

Risk-Constrained Kelly Gambling

Optimization and Algorithms Project Presentation

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Outline

Part I – Implementation in CVX

- Kelly Problem
- Risk-Constrained Kelly Problem
- Our implementation
- Results

Part II – The Optimal Strategy

- Problem Formulation
- Our implementation
- Results

Part I - Implementation in CVX

- 1. Kelly Problem
- 2. Risk-Constrained Kelly Problem
- 3. Our implementation
- 4. Results

1. Kelly problem

Implementation in CVX

1. Kelly problem

2. Risk-Constrained Kelly Problem

3. Our implementation

4. Results

- We consider the classic Kelly gambling problem with general distributions of outcomes.
- John Kelly proposed a systematic way to allocate a total wealth across a number of bets so as to maximize the long term growth rate when the gamble is repeated [1].

1. Kelly problem

Implementation in CVX

1. Kelly problem

2. Risk-Constrained Kelly Problem

3. Our implementation

4. Results

- With this strategy – Kelly optimal bets – there is a risk of the wealth dropping substantially from its original value before increasing.

- The wealth growth is given by

$$w_t = (r_1^T b) \dots (r_{t-1}^T b)$$

with t equal to $1, 2, \dots$ with I.I.D. returns.

1. Kelly problem

Implementation in CVX

1. Kelly problem

2. Risk-Constrained Kelly Problem

3. Our implementation

4. Results

- The goal is to choose b so that the wealth becomes larger.
- In Kelly gambling we want to find a b in order to maximize $E \log(r^T b)$, the growth rate of wealth.

$$\begin{aligned} & \text{maximize} && E \log(r^T b) \\ & \text{subject to} && \mathbf{1}^T b = 1, b \geq 0 \end{aligned}$$

- The solution of b optimal values is called *Kelly Optimal bets*.

Part I - Implementation in CVX

- 1. Kelly Problem
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2. Risk-Constrained Kelly Problem

Implementation in CVX

1. Kelly problem

2. Risk-Constrained Kelly Problem

3. Our implementation

4. Results

- In Risk-Constrained Kelly we add a drawdown risk constraint:

$$\begin{aligned} & \text{maximize} && \mathbf{E} \log(r^T b) \\ & \text{subject to} && \mathbf{1}^T b = 1, b \geq 0 \\ & && \mathbf{Prob}(W^{\min} < \alpha) < \beta \end{aligned}$$

- The new constraint limits the probability of a drop in wealth to value α to be no more than β .

2. Risk-Constrained Kelly Problem

Implementation in CVX

1. Kelly problem

2. Risk-Constrained Kelly Problem

3. Our implementation

4. Results

- A bound of the drawdown risk is developed to make the problem easily solvable in CVX.

$$\mathbf{Prob}(W^{min} < \alpha) < \alpha^\lambda = \beta$$

- It is valid as long α and β are between 0 and 1 and $\lambda = \frac{\log(\beta)}{\log(\alpha)}$.

2. Risk-Constrained Kelly Problem

Implementation in CVX

1. Kelly problem

2. Risk-Constrained Kelly Problem

3. Our implementation

4. Results

- The parameter λ is the risk aversion parameter.
- A higher value means the problem only considers risk-free bets while a low value limits the ratio of variance to the mean growth.

Part I - Implementation in CVX

- 1. Kelly Problem
- 2. Risk-Constrained Kelly Problem
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3. Our implementation

Implementation in CVX

1. Kelly problem

2. Risk-Constrained Kelly Problem

3. Our implementation

4. Results

- The Kelly gambling problem is a convex optimization problem since the objective is concave and the constraints are convex.
- We inserted the function to maximize and the constraints directly on CVX.

3. Our implementation

Implementation in CVX

1. Kelly problem

- For the Kelly problem we used

$$\begin{aligned} & \text{maximize} && \sum_{i=1}^K \pi_i \log(r^T b) \\ & \text{subject to} && \mathbf{1}^T b = 1, b \geq 0 \end{aligned}$$

2. Risk-Constrained Kelly Problem

- And for the Risk-constrained Kelly problem we used

$$\begin{aligned} & \text{maximize} && \sum_{i=1}^K \pi_i \log(r^T b) \\ & \text{subject to} && \mathbf{1}^T b = 1, b \geq 0 \\ & && \log\left(\sum_{i=1}^K \exp(\log \pi_i - \lambda \log(r_i^T b))\right) \leq 0 \end{aligned}$$

3. Our implementation

4. Results

Part I - Implementation in CVX

- 1. Kelly Problem
- 2. Risk-Constrained Kelly Problem
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4. Results

Implementation in CVX

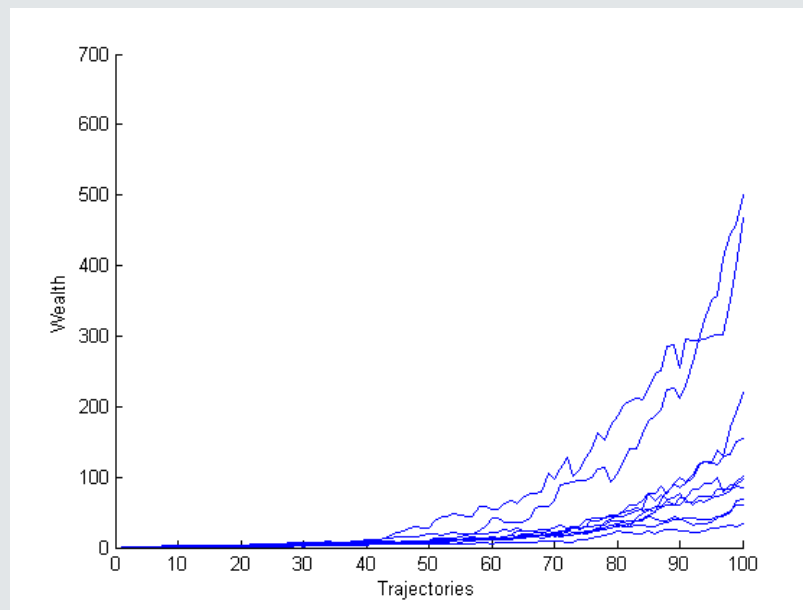
1. Kelly problem

2. Risk-Constrained Kelly Problem

3. Our implementation

4. Results

- Wealth trajectories for the Kelly optimal bet.



4. Results

Implementation in CVX

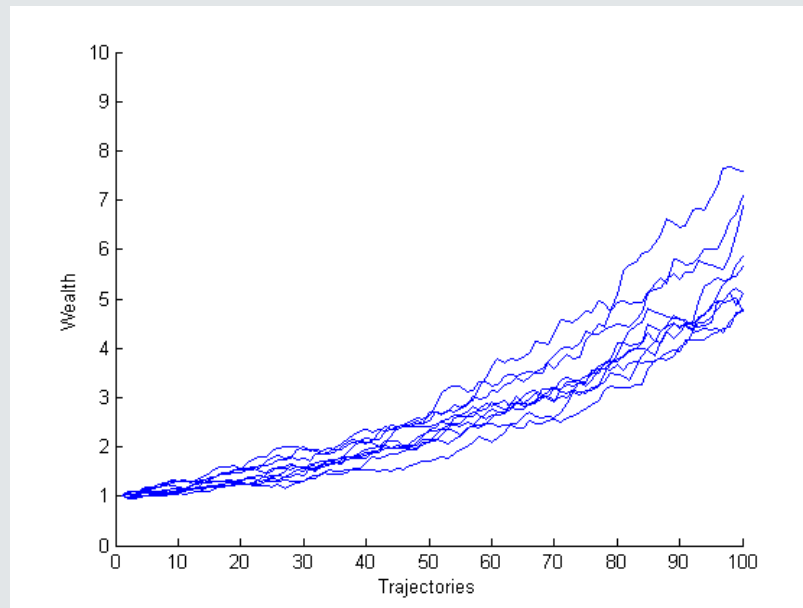
1. Kelly problem

2. Risk-Constrained Kelly Problem

3. Our implementation

4. Results

- Wealth trajectories for the Risk-Constrained Kelly optimal bet.



4. Results

Implementation in CVX

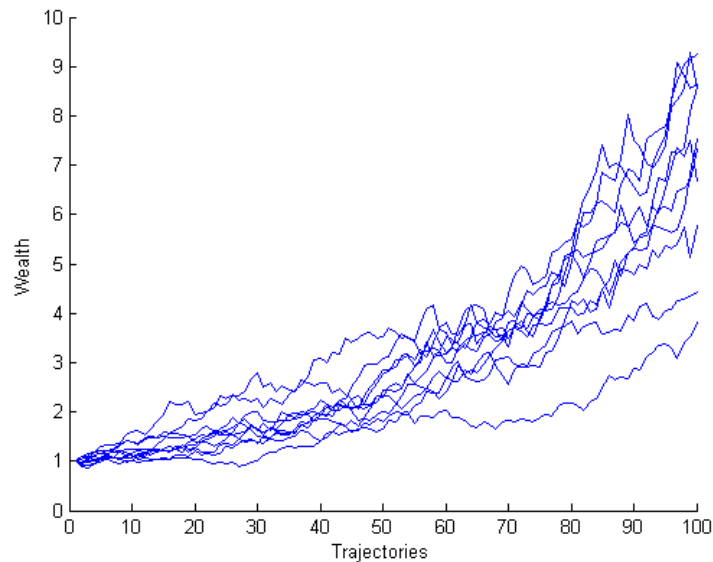
1. Kelly problem

2. Risk-Constrained Kelly Problem

3. Our implementation

4. Results

- Wealth trajectories for a random bet.



4. Results

Implementation in CVX

1. Kelly problem

2. Risk-Constrained Kelly Problem

3. Our implementation

4. Results

- We can conclude that:
 - The Risk-Constrained Kelly with the selected parameters represent a **conservative approach** for betting;
 - Solving an optimization problem translates in a **better final result** given the constraints.

Part II – The Optimal Strategy

- 1. Problem Formulation
- 2. Our implementation
- 3. Results

1. Problem Formulation

The Optimal Strategy

1. Problem Formulation

2. Our implementation

3. Results

- Only one bet;



- We cannot evaluate the performance of the optimal strategy;
- Still using Kelly gambling;



1. Problem Formulation

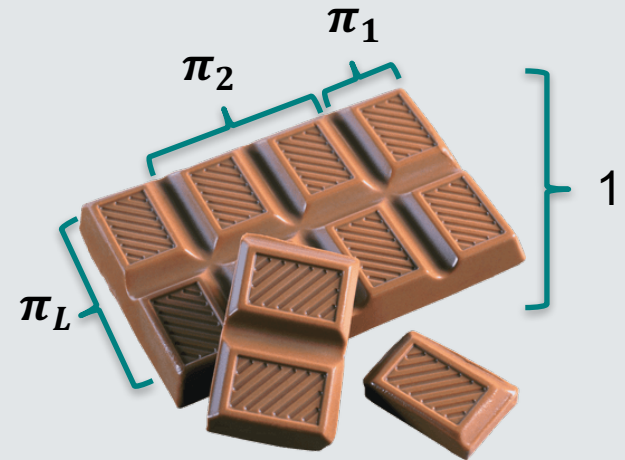
The Optimal Strategy

1. Problem Formulation

2. Our implementation

3. Results

- We have L hypothesis for vector π_i
- Consider no drawdown $\lambda = 0$



1. Problem Formulation

The Optimal Strategy

1. Problem Formulation

- The goal is to choose b so that the wealth becomes larger.
- In Kelly gambling we wanted to find a b in order to maximize $E \log(r^T b)$, the growth rate of wealth.

$$\begin{aligned} & \text{maximize } \pi_i \log(r^T b) \\ & \text{subject to } \mathbf{1}^T b = 1, b \geq 0 \end{aligned}$$

- The solution of b optimal values cannot depend on π_i .

3. Results

1. Problem Formulation

The Optimal Strategy

1. Problem Formulation

- We came up with 2 solutions

Since we bet just one...

$$\dots r \in R_+$$

- The First one:

$$\overline{\pi}_i = \sum_{i=1}^L \left(\frac{1}{L} * \pi_i \right)$$



$$\begin{aligned} & \underset{b}{\text{maximize}} \quad \overline{\pi}_i * \log(r^T b) \\ & \text{subject to} \quad \mathbf{1}^T b = 1, b \geq 0 \\ & \quad \quad \quad \mathbf{1}^T \pi_i = 1, \pi_i \geq 0 \end{aligned}$$

1. Problem Formulation

The Optimal Strategy

1. Problem Formulation

2. Our implementation

3. Results

- It was an approximation of the L, π_i vectors;
- So in average we could still get the best probability outcome for the best value of the return matrix but with a low probability to happen;

1. Problem Formulation

The Optimal Strategy

1. Problem Formulation

2. Our implementation

3. Results

- The Second one:

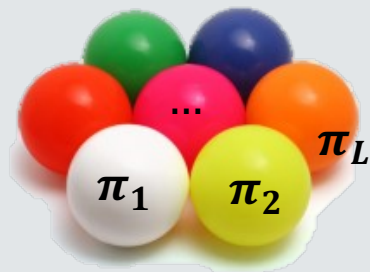
$$\sum_{i=1}^L \left(\sum_{i=1}^K \pi_i * \log(r_i^T \mathbf{b}) \right)$$



$$\underset{\mathbf{b}}{\text{maximize}} \sum_{i=1}^L \left(\sum_{i=1}^K \pi_i * \log(r_i^T \mathbf{b}) \right)$$

$$\text{subject to} \quad \mathbf{1}^T \mathbf{b} = 1, \mathbf{b} \geq 0$$

$$\mathbf{1}^T \boldsymbol{\pi}_i = 1, \boldsymbol{\pi}_i \geq 0$$



1. Problem Formulation

The Optimal Strategy

1. Problem Formulation

2. Our implementation

3. Results

- Wrapping up our final formulation of the problem is:

$$\underset{\mathbf{b}}{\text{maximize}} \sum_{i=1}^L \left(\sum_{i=1}^K \pi_i * \log(r_i^T \mathbf{b}) \right)$$

$$\begin{aligned} \text{subject to} \quad & \mathbf{1}^T \mathbf{b} = 1, \mathbf{b} \geq 0 \\ & \mathbf{1}^T \boldsymbol{\pi}_i = 1, \boldsymbol{\pi}_i \geq 0 \end{aligned}$$

- Which would give us a sub-optimal solution, instead of a optimal, since it depends on the $\boldsymbol{\pi}_i$ vector.

Part II – The Optimal Strategy

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2. Our Implementation

The Optimal Strategy

1. Problem Formulation

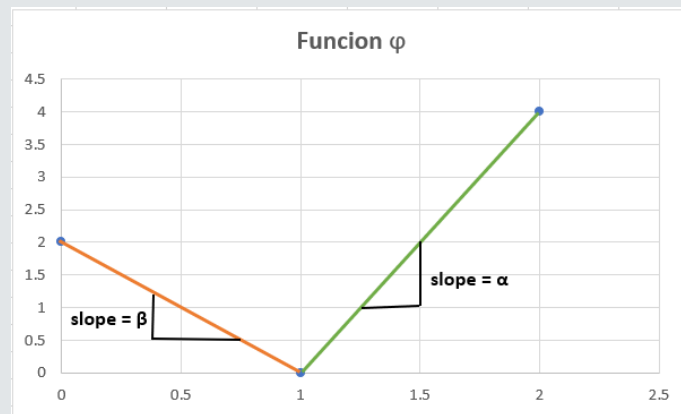
2. Our implementation

3. Results

$$\text{maximize } E \log(r^T b) - \sum_{K=1}^{N-1} \phi_K(b_K)$$

$$\text{subject to } \sum b = 1, b \geq 0$$

How to compute ϕ ???



2. Our Implementation

The Optimal Strategy

1. Problem Formulation

2. Our implementation

3. Results

$$\left. \begin{aligned} \emptyset_{k\ left} &= \beta * x + b_{left} \\ \emptyset_{k\ right} &= \beta * x + b_{right} \end{aligned} \right\} b_{left} ? b_{right} ?$$

$$\emptyset_k = 0 \quad \longrightarrow \quad b_{left} = -\beta * b_{ref} ; b_{right} = -\alpha * b_{ref}$$

2. Our Implementation

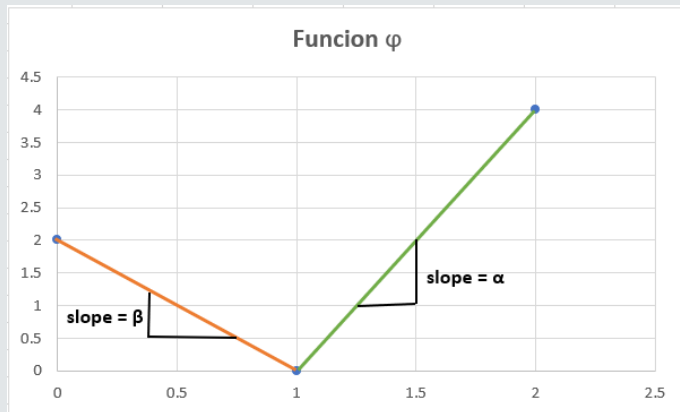
The Optimal Strategy

1. Problem Formulation

2. Our implementation

3. Results

$$\phi_k = \frac{\phi_{k\text{ left}} + \text{abs}(\phi_{k\text{ left}})}{2} + \frac{\phi_{k\text{ right}} + \text{abs}(\phi_{k\text{ right}})}{2}$$



Part II – The Optimal Strategy

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3. Results

The Optimal Strategy

1. Problem Formulation

2. Our implementation

3. Results

β	α	b_{ref}	b	ϕ	f
-0,0091	0,00222	3,15E-02	5,58E-10	1,44E-05	0,02599
-0,0126	0,00313	3,80E-02	3,90E-02	6,32E-11	0,02599
-0,0026	0,00164	1,03E-11	3,14E-10	6,22E-05	0,02267
-0,0062	0,00901	6,71E-02	1,02E-01	1,82E-04	0,02530
-0,0043	0,00816	4,35E-02	1,14E-09	2,34E-05	0,02596
-0,0057	0,00780	5,36E-11	3,07E-10	2,96E-04	0,02267
-0,0075	0,00175	2,40E-02	1,14E-01	2,45E-05	0,02510
-0,0068	0,00136	2,49E-02	8,61E-10	1,79E-05	0,02517
-0,0165	0,00439	3,60E-02	8,07E-10	8,88E-06	0,02597
-0,0084	0,00036	7,34E-12	3,09E-10	1,35E-05	0,02267
-0,0124	0,00364	3,14E-02	7,27E-10	2,42E-05	0,02572
-0,0193	0,00194	7,27E-02	3,37E-01	6,69E-04	0,02491
-0,0159	0,00843	5,83E-12	2,66E-10	3,20E-04	0,02267
-0,0025	0,00382	1,47E-11	2,77E-10	1,45E-04	0,02267
-0,0005	0,00227	5,23E-12	2,33E-10	8,61E-05	0,02267
-0,0133	0,00901	3,92E-11	8,52E-10	3,42E-04	0,02267
-0,0153	0,00580	5,52E-02	2,50E-02	2,64E-04	0,02576
-0,0159	0,00884	3,56E-02	8,36E-02	2,07E-05	0,02596
-0,0084	0,00767	6,72E-02	3,00E-01	2,46E-04	0,02529
0,0000	0,00000	4,73E-01	4,51E-10	0	-0,01161

Thank you for your attention

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