parameters that would converge towards their optimal levels due to the 12 dimensions. We therefore ran a preliminary simplified model with only 3 parameters, labelled as below:

a) The average of ROO(t), RCC(t-1), ROC(t-1) (to replace a1 through a4)
b) The first parameter multiplied by trading volume differences (to replace a5 through a8)
c) The first parameter multiplied by volatility differences (to replace a9 through a12)

We then performed a Nelder-Mead quasi-Newton optimization method on these 3 parameters (setting initial values as random uniform between -1 and 1 multiple times) to see a pattern of convergence towards the 3 parameters that maximize Sharpe Ratio. After obtaining these values, we plugged them into the full 12-parameter model as the initial values:

{a,a,a,a,b,b,b,b,c,c,c,c}

Running the same optimization method on these parameters then allowed us to solve for the optimal 12 unique parameters defined above to maximize our Sharpe Ratio. Note that using the average of ROO(t), RCC(t-1) and ROC(t-1) to replace each of the first 4 parameters was determined to be a valid process due when we tested for the high correlation between them.