

QML Functions

QML Alpha LLC, March 1st, 2019

1. Factors Tab

FN

residual of x with respect to factors

$$F_f: x_a = \sum_{f=0}^K c_f F_{f,a} + y_a, \text{ for all } d, \text{ replace } x \text{ with } y.$$

Buckets

create quintiles for all input factors and construct groups as their intersection.

b1	0	1	2	3
b2	4	5	6	7
b3	8	9	10	11
	a1	a2	a3	a4

Clusters

k-mean clustering starts with previous day clusters (assure consistent naming).

Interaction

create new alphas for each alphaXfactor pair (component-wise product).

2. Groups Tab

Market DeMean

extract mean of the alpha $y_a = x_a - \text{Mean}(x)$, for all d .

Market Normalize

divide positive (negative) values by sum of all positive (negative) ones.

$$y_a = x_a / \text{Sum}(x_b; \text{same sign as } x_a)$$

This transformation makes the sum of all positive to be equal to 1, and the sum of all negatives to be equal to -1.

Group DeMean

similar to **Market DeMean**, applied to each group.

Group Normalize

similar to **Market Normalize**, applied to each group.

Scale

amplify the alpha values such that the sum of all positive is less or equal than 1, the sum of all negative is greater or equal than -1, and at least one equality holds.

Project

all values that correspond to the groups selected are preserved and everything else is changed to **nan**.

Interaction

the selected alphas are decomposed on the selected groups.

3. Operations Tab

Sign	$y = \text{sign}(x), \text{ for all } d, \text{ all } a$
Rank	$y_a = \text{Rank}(x_a) / \text{Count}, \text{ for all } d, \text{ produces numbers between 0 and 1.}$
MT	$y_d = \text{Sign}(\sum_{k \geq 0}^d, \text{ having same month as } d \ x_k) \text{ for all } a,$
Flip	$y = -x, \text{ for all } d, \text{ all } a$
FlipIF	if PnL for the history is positive then no change otherwise apply flip
Grandfathering	if no value then fill with the last know value (recursively)
Log	$y = \log_{10}(x + \text{shift}), \text{ for all } d, \text{ all } a$
abs	$y = \text{abs}(x), \text{ for all } d, \text{ all } a$
Tails	% tails of the distribution (50% max = no change)
NaN2Zero	replace all nan values by zero
Zero2NaN	replace all zero values by nan
Quantiles	split the alpha into its quintiles
Split	split the alpha below and above the threshold
Delta	$y_d = x_d - x_{d-h}, \text{ for all } a$
MA	$y_d = \sum_{k=d-h}^d x_k, \text{ for all } a$
Stoch	$y_d = \frac{\max(x_k, k=d-h, \dots, d) - x_d}{\max(x_k, k=d-h, \dots, d) - \min(x_k, k=d-h, \dots, d)}, \text{ for all } a$
Momentum	$y_d = \frac{x_d}{x_{d-h}} - 1, \text{ for all } a$
Stdev	$y_d = \text{stdev}(x_k, k = d - h, \dots, d), \text{ for all } a$
CCI	$y_d = \frac{x_d - \text{average}(x_k, k=d-h, \dots, d)}{\text{stdev}(x_k, k=d-h, \dots, d)}, \text{ for all } a$
ADI	$y_d = \frac{2x_d - \max(x_k, k=d-h, \dots, d) - \min(x_k, k=d-h, \dots, d)}{\max(x_k, k=d-h, \dots, d) - \min(x_k, k=d-h, \dots, d)}, \text{ for all } a$
RSI	$y_d = \frac{\text{count}(x_k > 0, k=d-h, \dots, d)}{h}, \text{ for all } a$

SR	$y_d = \frac{\text{average}(x_k * \text{ret}_{k+1+\text{delay}}, k=d-h-1-\text{delay}, \dots, d-1-\text{delay})}{\text{stdev}(x_k * \text{ret}_{k+1+\text{delay}}, k=d-h-1-\text{delay}, \dots, d-1-\text{delay})}$, for all a
CORR	$y_d = \text{correlation}(x_k, \text{ret}_k, k = d - h, \dots, d)$, for all a
MACD	$y_d = \text{MA}(x_k, k = d - h_{\text{short}}, d) - \text{MA}(x_k, k = d - h_{\text{long}}, d)$, for all a
Convergence	$y_d = \max(x_k, k = d - h_{\text{long}}, d) - \max(x_k, k = d - h_{\text{short}}, d) - \min(x_k, k = d - h_{\text{short}}, d) + \min(x_k, k = d - h_{\text{long}}, d)$, for all a
NormDist	$y_a = \text{InvNormalDistribution}(\text{Rank}(x_a))$, for all d
BETA mask	$y_a = \frac{\text{covariance}(x_k, \text{mask}_k, k=d-h, d)}{\text{stdev}(\text{mask}_a, k=d-h, d)}$, for all d
Delay	$y_d = x_{d-h}$, for all a
DecayLin	$y_d = \frac{2}{h*(h+1)} \sum_{k=d-h}^d (k - h + 1)x_k$, for all a
DecayHL	$y_d = \lambda x_d + (1 - \lambda)y_{d-1}$, for all a
DecayTarget	apply DecayHL with $\lambda = 0.5$ until the target is achieved (10 times max)
Decay %	$y_{d,a} = \lambda_{d,a} x_{d,a} + (1 - \lambda_{d,a})y_{d-1,a}$, $\lambda_{d,a}$ is computed to generate asset-wise bounded turnover
Max Concentration	$y = \text{assert}(x \text{ belong } [-thr, thr],)$ for all d , all a
Distribute	similar to Max Concentration, but will redistribute the excess weights
Max Traded Volume	limit volume traded in dollar relative to budget (\$Mil)
Min Traded Volume	do not trade small amounts
Max Pos Volume	limit positions as fraction of traded volume
Implied Alpha	$Y = QX$, multiply daily position by covariance matrix (as defined by the risk model)
Implied Position	$Y = Q^{-1}X$, multiply daily position by inverse covariance matrix

4. Aggregate Tab

Average	weighted average
MVO	weights are computed to optimize reward to risk ratio: $\begin{cases} \max W^T R \\ \text{subject to } W^T Q W = 1 \end{cases}$
Stable Set	simple average of alphas whose pairwise correlation is below threshold
DD	weights are generated from historical drawdowns: $w_{d,p} = \frac{1}{1+100*DD(p,hist)}$
SR	weights are generated from historical Sharpe Ratios
Omega	weights are generated from historical Omega Ratios (positive mass/total mass of PnL)
LogPerformance	weights are defined as: $w_{d,p} = \log_e(1 + Rank(SR(p)))$
Combine	change from one alpha to another: $y_d = \begin{cases} x_d^1, & \text{if } d < D \\ x_d^2 & \text{if } d \geq D \end{cases}, \text{ for all } a$
SPerf	initially, weights are equal, after a while the weight is scaled up if alpha realized 2% of its weight and it is scaled down if it enters a drawdown of 2% or more
OrthogonalPerf	sequentially add best performing alphas with equal weights.

After each addition, the remaining alphas are neutralized against the selected ones and their performance is reevaluated

5. Machine Learning Tab

Factor Learning	construct many alphas by interacting the original alpha with factors and apply MVO aggregation method
Group Learning	construct many alphas by interacting the original alpha with groups and apply one of the available aggregation or Machine Learning methods: SR, MVO, Fisher, CART.
Regression	linear regression with the independent variables being the selected alphas and the dependent variable defined in the regression page
Patterns	rule-based induction learning. Positive/negative observations are defined based on the value of the threshold around the mean. Positive Rules are detected such that their Positive Homogeneity (i.e., frequency of the positive observations) is above the specified value, and their Positive Prevalence (i.e., the fraction of observations that trigger the rule) is larger than prescribed. Similar requirements are imposed to Negative Rules. The value of the alpha is generated as the weighted vote between Positive and Negative Rules.
Data is digitized using a grid in each attribute. The complexity of the rules is bounded to maximum "Degree" number of attributes.	
Fisher	Fisher Linear Discriminant Analysis
LDA	Linear Discriminant Analysis based on the centers of positive and negative sets
NN	Discretized version of Nearest Neighborhood for multiple subsets of alphas
CART	Classification And Regression Trees based on branching with linear discriminants
PLS	Partial Least Square regression
Logit	Logistic regression

6. Statistical Factors Tab

PCA Factors	Generate Principal Components of the selected alpha.
PCA Remove	The alpha is changed so that exposure to its Principal Component are removed
Orthogonal	Alphas are orthogonalized
Corr	Construct the factor-factor covariance matrix
Match Corr	Align factors by matching correlation
Hungarian	Align factors by Hungarian Algorithm