MC²: a cryptocurrency portfolio solution

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**MC² Mission**

**Problem**

The $200 B cryptocurrency market is a high growth opportunity for investors, but its volatility prevents many institutional investors from taking advantage of this asset.

**Mission**

Build a cryptocurrency portfolio that is controlled for volatility and provides consistent return.
Mission Accomplished - Consistent Return

MC2 Portfolio, Benchmark, and Bitcoin

Long/Short Strategy with limited market exposure enabled great returns while smoothing out the market dips (market drawdown)
Mission Accomplished - Reduced Volatility
How We Did It - Snapshot of June 1, 2019

Coins to Buy on 6/1/2019

Coins to Short on 6/1/2019
How We Did It
High Level Approach

Step 1: Feature Engineering & Selection

AWS DB → Feature Extraction
- Momentum
- Lead/Lag
- Reversal
- LSTM

Characteristic Portfolio
- Momentum
- Lead/Lag
- Reversal
- LSTM

Information Ratio
- Momentum
- Lead/Lag
- Reversal
- LSTM

Selected?
- No
- No
- Yes
- No

Step 2: Portfolio Construction

Constraint Strategy

Daily Optimizer

Weighted Portfolio of 500 coins

Reversal
## Feature Engineering

<table>
<thead>
<tr>
<th>Feature</th>
<th>Momentum</th>
<th>Lead Signal</th>
<th>Reversal Signal</th>
<th>Predicted ROI</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Intuition</strong></td>
<td>Measure Trend</td>
<td>&quot;Star&quot; currencies move first, other</td>
<td>Detect a reversal of uptrend or</td>
<td>Daily predicted ROI from previous 50</td>
</tr>
<tr>
<td></td>
<td>Strength of Trend</td>
<td>follow (right chart)</td>
<td>downtrend</td>
<td>days (LSTM)</td>
</tr>
<tr>
<td></td>
<td>Bullish vs Bearish</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Computation</strong></td>
<td>Price(_T) - Price(_T-N_days)</td>
<td>mean, weighted-avg</td>
<td>Price(_T) - avg(Prices)</td>
<td></td>
</tr>
<tr>
<td><strong>Tunable Parameters</strong></td>
<td># of day N 10,20,30,40</td>
<td># days, # top currencies</td>
<td># days best 60 day</td>
<td>Coin’s Features, Epochs, dropout</td>
</tr>
</tbody>
</table>

### Intuition

Measure Trend, Strength of Trend, Bullish vs Bearish

"Star" currencies move first, other follow (right chart)

Detect a reversal of uptrend or downtrend

Daily predicted ROI from previous 50 days (LSTM)

### Computation

- Price\(_T\) - Price\(_T-N\_days\)
- Mean, weighted-avg
- Price\(_T\) - avg(Prices)

### Tunable Parameters

- # of day N: 10, 20, 30, 40
- # days, # top currencies
- # days best 60 day

**Coin’s Features, Epochs, dropout**

### Diagrams

- **Zero momentum**
  - Bitcoin leads Cardano

- **Bitcoin 40 Day Momentum**
  - The chart shows the momentum of Bitcoin over 40 days.

- **Bitcoin and Cardano**
  - The chart compares the prices of Bitcoin and Cardano.

- **Bitcoin 60 Day Reversal**
  - The chart indicates the reversal of the trend in Bitcoin over 60 days.
Feature Selection starts with Characteristic Portfolio

For a feature \( a \), we can construct a **Characteristic Portfolio** that has minimum risk and a unit exposure to feature \( a \). The Characteristic Portfolio will help us compute the information ratio (IR) for feature selection.

For a feature \( a \),

\[ a = \{a_{c1}, a_{c2}, \ldots, a_{c500}\} \]

\[ V = \text{Covariance Matrix} \]

\[
\begin{bmatrix}
C_1 & C_2 & \cdots & C_{500} \\
\sigma^2_1 & \sigma^2_{1,2} & \cdots & \sigma^2_{1,500} \\
\sigma^2_{2,1} & \sigma^2_2 & \cdots & \sigma^2_{2,500} \\
\vdots & \vdots & \ddots & \vdots \\
\sigma^2_{500,1} & \sigma^2_{500,2} & \cdots & \sigma^2_{500,500}
\end{bmatrix}
\]

\[ w_a = \frac{V^{-1}a}{a^TV^{-1}a} \]

Solve for characteristic portfolio weight

\[ w_a = \{w_{c1}, w_{c2}, \ldots, w_{c500}\} \]

Average (returns)

STDEV (Returns)

**Analytical Solution**

**Secret sauce**

**IR (Daily returns computed)**

See appendix for detailed formulas
Feature Selection Using Characteristic Portfolio Results

20 Day Momentum

60 Day Reversal

$$\Delta(\text{Days})$$

$$\Delta(\text{Days})$$

$$\text{IR} = \frac{\text{Average (returns)}}{\text{STDEV (Returns)}}$$
Portfolio Construction

Modern Portfolio Theory (MPT)

- There is a trade-off between risk and return
- Risk is measured as the standard deviation of return
- Efficient Frontier

Capital Asset Pricing Model (CAPM)

\[ E(R_i) = R_f + \beta_i (E(R_m) - R_f) + \epsilon_i \]

- Systematic risk and specific risk
- Idiosyncratic risk can be reduced through diversification
- Beta (coefficient) measures the exposure to the market movement

Source:
https://towardsdatascience.com/python-markowitz-optimization-b5e1623060f5
Lagrange Optimization

Utility function (maximize):
\[ \alpha - \lambda \times \text{Var} \]
\( \lambda \): how much we want to penalize the risk

Constraints:
- Fully invested / money neutral
- Tracking market / limit market exposure

Bounds:
- Maximum exposure to a single currency

Input:
- Aggregated alphas (normalized)
- Risk exposure and covariance matrix

Output:
- Weights for each asset
Portfolio Construction

Optimizer

Sequential Least SQuares Programming Algorithm (SLSQP)
- Gradient Based
- NonLinear Constraints
- Widely used among quantitative funds
- Scipy implementation

https://en.wikipedia.org/wiki/Sequential_quadratic_programming
Backtesting

Proposed Strategies

**Long-Short**
Constraints:
\[
\sum(w_i) = 0
\]
\[
\sum(w_i \cdot beta_i) = b
\]
Bounds:
\[-0.05 \leq w \leq 0.05\]
Params:
\(\lambda, b \sim (0, 0.3)\)

**Long-Only Active**
Constraints:
\[
\sum(w_i) = 1
\]
\[
\sum(w_i \cdot beta_i) = b
\]
Bounds:
\[0 \leq w \leq 0.05\]
Params:
\(\lambda, b \sim (0.5, 1)\)

Parameter tuning

**Dev data**
2016 - 2018

**Test data**
2019

**Performance measurement**
Return
Sharpe ratio
Results

<table>
<thead>
<tr>
<th></th>
<th>1 year</th>
<th>2 year</th>
<th>3 year</th>
<th>Since 2016</th>
</tr>
</thead>
<tbody>
<tr>
<td>market neutral</td>
<td>3.17</td>
<td>2.59</td>
<td>3.98</td>
<td>5.30</td>
</tr>
<tr>
<td>long only</td>
<td>-0.29</td>
<td>-0.27</td>
<td>2.66</td>
<td>4.38</td>
</tr>
<tr>
<td>benchmark</td>
<td>1.10</td>
<td>-0.06</td>
<td>1.33</td>
<td>1.33</td>
</tr>
<tr>
<td>bitcoin</td>
<td>1.48</td>
<td>-0.16</td>
<td>1.33</td>
<td>1.34</td>
</tr>
</tbody>
</table>
Achievements and Learnings

- Generalized traditional financial market theory to cryptocurrency and layered in machine learning techniques

- Key Learnings
  - Cryptocurrency Market
  - Financial Engineering Techniques
  - Python Optimizer

- Key Challenges
  - Market History is limited
  - Volatile Data

- 100M in revenue gains since May, 2016 and low draw back
Next Steps and Areas for Improvement

- Coin Clustering
  - Stable Coins
  - Market Leaders
  - Interest Bearing Coins
- Back Testing in varied market scenarios
- Explore New Signals
- Tune LSTM signal
- Refine the Risk Model to include more factors
- Refine the Optimizer
- Integrate Transaction Costs
Testimonials From the Field

“Interesting approach, let’s talk when you integrate transaction costs” - Manager at Hedge Fund


“I am going to use a similar code structure at my job.” Ted and Marcus
Wrap Up

We set out to build a cryptocurrency portfolio that balanced volatility and return by applying a systematic investment approach to crypto currency.

We leveraged financial engineering including Min Variance Optimization and Characteristic Portfolio in a machine learning like environment. We also experimented with machine learning algorithms like neural net.

Bottom line, our portfolio’s max draw down never dipped significantly despite huge drops in the market over the past 3 years.

Interested? For more information, please check out our website at

http://groups.ischool.berkeley.edu/crypto_portfolio/crypto_portfolio/.