# Financial Portfolio Optimization with (O)R Operations Research & R

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## Optimization Modeling & R

**Facts** about OR/Optimization and R:

- Statisticians love to build optimization models matrix-wise.
- CRAN (Optimization Task View) is focussed on solvers.
- Optimization under Uncertainty is not covered.
- ▶ OR people use MatLab/Julia, Python, and/or C++.

Strategy: Simplify and do it - and implement as R packages.

**Issue:** It is impossible to design a *one fits all* product/package!

**Solution:** Simple, extensible, lightweight, and *lovable* optimization *modeling* framework.

# Optimization modeling gap - Academic Optimization

- Everything is done for one (or two) research paper(s).
- ► Focus on one specific solution method or one specific solver.
  - The model is created in a solver-readable matrix format.
  - Data and model is mixed (messed) up.
  - Need mathematical proofs to impress non-scientists.
- PhD students are forced to do the implementation.
- If a deadline is missed: you send the project to the next conference or special issue of a journal.

# Optimization modeling gap - Real-World

No one cares about how it is solved, i.e.

- dirty heuristics are ok, no proofs necessary.
- Data and model should be separated.
  - Different groups and persons are working on it.
- Simplifications are crucial
  - to communicate and maintain the model, and to
  - implement optimization results into your business process.

If a deadline is missed: you lose money, clients, reputation, your wife & life, and so on...

... the gap is obvious.

#### Common Issue

#### Optimization is a side-product ("someone has to do it").



# Learning from OR - Deterministic Optimization

Reconsider the basic optimization problem:

minimize x f(x, P)subject to  $x \in \mathcal{X}(P)$ 

- $f(\cdot)$  is a cost function,
- x are decision variables (to be computed), and
- P are (precisely known) parameters.
- $\mathcal{X}$  denotes a set of constraints.

The real-world is uncertain (unfortunately), i.e.  $\tilde{P}$ !

Why not use  $P = \mathbb{E}(\tilde{P})$ ?

# Learning from OR - Deterministic Optimization

Reconsider the basic optimization problem:

maximize  $x \quad f(x, P)$ subject to  $x \in \mathcal{X}(P)$ 

- $f(\cdot)$  is a profit function,
- x are decision variables (to be computed), and
- P are (precisely known) parameters.
- $\mathcal{X}$  denotes a set of constraints.

The real-world is uncertain (unfortunately), i.e.  $\tilde{P}$ !

Why not use  $P = \mathbb{E}(\tilde{P})$ ?

## Stochastic Optimization



alive  $(\mathbb{E} [\text{position}]) = \text{true}, \text{ but } \mathbb{E} [\text{alive (position)}] = \text{false!}$ 

## Stochastic Portfolio Optimization

Numerical example [Wiesemann 2010] - simple wealth maximization model with 5 indices (ATX, CAC, DAX, FTSE, SMI):



## Modern Portfolio Theory

Calculate an optimal portfolio x given a assets given a vector of expected returns M and a co-variance matrix  $\mathbb{C}$  subject to further constraints  $\mathcal{X}$ , i.e. the well-known Markowitz approach:

minimize 
$$x \quad x \mathbb{C} x^T$$
  
subject to  $x \times M \ge \mu$   
 $x \in \mathcal{X}$ .

**Issues** with this approach:

- Uncertainty is just implicitly modeled  $\rightarrow$  deterministic!
- QP framework too rigid and specific (OR perspective).
- ▶ General extensions (CVaR, ...) are put on top of this base.

# Stochastic Programming - Integrating Uncertainty

Stochastic Programming naturally separates the *objective* and *subjective* part of a decision problem.

1. **Optimization model** specifies the event space at each decision stage to integrate **objective** real-world constraints and dynamics, i.e. the event handling (**quantitative** aspects of the solution).

2. **Uncertainty model** is chosen independently from optimization model to reflect **subjective** beliefs of the decision taker (**qualitative** aspects of the solution).

## Stochastic Portfolio Optimization

Objective and subjective parts within portfolio optimization:

- ▶ X set of regulatory & organizational constraints.
- ► *S* asset return uncertainty model.

Flexible to integrate any risk measure (VaR, Omega, ...):

▶  $\ell_x$  - loss distribution for some portfolio *x*, i.e.  $\ell_x = \langle x, S \rangle$ .

(Bi-criteria) optimization meta-model:

maximize x Return $(\ell_x)$ minimize x Risk $(\ell_x)$ subject to  $x \in \mathcal{X}$ 

#### Optimization in R - matrix-based (modopt)

```
# maximize: 2*x1 + x2;
# subject to: x1+x2 <= 5;
# subject to: x1 <= 3;
# x1 >= 0, x2 >= 0
```

```
f <- c(2, 1)
A <- matrix(c(1, 1, 1, 0), nrow=2, byrow=TRUE)
b <- c(5, 3)</pre>
```

```
solution <- linprog(-f, A, b)
print(solution$x)</pre>
```

#### Optimization in R - matrix-based (modopt)

```
# Markowitz minimization
```

```
H <- covariance
f <- rep(0, assets)</pre>
Aeq <- rep(1, assets)
beg <- 1
lb <- rep(0, assets)</pre>
ub <- rep(1, assets)
solution <- quadprog(H, f, NULL, NULL,</pre>
    Aeq, beq, lb, ub)
portfolio <- solution$x
print(portfolio)
```

# Optimization Modeling in R

The ingredients of every optimization problem are:

- Parameters: Input.
- Variables: Output.
- Objective function(s): Minimization, Maximization.
- Constraints.

Provide functions for exactly these (and only these) ingredients within  $\ensuremath{\mathtt{R}}.$ 

Optimization Modeling in R (modopt)

model()

x1 <- 0; x2 <- 0
variable(x1, lb=0)
variable(x2, lb=0)</pre>

maximize("2\*x1 + x2")
subject\_to("x1+x2 <= 5")
subject\_to("x1 <= 3")</pre>

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optimization()

# Optimization Modeling in R with modopt

Light-weight: Just a handful of functions to add objective function(s), constraints, parameters, to initialize (optimization) variables, and to define (optimization variable) sets.

- model() to create a new optimization model.
- optimization() to execute the current model.

The design of the package is heavily influenced by the standalone optimization modeling languages AMPL and ZIMPL as well as CVX and YalMip for MatLab.

# Optimization modeling in R with modopt

Advantages of this approach:

- Readable and teachable optimization models.
  - Model libraries (OR people love these).
- Clear separation of data, model, and optimization.
- Domain-specific modeling shortcuts.
  - Simplified portfolio optimization modeling.
- Modeling simplifications for special optimization purposes.

Multi-stage Stochastic Programming.

Simplified portfolio optimization modeling

**Strategy:** Simplify and do it (and extend after simplification). modopt.portfolio - minimum additional input:

- ► Preferred: Discrete representation of return scenarios.
- Alternative: Markowitz-style mean vector *M* and covariance matrix C.

Convert each input into the other (e.g. in case of  $M/\mathbb{C}$  sample scenarios) to allow for any optimization remodeling.

## Simplified portfolio optimization modeling

Loss distribution-based risk measures (OR)

```
sd(loss)
mad(loss)
cvar(loss, alpha)
var(loss, alpha)
ginimd(loss)
minimax-young(loss)
omega(loss, threshold)
avgdd(loss)
```

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Mean/Covariance-based risk measures

```
markowitz(loss)
```

. . .

## Stochastic Portfolio Optimization:

Basic Markowitz in modopt.portfolio:

```
minimize("markowitz(loss)")
minimize("subject to mean(loss) >= 0.02")
```

CVaR minimization with Markowitz constraint:

```
minimize("minimize cvar(loss, 0.05)")
subject_to("sd(loss) <= 0.02")
subject_to("mean(loss) >= 0.01")
```

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Conversion example:

```
minimize minimax-young(loss)
subject to mean(loss) >= 0.02
```

#### Stochastic Portfolio Optimization - Conversion Example

```
set("Asset", 1:dim(scenario_set)[2])
set("Scenario", 1:dim(scenario_set)[1])
parameter(scenario_set, "Asset, Scenario")
parameter(scenario_prob, "Scenario")
```

```
variable(loss, "Scenario")
variable(portfolio, "Asset")
```

```
subject_to("sum('portfolio[Asset] *
    scenario[Asset, Scenario]', 'Asset')
    == loss[Scenario]", "Scenario")
```

Simplified portfolio optimization modeling

Specific additions of modopt.portfolio.minimax-young are

```
variable(gamma)
variable(scenario_downside, "Scenario", lb=0)
```

```
subject_to("scenario_downside[Scenario] - gamma +
    loss[Scenario] >= 0", "Scenario")
```

```
maximize("gamma")
```

optimization() will calculate the optimal portfolio but also provide the optimization model within R for further modification.

Simplified portfolio optimization modeling

Other objective functions & constraints:

```
track(sp500)
cardinality(10)
```

. . .

Once a clear idea of how to reformulate a new objective and/or constraints, one may add this converter to modopt.portfolio.

Multi-stage decision optimization under uncertainty

Design goal: Modeling language independent of

- optimization modeling approach:
  - Expectation-based convex multi-stage stochastic programming,

- Worst-case optimization,
- ▶ ...
- underlying solution technique:
  - Tree-based deterministic equivalent formulation.
  - Primal/dual linear decision rules, upper/lower bounds.
  - ▶ ...

Stylized multi-stage stochastic programming example from [Heitsch el al. 2006]:

$$\begin{array}{ll} \text{minimize} & \mathbb{E}\left(\sum_{t=1}^{T}V_{t}x_{t}\right)\\ \text{subject to} & s_{t}-s_{t-1}=x_{t} & \forall t=2,\ldots,T\\ & s_{1}=0,s_{T}=a,\\ & x_{t}\geq0,s_{t}\geq0. \end{array}$$

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A simple multi-stage model in R (modopt.multistage)

```
parameter(a)
variable(x, lb=0); variable(s, lb=0)
```

```
maximize(id="objective", "E(x)")
subject_to(id="non_anticitpativity", "s - s(-1) = x")
subject_to(id="root_stage", "s = 0")
subject_to(id="terminal_stage", "s = a")
```

```
deterministic("T", a)
stochastic("0..T", x, s, "objective")
stochastic("1..T", "non_anticipativity")
stochastic("0", "root_stage")
stochastic("T", "terminal_stage")
```

#### Contact

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