OPTIMIZATION UNDER CONNECTED UNCERTAINTY

Kartikey Sharma, Omid Nohadani

Northwestern University
Industrial Engineering and Management Sciences

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Motivation

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- Examples:
 - ► Auto-correlated demand in an inventory management problem
 - ▶ Auto-correlated returns in a portfolio optimization problems.
- Robust Optimization across multiple periods: Separate uncertainty sets for each period
 - Does not capture correlation



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Example: Ellipsoid Uncertainty set can be expressed as combination of two uncertainty sets.

$$\mathcal{U} = \{ \mathbf{d} = (d_1, d_2) \mid ||\mathbf{d}||_2 \le \rho \}$$

where

$$\mathcal{U}_1 = \left\{ d_1 \mid |d_1| \le \rho \right\} \qquad \mathcal{U}_2(d_1) = \left\{ d_2 \mid |d_2| \le \sqrt{\rho^2 - d_1^2} \right\}$$

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The parameters of the uncertainty set at each period are a function of past realizations.

- ► Scenario Tress:Infanger and Morton [1996], De Queiroz and Morton [2013]
- RO: Zhao and Zeng [2012], Jiang et al. [2012], Bertsimas and Vayanos [2015], Lorca and Sun [2015,2017], and Nohadani and Roy [2017].
- ▶ DRO: Analui and Pflug [2014], Xin and Goldberg [2015]

RO Example

Consider

$$\begin{aligned} \max_{\mathbf{x}_1, \mathbf{x}_2} \mathbf{c}_1^\top \mathbf{x}_1 + \mathbf{c}_2^\top \mathbf{x}_2 \\ \text{s.t. } \mathbf{d}_1^\top \mathbf{x}_1 + \mathbf{d}_2^\top \mathbf{x}_2 &\leq B \ \forall \mathbf{d}_2 \in \mathcal{U}_2(\mathbf{d}_1) \ \forall \mathbf{d}_1 \in \mathcal{U}_1 \\ \mathbf{x}_1, \mathbf{x}_2 &\in \mathcal{X} \end{aligned}$$

Uncertainty for d_2 explicitly depends on d_1 .

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Ellipsoid

$$U_2(\mathbf{d}_1) = {\mathbf{d}_2 \mid \mathbf{d}_2 = \boldsymbol{\mu}_2(\mathbf{d}_1) + \mathbf{L}_2\mathbf{u}_2 : \|\mathbf{u}_2\|_2 \le r_2}$$

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Ellipsoid

$$U_2(\mathbf{d}_1) = \{\mathbf{d}_2 \mid \mathbf{d}_2 = \mu_2(\mathbf{d}_1) + \mathbf{L}_2\mathbf{u}_2 : \|\mathbf{u}_2\|_2 \le r_2\}$$

Center

$$\boldsymbol{\mu}_2(\mathbf{d}_1) = \mathbf{A}_2 \boldsymbol{\mu}_1(\mathbf{d}_0) + \mathbf{F}_2 \mathbf{d}_1 + \mathbf{c}_2$$

$$\sup_{P_1 \in \widetilde{\mathcal{U}}_1} \mathbb{E}_{\mathbf{d}_1 \sim P_1} \left[\mathbf{d}_1^{\top} \mathbf{x}_1 \right] \le B. \tag{DRO}$$

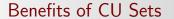
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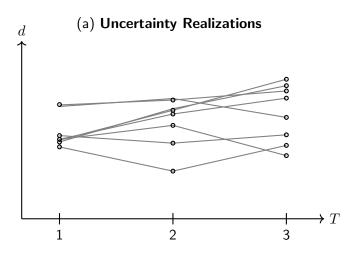
$$\frac{\widetilde{\mathcal{U}}_1}{\left|\mathcal{U}_1 = \left\{P_1 \in \mathcal{M}(\Xi_1) \middle| \ \left|\mathbb{E}_{P_1}[\mathbf{d}_1] - \boldsymbol{\mu}_1\right| \leq \boldsymbol{\delta}_1, \ \mathbb{E}_{P_1}[(\mathbf{d}_1 - \boldsymbol{\mu}_1)(\mathbf{d}_1 - \boldsymbol{\mu}_1)^\top] \leq \boldsymbol{\Sigma}_1\right\},\right.$$

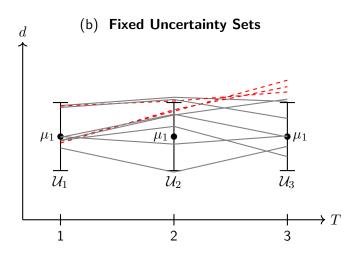
$$\sup_{P_1 \in \widetilde{\mathcal{U}}_1} \mathbb{E}_{\mathbf{d}_1 \sim P_1} \left[\mathbf{d}_1^\top \mathbf{x}_1 + \sup_{P_2 \in \widetilde{\mathcal{U}}_2(\mathbf{d}_1)} \mathbb{E}_{\mathbf{d}_2 \sim P_2} \left[\mathbf{d}_2^\top \mathbf{x}_2 \right] \right] \leq B. \text{ (DRO)}$$

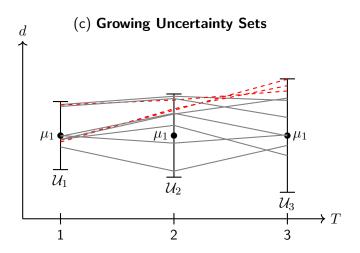
$$\frac{\widetilde{\mathcal{U}}_1}{\mathcal{U}_1} = \left\{ P_1 \in \mathcal{M}(\Xi_1) \middle| \ \middle| \mathbb{E}_{P_1}[\mathbf{d}_1] - \boldsymbol{\mu}_1 \middle| \leq \boldsymbol{\delta}_1, \ \mathbb{E}_{P_1}[(\mathbf{d}_1 - \boldsymbol{\mu}_1)(\mathbf{d}_1 - \boldsymbol{\mu}_1)^\top] \leq \boldsymbol{\Sigma}_1 \right\},$$

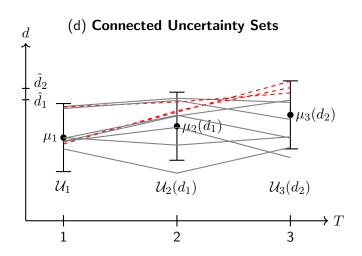
$$\widetilde{\mathcal{U}}_2(\mathbf{d}_1) = \left\{ P_{2|1} \in \mathcal{M}(\Xi_2) \middle| \ \left| \mathbb{E}_{P_{2|1}}[\mathbf{d}_2] - \boldsymbol{\mu}_2(\mathbf{d}_1) \middle| \leq \boldsymbol{\delta}_2, \ \mathbb{E}_{P_{2|1}}[(\mathbf{d}_2 - \boldsymbol{\mu}_2^0)(\mathbf{d}_2 - \boldsymbol{\mu}_2^0)^\top] \preceq \boldsymbol{\Sigma}_2 \right\}$$

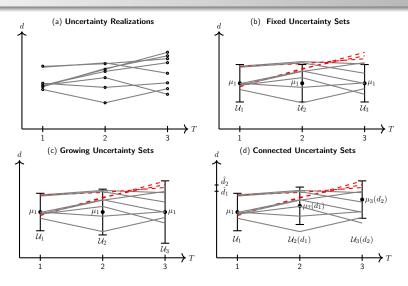


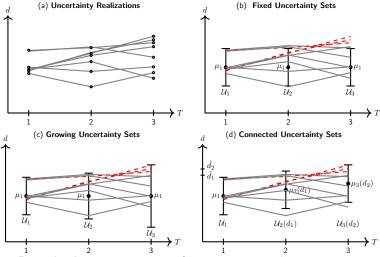




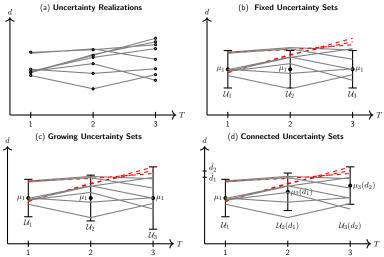








Provides better coverage of uncertainty realizations



- Provides better coverage of uncertainty realizations
- ► Incorporates information about structure of uncertainty realizations.



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$$\sup_{P_1 \in \widetilde{\mathcal{U}}_1} \mathbb{E}_{P_1} \left[h_1 + \sup_{P_{2|1} \in \widetilde{\mathcal{U}}_2(\mathbf{d}_1)} \left\{ \mathbb{E}_{P_{2|1}} \left[h_2 + \dots + \sup_{P_{T|T-1} \in \widetilde{\mathcal{U}}_T(\mathbf{d}_{T-1})} \left\{ \mathbb{E}_{P_{T|T-1}} \left[h_T \right] \right\} \right] \right\} \right] \leq B.$$

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▶ Each nested \sup is a concave function \mathbf{d}_t .

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- Reformulate as infinite dimensional optimization problem.

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- ▶ IOP

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$$\mathbb{E}\left[\sum_{t=1}^{T} h_t(\mathbf{x}_t, \mathbf{d}_t)\right] \le B$$

Robust counterpart

$$\sup_{P_1\in \tilde{\mathcal{U}}_1}\mathbb{E}_{P_1}\left[h_1+\sup_{P_{2|1}\in \hat{\mathcal{U}}_2(\mathbf{d}_1)}\left\{\mathbb{E}_{P_{2|1}}\left[h_2+\cdots+\sup_{P_{T|T-1}\in \hat{\mathcal{U}}_T(\mathbf{d}_{T-1})}\left\{\mathbb{E}_{P_{T|T-1}}\left[h_T\right]\right\}\right]\right\}\right]\leq B.$$

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- ▶ IOP $\xrightarrow{\text{conser. approx.}}$ Semi-infinite opt. prob. $\xrightarrow{\text{ellips. support}}$ SDP
- \blacktriangleright Conserv. Approx. \Leftrightarrow approximating \sup by a linear function

$$\begin{aligned} \max_{x_1, x_2} & \min_{P \in \mathcal{U}} \mathbb{E}_P[u(\mathbf{r}_1^{\top} \mathbf{x}_1) + u(\mathbf{r}_2^{\top} \mathbf{x}_2)] \\ \text{s.t.} & \sum_{i=1}^n x_{1i} = 1 \\ & \sum_{i=1}^n x_{2i} = 1 \\ & \mathbf{x}_1, \mathbf{x}_2 \ge 0 \end{aligned}$$

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▶ Maximize $u(z) = \min\{1.5z, 0.015 + z, 0.06 + 0.2z\}$

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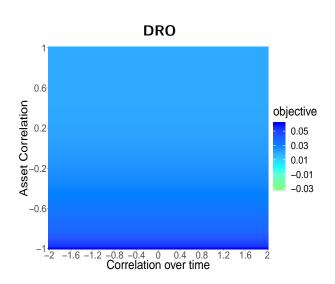
- Maximize $u(z) = \min\{1.5z, 0.015 + z, 0.06 + 0.2z\}$
- 2 Stocks

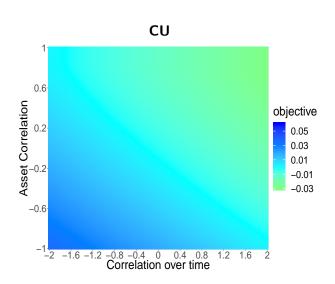
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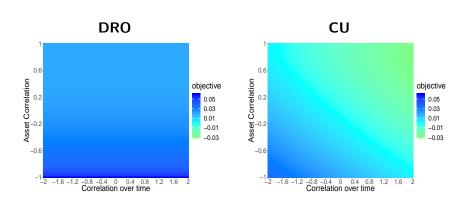
- Maximize $u(z) = \min\{1.5z, 0.015 + z, 0.06 + 0.2z\}$
- 2 Stocks
- ▶ Moment based uncertainty set. $\mu_2(\mathbf{r}_1) = \omega \mathbf{r}_1 + (1 \omega)\mu_1$

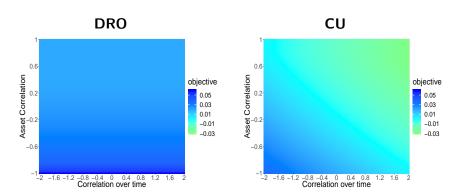
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- 2 Stocks
- ▶ Moment based uncertainty set. $\mu_2(\mathbf{r}_1) = \omega \mathbf{r}_1 + (1 \omega)\mu_1$
- $\mu_1 = [0.06, 0.03], \sigma^2 = 0.005$ for both assets

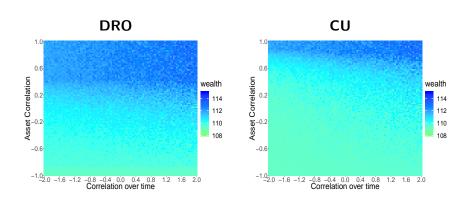




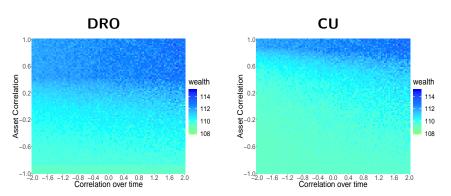




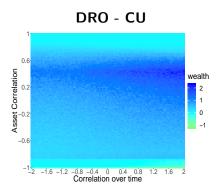
Objective value decreases with asset correlation and correlation over time.

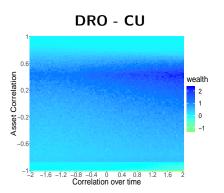


Portfolio Optimization: Realized Wealth



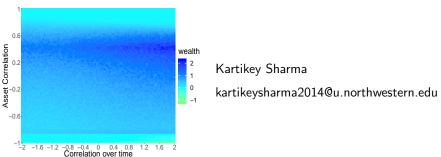
Average realized wealth increases with asset correlation and correlation over time.





Benefit of CU increases with correlation over time. It achieves a peak for an asset correlation value 0.4-0.5

- In many problems, uncertainty depends on past realizations.
- Connected uncertainty sets incorporate this behavior and lead to less variable solutions.
- ► The reformulated problems are difficult → decision rules and conservative approximations.



- [1] Bita Analui and Georg Ch Pflug. On distributionally robust multiperiod stochastic optimization. *Computational Management Science*, 11(3):197–220, 2014.
- [2] Dimitris Bertsimas and Phebe Vayanos. Data-driven learning in dynamic pricing using adaptive optimization. *Preprint*, 2015.
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- [6] Omid Nohadani and Arkajyoti Roy. Robust optimization with time-dependent uncertainty in radiation therapy. IISE Transactions on Healthcare Systems Engineering, 7(2):81–92, 2017.
- [7] Linwei Xin and David A Goldberg. Distributionally robust inventory control when demand is a martingale. *arXiv preprint arXiv:1511.09437*, 2015.
- [8] Long Zhao and Bo Zeng. Robust unit commitment problem with demand response and wind energy. In 2012 IEEE power and energy society general meeting, pages 1–8. IEEE, 2012.



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► Linear constraints with polyhedral or ellipsoidal uncertainty sets are reformulated as LPs and SOCPs.

Robust Knapsack

Two period knapsack problem with uncertain weight coefficients.

$$\begin{aligned} & \min_{\mathbf{x}_1, \mathbf{x}_2} \ \mathbf{c}_1^\top \mathbf{x}_1 + \mathbf{c}_2^\top \mathbf{x}_2 \\ & \text{s.t.} \ \mathbf{d}_1^\top \mathbf{x}_1 + \mathbf{d}_2^\top \mathbf{x}_2 \leq B \ \ \forall \mathbf{d}_2 \in \mathcal{U}_2(\mathbf{d}_1) \ \ \forall \mathbf{d}_1 \in \mathcal{U}_1 \\ & \mathbf{x}_1, \mathbf{x}_2 \in \mathcal{X} \end{aligned}$$

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▶ Ellipsoidal uncertainty sets. Parameters from samples.

Two period knapsack problem with uncertain weight coefficients.

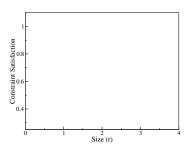
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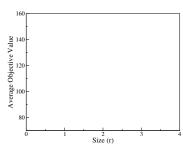
- ▶ Ellipsoidal uncertainty sets. Parameters from samples.
- Solution quality evaluated on new uncertainty samples.

Two period knapsack problem with uncertain weight coefficients.

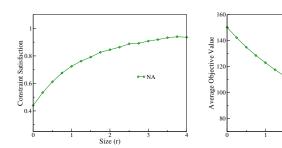
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- ▶ Ellipsoidal uncertainty sets. Parameters from samples.
- Solution quality evaluated on new uncertainty samples.
- Performance evaluated with Normal and Lognormal distributions.





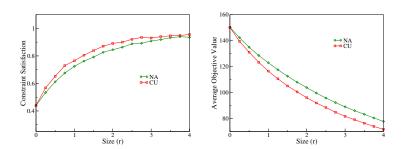
▶ Better constraint satisfaction at the price of lower objective value.



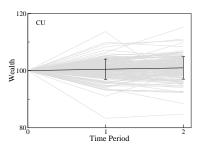
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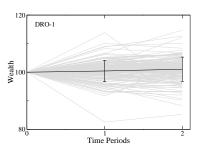
◆ NA

Size (r)



▶ Better constraint satisfaction at the price of lower objective value.





Given the sets
$$\widetilde{\mathcal{U}}_1,\ldots,\widetilde{\mathcal{U}}_T(\mathbf{d}_{T-1})$$
, the robust counterpart of constraint
$$\mathbb{E}\left[\sum_{t=1}^T h_t(\mathbf{x}_t,\boldsymbol{\xi}_t)\right] \leq B \text{ is }$$

$$\sup_{P_1 \in \widetilde{\mathcal{U}}_1} \mathbb{E}_{P_1} \Big[h_1(\mathbf{x}_1,\mathbf{d}_1) + \sup_{P_{2|1} \in \widetilde{\mathcal{U}}_2(\mathbf{d}_1)} \Big\{\mathbb{E}_{P_{2|1}} \Big[h_2(\mathbf{x}_2,\mathbf{d}_2) + \cdots + \sup_{P_{T|T-1} \in \widetilde{\mathcal{U}}_T(\mathbf{d}_{T-1})} \Big\{\mathbb{E}_{P_{T|T-1}} \Big[h_T(\mathbf{x}_T,\mathbf{d}_T)\Big]\Big\}\Big]\Big\}\Big] \leq B.$$