

Integer Programming Models: Constructing an Index Fund

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 - This is the case if the bidder has a limited budget or the goods are similar or interchangeable.

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- Question: How should auctioneer determine winners and losers in order to maximize his revenue?

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$$\begin{aligned} & \max \sum_{j \in B} p_j x_j - \sum_{j \in S} p_j y_j \\ \text{Subject to : } & \sum_{j: i \in B_j} \lambda_i^j x_j = \sum_{j: i \in S_j} \lambda_i^j y_j \\ & x_j = 0 \text{ or } 1, \forall j = 1, \dots, m, \\ & y_j = 0 \text{ or } 1, \forall j = 1, \dots, n \end{aligned}$$

The Lockbox Problem

The Lockbox Problem

Construct the Problem

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Construct the Problem

- National firm in US receives checks from all over the country.
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- Idea: Open offices all over country to receive checks and to minimize delay.

The Lockbox Problem

The Lockbox Problem

Example

The Lockbox Problem

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- Suppose we receive payments from 4 regions (West, Midwest, East, and South).

The Lockbox Problem

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The Lockbox Problem

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- Average daily value from each region is: \$600 K, \$240 K, \$720 K, \$360 K respectively.
- We are considering opening lockboxes in Los Angeles, Pittsburgh, Boston, and/or Houston.
- Operating a lockbox costs \$90,000 per year.

The Lockbox Problem

The Lockbox Problem

Example

The Lockbox Problem

Example

Clearing times				
From	L.A	Pittsburgh	Boston	Houston
West	2	4	6	6
Midwest	4	2	5	5
East	6	5	2	5
South	7	5	6	3

The Lockbox Problem

The Lockbox Problem

Example Cont.

The Lockbox Problem

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The Lockbox Problem

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- First we must calculate the lost interest for each possible assignment.
- For example, if the West sends its checks to a lockbox in Boston, then on average there will be $\$3,600,000 = (6 \times \$600,000)$ in process on any given day.
- Assuming an investment rate of 5%, this corresponds to a yearly loss of $\$180,000$.

The Lockbox Problem

The Lockbox Problem

Example Cont.

The Lockbox Problem

Example Cont.

Lost Interest				
From	L.A	Pittsburgh	Boston	Houston
West	60	120	180	180
Midwest	48	24	60	60
East	216	180	72	180
South	126	90	108	54

The Lockbox Problem

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Example Cont., Integer Programming Formulation

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$$60x_{11} + 120x_{12} + 180x_{13} + 180x_{14} + 48x_{21} + \dots$$
$$+ 90y_1 + 90y_2 + 90y_3 + 90y_4.$$

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The Lockbox Problem

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$$x_{11} + x_{21} + x_{31} + x_{41} \leq 4y_1.$$

The Lockbox Problem

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Integer Programming Formulation

The Lockbox Problem

Integer Programming Formulation

- $\min 60x_{11} + 120x_{12} + 180x_{13} + 180x_{14} + 48x_{21} + 24x_{22} + 60x_{23} + 60x_{24} + 216x_{31} + 180x_{32} + 72x_{33} + 180x_{34} + 126x_{41} + 90x_{42} + 108x_{43} + 54x_{44} + 90y_1 + 90y_2 + 90y_3 + 90y_4.$

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 - $x_{41} + x_{42} + x_{43} + x_{44} = 1$
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- All variables binary.

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- In fact, we have an integer solution, which must therefore be optimal!

The Lockbox Problem

The Lockbox Problem

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$$q = 2, \mathbf{C}_{ij} = \begin{pmatrix} 0 & 4 & 5 & 8 & 2 \\ 4 & 0 & 3 & 4 & 6 \\ 5 & 3 & 0 & 1 & 7 \\ 8 & 4 & 1 & 0 & 4 \\ 2 & 6 & 7 & 4 & 0 \end{pmatrix}$$

- Compare the linear programming relaxations of your two formulations in question (2).

The Lockbox Problem

Exercise Solution

The Lockbox Problem

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Exercise Solution Cont.

The Lockbox Problem

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- An optimum fractional solution of the system in (a) is $x_{ii} = 1$ and $y_i = 0.4$ for $i = 1, \dots, n$ (other values are 0). The objective value of this solution is 0. On optimum solution of the same LP but with the constraint from (2) gives $y_3 = y_5 = 1; x_{15} = x_{55} = x_{23} = x_{33} = x_{43} = 1$ with a value of 6. This is even an integer solution.

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- Conclusion: The constraint from (2) is stronger (and therefore better).

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- Indexing: absolutely no attempt is made to identify mispriced securities.
- The goal is to choose a portfolio that mirrors the movements of a broad market population or a market index. Such a portfolio is called an index fund.

Constructing an Index Fund

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Constructing an Index Fund

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A Large-Scale Deterministic Model

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Testing the Model

- Stocks comprising the S&P 500 were chosen as the target population to test the model.
- A calibration period of sixty months was used.
- Then a portfolio of 25 stocks was constructed using model (M) and held for periods ranging from three months to three years.

Constructing an Index Fund

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- It turns out, however, that one does not need to solve this large linear program to obtain good upper bounds.

Constructing an Index Fund

Performance of Stocks

Constructing an Index Fund

Performance of Stocks

Performance of a 25 stock index fund	
Length	Ratio
1 QTR	1.006
2 QTR	.99
1 YR	.985
3 YR	.982

Constructing an Index Fund

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Constructing an Index Fund

Properties Cont.

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- **Property 3:** In an optimal solution of the Lagrangian relaxation, y_j is equal to 1 for the q largest values of C_j , and the remaining y_j are equal to 0.

Constructing an Index Fund

A Linear Programming Model

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Constructing an Index Fund

Rebalancing the Portfolio

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Constructing an Index Fund

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Portfolio Optimization with Minimum Transaction Levels

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Markowitz Model

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Portfolio Optimization with Minimum Transaction Levels

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Portfolio Optimization with Minimum Transaction Levels

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Solve for the Optimal Portfolio

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- When solving the classical Markowitz model, the optimal portfolio often contains positions x_j that are too small to execute.

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$$\mu^T \cdot x \geq R$$

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- with the additional property that:
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Portfolio Optimization with Minimum Transaction Levels

Solve for the Optimal Portfolio

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- Let x^* be the optimal solution found.

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- If x^* satisfies the constraint, then it is optimum to Markowitz model and we can stop.

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 - One obtained from Markowitz model by adding the constraint $x_k = 0$ (down branch),

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- Otherwise, let k be an index for which $x_k > 0$.
- Form two subproblems:
- One obtained from Markowitz model by adding the constraint $x_k = 0$ (down branch),
- The other obtained from Markowitz model by adding the constraint $\sum_{j \neq k} \frac{x_j}{u_j} \leq K - 1$ (up branch).

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- When a set T of variables has been branched up, the constraint added to the basic Markowitz model becomes:

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$$\sum_{j \notin T} \frac{x_j}{u_j} \leq K - |T|.$$

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