TEACHING DOSSIER

Giorgio Costa

Ph.D. Candidate in Operations Research
Department of Mechanical and Industrial Engineering
University of Toronto
2019

Contents

1 Brief Biography

I am a PhD candidate in Operations Research at the University of Toronto, and I expect to graduate this upcoming Summer 2020. During my doctoral studies, I have had the opportunity to work as a teaching assistant and, more recently, as a instructor in multiple courses at both the undergraduate and graduate levels. As a teaching assistant, I have participated in multiple courses in the Department of Mechanical and Industrial Engineering (MIE) and the Master of Mathematical Finance program (MMF). As an instructor, I have taught several courses in MIE and in the Department of Electrical and Computer Engineering (ECE). Aside from my teaching roles, I have also had the opportunity to participate in the curriculum development and program accreditation process in the Faculty of Applied Science and Engineering at the University of Toronto. Finally, I am currently serving as co-advisor to two undergraduate thesis students.

My research interests lie at the intersection of Operations Research, Data Science, and Machine Learning. Specifically, I study the application of optimization theory to solve problems in finance and risk management. My doctoral studies have also allowed me to perform research at a professional level at the Toronto–Dominion Bank. This combination of research and professional experience have helped me become a well-rounded lecturer, where I draw from both theory and applications to provide students with a holistic experience.

2 Teaching Philosophy

My passion for teaching has helped to shape my teaching philosophy. Simply put, my philosophy is grounded on having well-defined learning outcomes for each course, and use this to create a conducive road map for teaching and learning. Moreover, the design of courses and coursework should emphasize higher-order cognitive skills, like critical thinking, while still managing to deliver the required disciplinary content. A good teacher should be able to reconcile their own method of instruction to accommodate a diverse set of learners. My teaching philosophy is to always put myself in the shoes of my students, taking different angles to ensure I can capture the attention of most, if not all, students. I will use this opportunity to discuss the four pillars of my philosophy: my motivation to teach, learning outcomes and skills assessment, the design of coursework and lecture delivery, and my engagement with students.

I. Motivation to teach

As a researcher, I have always had a passion for academia. Both the pursuit of pure knowledge, and the freedom to focus on solving different problems that affect individuals, organizations, and nations, are the pillars of academia to which I relate the most. However, as much as I enjoy research, there is nothing I find more rewarding than teaching. Thus far, my experience as a teacher has been quite fulfilling and humbling. Students are excellent at posing 'outside-the-box' questions, and these always provide good food-for-thought. I often end up thanking students who pose such questions, since they improve my own understanding of the material. I have only been teaching for a few years, and, from conversations with seasoned professors, I am aware that teachers never stop learning themselves. Just as with research, I find this life-long path a very welcome challenge.

II. Learning outcomes and skills assessment

I learned a valuable lesson about how to prepare and articulate learning outcomes and develop ways to reliably assess these skills when the Canadian Engineering Accreditation Board (CEAB) visited the Faculty of Applied Science and Engineering at the University of Toronto. The CEAB performs quality assurance of engineering schools across Canada. This experience taught me the value of having well-defined learning outcomes for each course. These objectives should be reflected within the lectures, coursework, and exams.

Not only do the learning outcomes provide a road map for the curriculum, but should also serve to design the evaluation rubric of the course, ensuring each outcome is assessed throughout the course. Moreover, the learning outcomes should align with the broader degree requirements. This, in turn, provides a level of assurance that a student's degree develops fundamental skills beyond subject matter expertise, such as critical thinking. At the end of the day, this translates to give the students a better understanding of the skills they are developing and how they can leverage these skills after graduation. Thus, this pillar of my philosophy regarding learning outcomes and skills assessment is fundamental to properly structure a course.

III. Design of coursework and lecture delivery

It is my personal belief that the main purpose of a university lecture is to condense, digest, and motivate. The lecture should address the fundamental question each student faces eventually: "what is the point?". Indeed, why should a student attend a lecture, let alone university, if they could gain all this knowledge directly from a book or the internet? What is the value-add of sitting through a lecture? In engineering, quantitative finance, and many other disciplines, most of the core concepts tend to be quite abstract and, plainly stated, difficult to grasp. A teacher should help students navigate the material, condensing and summarizing it to avoid overwhelming students. Moreover, a teacher should provide intuition and context to help a student digest this material. As an example, my pedagogical approach to mathematics is to introduce a concept and cover all its theoretical caveats, explaining all the moving parts by writing on a traditional blackboard. I pause and let the material sink in for a minute, reiterating what we just saw. I proceed to complement this through a high-level verbal example or case scenario in an applied setting, making the material relatable outside of the classroom. Finally, I proceed to elaborate with a simple numerical example that ties together all the moving parts, and highlights the key takeaways from the material. I find these last two steps are crucial, providing clarity and helping the material to sink in. This helps students see the bigger picture and realize how these small steps fit in within the rest of the course, within their major, and even beyond the walls of the university.

The coursework should complement the lectures, but the material should not be redundant. Instead, assignments and projects should give students some flexibility and encourage their creativity. For example, we could ask students to apply the core principles seen in class in a different context, or go one step further and ask them to implement a method not covered in class. The latter can be achieved by providing students with guidance so that they can conduct their own research. Pushing the students outside of the classroom 'bubble' develops their critical thinking skills, and encourages discussion between students. My personal experience as an undergraduate student reminds me that students sometimes learn more from their peers than from their instructors. Thus, it is important to foster a collaborative environment, allowing the students to work in groups, and encouraging them to discuss the material outside of the classroom. Finally, I like to design my coursework to mimic a professional environment, giving students a taste of how to apply theoretical content from the classroom to real-world applications outside the university.

IV. Student engagement

The last pillar I will discuss is the engagement with students. Beyond being approachable and answering emails, I truly believe that students should be made feel welcome, both within and outside of the scheduled course time. This can be achieved subtly, by answering emails and other online messages in a timely fashion and with a comprehensive answer. More explicitly, I always remind my students at the start and end of each lecture they are welcome to come speak with me in person or online, whichever is most comfortable for them. Finally, and most important of all, I always treat students with the utmost respect, and never dismiss their questions or concerns. When answering a student, either in front of their peers, or in private, I like to remind the students that "this is a good question", subtly reassuring them that everyone should feel comfortable to ask questions. My engagement with students is not only beneficial to them, but also for myself. It helps me understand where the students are having the most trouble, and it teaches me what I can do different to improve my courses. Each student has their own way of learning, and communicating with students is essential to understand their needs.

In my experience as both a lecturer and teaching assistant, I have taught many different courses in topics such as mathematical optimization, financial engineering, and risk management. In addition, I would also welcome the opportunity to teach a wider variety of subjects. Regardless of the subject matter, I always focus on the four pillars of my teaching philosophy, but also keeping in mind that I can always build upon them and improve as a teacher. At the end of the day, this is about empowering the students, providing them with an environment where they can develop and grow.

3 Teaching Experience

3.1 Course Instruction

MIE377 – Financial Optimization Models (Spring 2018, Spring 2019)

MIE377 is a core course for third-year undergraduate students in the Division of Engineering Science pursuing the specialization in Engineering Mathematics, Statistics and Finance (EMSF). The class size is approximately 30 students. The course consists of three hours of lecture every week, as well as a one-hour practical tutorial per week. In addition, there is a bi-weekly one-hour computational laboratory component, with six laboratory sessions per semester.

The course content focuses on developing a good understanding of general optimization theory, and its applications to finance and risk management. The first month of the course is devoted to studying general non-linear optimization. The remainder of the course focuses on techniques to optimize portfolios. Finally, the last component of the course introduces students to stochastic processes and Monte Carlo simulations.

As the course instructor, I redeveloped the coursework by incorporating two long-term team projects into the course. These computational projects emphasize the application of theory learned in class to real-world applications using real financial data. Aside from these projects, the coursework consists of one midterm exam, one final exam, and two assignments. Every year that I teach the course, I prepare entirely new exams, assignments and projects. I would like to add that I am scheduled to teach MIE377 again this upcoming Spring 2020 term.

MIE375 – Financial Engineering (Fall 2018)

MIE375 is a core course for third-year undergraduate students in the EMSF specialization within the Division of Engineering Science. This course is the prerequisite of MIE377. The class size is approximately 30 students, and the course consists of three hours of lecture and a one-hour practical tutorial per week.

The purpose of this course is to introduce engineering students to finance. In particular, the course emphasizes the mathematical derivation of many financial instruments, and applies statistics to parametrize financial risk and reward. Finally, the students learn fundamental financial models, such as the capital asset pricing model (CAPM) and the Black–Scholes model. The coursework consists of a midterm exam, a final exam, and two assignments. As part of my commitment to student excellence, I developed new exams and assignments for the course.

ECE302 – Probability and Applications (Fall 2019)

ECE302 is a core course for third-year undergraduate students in the Department of Electrical and Computer Engineering. The course admits 300 students, and has three sections of 100 students each. As the instructor of one of these sections, I was responsible for delivering lectures to 100 students for three hours per week. In addition, the students have a two-hour practical tutorial per week. This large course requires six teaching assistants to accommodate the number of students. As part of my duties as instructor, I was also responsible for managing the teaching assistants.

The purpose of this course is to introduce students to probability theory, starting with the basics of set theory, discrete and continuous random variables, descriptive statistics such as expected value and variance, and some basic models of probability like Markov chains.

3.2 Teaching Assistant Experience

MIE479 – Capstone Design Project (Fall 2019)

- Level: undergraduate, core course
- Class size: 30 students
- Responsibilities: advising students through periodic research meetings, leading tutorials, marking of coursework, responding to student queries.

MMF2000 – Risk Management (Fall 2019, 2018; Summer 2018, 2017)

- Level: graduate, core course
- Class size: 30 students
- Responsibilities: marking of coursework, responding to student queries.

MMF1921 – Operations Research (Summer 2019, 2018, 2017)

- Level: graduate, core course
- Class size: 30 students
- Responsibilities: leading tutorials, coursework development (computational projects), marking of coursework, responding to student queries.

MIE1621 – Non-Linear Optimization (Fall 2016)

- Level: graduate
- Class size: 45 students
- Responsibilities: leading tutorials, marking of coursework, responding to student queries.

3.3 Undergraduate Supervision

I am serving as the co-supervisor of two undergraduate thesis students during this academic year (2019–2020). Since this is their first real research opportunity, I meet them weekly to provide guidance and discuss their progress. As a research co-supervisor, my purpose is to help them structure their research projects and to guide them through the research process by suggesting relevant literature and techniques, by reading their work and providing feedback, and by challenging their statements, results and conclusions to strengthen their research. To ensure a rewarding experience, my goal for them is to conduct research that can be submitted to a peer-reviewed journal by the end of the academic year. A list of supervised students follows.

- Yu Zhang, undergraduate student, co-supervised with Prof. Roy H. Kwon
  Thesis: Dimensionality reduction of fundamental financial features for portfolio optimization
- Yang Yang, undergraduate student, co-supervised with Prof. Roy H. Kwon
  Thesis: Improving mean–variance optimization through the DCF method

4 Evidence of Teaching Effectiveness

The Faculty of Applied Science and Engineering at the University of Toronto only provides a teaching evaluation for lecturers, but not for teaching assistants. Thus, I am only able to provide my scores for the courses where I have worked as the lecturer. I am delighted to say my rating as a lecturer is, on average, 4.5 out of 5.0.

The following table presents a summary of my evaluations as course instructor for MIE377 and MIE375. Since I am currently teaching the course ECE302, there is no rating available yet. The scores are based on a scale of 1 (strongly disagree) to 5 (strongly agree).

Statement	Course (Term)	Mean Rating	Faculty Rating
I found the course intellectually stimulating	MIE377 (Spring 2019)	4.5	3.6
	MIE377 (Spring 2018)	4.6	3.6
	MIE375 (Fall 2018)	4.0	3.7
The course provided me with a deeper understanding of the subject matter	MIE377 (Spring 2019)	4.5	3.7
	MIE377 (Spring 2018)	4.6	3.8
	MIE375 (Fall 2018)	5.0	3.9
The instructor created an atmosphere that was conductive to my learning	MIE377 (Spring 2019)	4.7	3.7
	MIE377 (Spring 2018)	4.6	3.7
	MIE375 (Fall 2018)	5.0	3.8
Course projects, assignments, tests, and/or exams improved my understanding of the course material	MIE377 (Spring 2019)	4.7	3.6
	MIE377 (Spring 2018)	4.4	3.7
	MIE375 (Fall 2018)	4.3	3.7
Course projects, assignments, tests, and/or exams provided an opportunity for me to demonstrate an understanding of the course material	MIE377 (Spring 2019)	4.7	3.6
	MIE377 (Spring 2018)	4.4	3.6
	MIE375 (Fall 2018)	4.3	3.7
Institutional composite mean	MIE377 (Spring 2019)	4.6	3.6
	MIE377 (Spring 2018)	4.5	3.7
	MIE375 (Fall 2018)	4.5	3.8

5 Professional development

Prospective Professors-in-Training program

I am currently enrolled in the Prospective Professors-in-Training (PPIT) program offered by the Faculty of Applied Science and Engineering at the University of Toronto. The PPIT program prepares PhD students for the rigours of a career in academia. The program is comprised of two parts that introduce students to curriculum, teaching, and learning within the context of engineering education and the tools required to hold an academic position. The course also includes the development of strategies to effectively balance time and resources between teaching, research, and administration.

Appendix A Examples of Course Materials

A.1 Sample Course Syllabus

MIE377 – Financial Optimization Models

Spring 2019

Syllabus

Instructor: Giorgio Costa
Email: gcosta@mie.utoronto.ca
Office hours: Friday 14:10 – 15:10
Office: BA 8119

TA (Tut.): Raja Paidimarri
Email: raja.paidimarri@mail.utoronto.ca
Office hours: By appointment or by email

TA (Labs): Ricardo Pillaca
Email: ricardo.pillaca@mail.utoronto.ca
Office hours: By appointment or by email

Lectures: BA 2135 | Tue 12:00 – 13:00
| Fri 12:00 – 14:00

Tutorials: HA 316 | Mon 17:00 – 18:00

Labs: WB 255 | Mon 10:00 – 11:00

Textbooks: The course will be based on lecture notes and academic manuscripts (research papers). Pertinent papers will be posted on the course portal. 'Investment Science' by Luenberger (Second Edition) and 'Optimization methods in finance' by Cornuejols and Tütüncü will serve as supplementary texts.

Prerequisites: MIE 375

Course Description
This course deals with the formulation of optimization models for the design and selection of an optimal investment portfolio. Topics include Risk Management, Mean Variance Analysis, Models for Fixed Income, Scenario Optimization, Stochastic Programming, Index Funds, and Scenario Generation. These concepts are applied to create a variety of optimal portfolios that address the different objectives an investor may have.

Learning objectives

- Understand mathematical optimization principles for general non-linear problems.
- Understand time series analysis through the application of regression models and quantification of estimation error.
- Understand different measures of financial risk and return, and gain general insight on the practice of quantitative finance.
- Design optimization models to appropriately address an financial objective subject to pertinent constraints.

- Computationally implement and solve convex optimization problems (linear, quadratic, and non-linear) using real financial data.
- Assess the financial performance of a portfolio through various ex ante and ex post measures of risk, return, and risk-adjusted return.

Deliverables

Deliverable	Weight	Due Date
Assignment 1	2.5%	08-Feb-19
Midterm	30%	15-Feb-19
Computational Project 1	10%	05-Mar-19
Assignment 2	2.5%	22-Mar-19
Computational Project 2	10%	09-Apr-19
Final	45%	TBD

Homework

Assignment will consist of problem sets. Students may submit solutions in a handwritten or typed format, provided these are clear and legible. Solutions must clearly show all work and all steps required. Students are expected to work individually on Assignments 1 and 2 (i.e., no group submissions are allowed). Collaboration is allowed, but each student must submit their own original work. Assignments must be submitted as a hard copy at the start of class on the due date.

Projects will involve research and implementation of mathematical finance models. The projects must be submitted as formal reports. All computations must be performed in MATLAB. Projects are team-based, and students are expected to work in groups of 2 or 3 students per team. Project reports and MATLAB code must be submitted electronically before the start of class on the due date.

Exams

The midterm exam will be held during class time on 15-Feb-2019 (Friday) and will be 1.5 hours long. The exam will be closed book and closed notes except for <u>one</u> side of a 3-by-5 inch notecard (it must be handwritten). Only a simple scientific non-financial calculator with no programming capability is allowed.

The final exam date and time are yet to be determined. The exam will be closed book and closed notes except for <u>both</u> sides of a 3-by-5 inch notecard (it must be handwritten). Only a simple scientific non-financial calculator with no programming capability is allowed.

Tutorials and computational laboratories

Tutorials will be held on a weekly basis. The tutorials serve two purposes: cover numerical examples to provide intuition and practice, and to cover additional detail not covered during the regular lectures. The teaching assistant will present a problem set and solve it during the tutorial.

There will be six laboratories throughout the semester. The laboratories serve to provide hands-on experience, where you will implement some of the mathematical models seen during the lectures. The teaching assistant will provide an overview of the problem, and will be there to facilitate and assist you while you solve the problem in MATLAB. The tentative laboratory schedule is given below.

Tentative Lecture Schedule

The following is a tentative schedule listing the topics that will be covered throughout this course.

	Topics	From	To
1	General optimization theory	08-Jan-19	22-Jan-19
2	Mean–variance optimization	25-Jan-19	29-Jan-19
3	Factor models	01-Feb-19	05-Feb-19
4	Black-Litterman model	08-Feb-19	12-Feb-19
	Reading Week	18-Feb-19	22-Feb-19
5	Mixed–integer programming	26-Feb-19	01-Mar-19
6	Robust optimization	05-Mar-19	12-Mar-19
7	Monte Carlo methods	15-Mar-19	22-Mar-19
8	CVaR optimization	26-Mar-19	02-Apr-19
9	Risk parity optimization	05-Apr-19	11-Apr-19

Academic Integrity

Academic misconduct will not be tolerated in this course. Please make yourself familiar with the academic conduct guidelines: http://academicintegrity.utoronto.ca. Work submitted must be your own, and you should reference any outside resources you use such as books or papers.

Additional Notes

The Faculty of Applied Science and Engineering's policy on petitions for course work will be employed for missed tests and late assignments. Students must submit term-work petitions and supporting documentation through the 'Term-Work Petition' system, which is accessible through the Engineering Portal. Students must keep all original supporting documentation for one year after the submission date. The Academic Advisor will decide on the validity and the course instructor will select the appropriate accommodation.

Students with diverse learning styles and needs are welcome in this course. If you have a disability or health consideration that may require accommodations, please feel free to contact the instructor and/or Accessibility Services at (416) 978-8060. For additional information, please visit http://accessibility.utoronto.ca.

A.2 Sample Course Assignment

MIE377 – Financial Optimization Models

Project 2

Due Date: 11-Apr-2019 by 11:59 PM

Please use MATLAB to solve this project. This is a group project, with groups of 2 or 3 students per group. Each group is expected to submit their own original work.

You are given:

- Raw market data consisting of adjusted closing prices for 20 U.S. stocks (Quandl.com, 2017), and factor rates of return for the Fama–French three-factor model (French, 2016).
  - → Note 1: This is the same data you were given for Project 1.
  - → Note 2: A MATLAB template is not provided for this project. However, you are allowed (and encouraged) to use your MATLAB code from Project 1.

You should hand in:

- A formal report composed of an introduction, methodology, results and conclusion. Please submit this as a PDF file. There is a 15 page limit.
- The MATLAB program and functions you wrote to solve this project.
- Please submit all your files inside a compressed folder, including your report and MATLAB code. The name of the submitted file should be **StudentID.zip**. Only one submission per team is required. Please submit this file electronically through the Quercus portal (a printed copy is not required).

Introduction

The purpose of this project is to study Conditional Value-at-Risk (CVaR) optimization. CVaR optimization is scenario-based, where we use Monte Carlo simulations to generate these scenarios. Moreover, we will use two different stochastic processes during the simulation.

Our investment universe in this project consists of 20 stocks ($n = 20$), with the company tickers shown in Table 1. We are given weekly adjusted closing prices corresponding to these 20 stocks from 30-Dec-2011 to 31-Dec-2015 (Quandl.com, 2017). We can use the historical prices to compute our observed asset weekly returns.

Table 1: List of assets

Company Tickers	F	CAT	DIS	MCD	KO	PEP	WMT	C	WFC	JPM
Company Tickers	AAPL	IBM	PFE	JNJ	XOM	MRO	ED	T	VZ	NEM

In addition, we are also given the historical factor returns for the Fama–French three-factor model French (2016) corresponding to the period 06-Jan-2012 to 31-Dec-2015. This includes the weekly risk-free rate.

Factor model

We can use factor models to explain the rates of return of our assets. We will use the Fama–French three-factor model in this project. The form of this regression model is the following

$$r_i - r_f = \alpha_i + \beta_{im}(f_m - r_f) + \beta_{is}SMB + \beta_{iv}HML + \varepsilon_i$$

where r_i is the asset return, r_f is the risk-free rate, α_i is the intercept from regression, β_{im} is the market factor loading, $(f_m - R_f)$ is the excess market return factor, β_{is} is the size factor loading, SMB is the size factor, β_{iv} is the value factor loading, HML is the value factor, and ε_i is the residual from regression.

The factor data have been provided as part of the project (French, 2016), including the weekly risk-free rate. The SMB and HML factors are subsets of the market, meaning they will be correlated to the market factor and to each other. Therefore, this model does not respect the ideal environment. However, the factor covariance terms still convey information about the asset variances and covariances, meaning we cannot ignore the factor covariance terms.

We will use an ordinary least squares regression model to calibrate our coefficients, namely the intercepts of regression $\boldsymbol{\alpha} \in \mathbb{R}^n$, the factor loadings $\boldsymbol{\beta} \in \mathbb{R}^{n \times m}$, and the diagonal matrix of residual variances $\boldsymbol{D} \in \mathbb{R}^{n \times n}$. We must also use the factor model to estimate the asset expected returns $\boldsymbol{\mu} \in \mathbb{R}^n$ and covariance matrix $\boldsymbol{Q} \in \mathbb{R}^{n \times n}$.

The aim is to use these coefficients to generate our asset scenarios via Monte Carlo simulations. We will model the three Fama–French factors as stochastic processes, and use Monte Carlo simulations to generate multiple scenarios for the factors. Once we have these, we can use the regression coefficients to generate the corresponding asset scenarios to serve as the input during CVaR optimization. This procedure is described in detail in Section **??**.

Monte Carlo simulations

We will use Monte Carlo simulations to generate our scenarios for the subsequent CVaR optimization. Our scenarios consist of the factor returns, where the behaviour of our factors can be described as a stochastic process. For this project, we will study two different stochastic processes to simulate our scenarios: (i) a Gaussian process, and (ii) a non-normal stochastic process with higher moments.

A Gaussian process is a stationary stochastic process where every step in time is the realization of a normally distributed random variable. In other words, a Gaussian process can be described as

$$\boldsymbol{f}_s = \bar{\boldsymbol{f}} + \boldsymbol{\omega}_s,$$

where $\boldsymbol{f}_s \in \mathbb{R}^m$ is a realization of our factors corresponding to scenario $s = 1, ..., S$, $\bar{\boldsymbol{f}} \in \mathbb{R}^m$ is the factor expected return calculated from our raw data, $\boldsymbol{\omega}_s \sim \mathcal{N}(0, \boldsymbol{F}) \in \mathbb{R}^m$ is the error term, $\boldsymbol{F} \in \mathbb{R}^{m \times m}$ is the factor covariance matrix, and $m = 3$ for the Fama–French model. This is telling us that every scenario is the result of a random draw from this multivariate normal distribution. Note that we can simulate this stochastic process in MATLAB by generating multivariate normal random numbers using the function mvnrnd, where $\boldsymbol{f}_s \sim \mathcal{N}(\bar{\boldsymbol{f}}, \boldsymbol{F})$ for $s = 1, ..., S$.

The second stochastic process we will study incorporates higher moments of the distribution, namely skewness and kurtosis. The objective of this is twofold. First, we wish to study if any of the factors exhibit a non-normal distribution. Second, we wish to evaluate whether the inclusion of higher moments in our model can lead to better out-of-sample performance of our optimal portfolios. Our hypothesis is that the inclusion of higher moments should yield a more realistic set of scenarios, thereby improving our subsequent optimization of CVaR. We can simulate random numbers with higher moments in MATLAB using the function pearsrnd. We must use this function to simulate each factor individually. Once we have the sample scenarios for each factor, we can synthetically correlate them to approximate our correlation matrix $\boldsymbol{\rho} \in \mathbb{R}^{m \times m}$. The correlation matrix stems from the factor covariance matrix $\boldsymbol{F}$. The procedure on how to synthetically correlate our simulations is described here.

Once we have generated our factor scenarios $\boldsymbol{f}_s$ for $s = 1, ..., S$, we can use the calibrated coefficients from the Fama–French factor model to generate our scenarios for the asset returns. Use the factor scenarios together with the coefficients $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ to generate the systematic part of our asset scenarios. Proceed to generate a vector of asset idiosyncratic noise $\boldsymbol{\varepsilon}_s \sim \mathcal{N}(0, \boldsymbol{D}) \in \mathbb{R}^n$ to generate the idiosyncratic part of our asset scenarios. We will generate 5,000 scenarios each time we construct (or rebalance) our portfolios.

Portfolio optimization

We will use two investment strategies to optimize our portfolios.

(a) We wish to implement an optimization model that attempts to minimize CVaR while maximizing the portfolio expected return.

$$\begin{aligned}
\min_{x,z,\gamma} \quad & \gamma + \frac{1}{(1-\alpha)S}\sum_{s=1}^{S} z_s - \lambda \boldsymbol{\mu}^T \boldsymbol{x} \\
\text{s.t.} \quad & z_s \geq 0, & s = 1, ..., S, \\
& z_s \geq -\hat{\boldsymbol{r}}_s^T \boldsymbol{x} - \gamma, & s = 1, ..., S, \\
& \mathbf{1}^T \boldsymbol{x} = 1, &
\end{aligned}$$

Short selling is allowed, and we will use $\lambda = 0.1$.

(b) A robust counterpart of this CVaR optimization model, where we consider the portfolio expected return to be noisy. We wish to construct a box uncertainty set around the expected return with a 90% confidence interval. As before, short selling is allowed and $\lambda = 0.1$.

We will optimize a 1-week CVaR (and robbust CVaR) with a 95% confidence level (not to be confused with the 90% confidence level we must use for robustness). In other words, we want to optimize our portfolio based on a 1-week CVaR$_{95\%}$. We can implement both the nominal CVaR optimization model and its robust counterpart using the MATLAB function linprog.

To construct the uncertainty set, we can simply use the method seen in class, where $\boldsymbol{\Theta} \in \mathbb{R}^{n \times n}$ is a diagonal matrix where

$$\Theta_{ij} = \begin{cases} \frac{\sigma_i^2}{N} & \text{for } i = j \\ 0 & \text{for } i \neq j \end{cases}$$

where σ_i^2 is the raw variance of asset i for $i = 1, ..., n$, and N is the total number of observations used for calibration. (Note: refer to pages 43 and 44 of the Robust MVO lecture notes posted online to see how to construct a box uncertainty set).

We will construct four portfolios in total, using the two simulation models (Gaussian and non-Gaussian) under the two investment strategies (nominal and robust CVaR). This will allow us to assess the effect of robustness, as well as the impact from the two simulation models.

Similar to Project 1, we will simulate a three-year investment horizon, from the start of 2013 to the end of 2015. In addition, we will rebalance[1] our portfolios every six months, at the start of every January and

[1]Portfolio rebalancing means we will update our portfolio weights by buying and selling shares of our stocks.

July, for a total of six investment periods. We must use one year of historical returns to calibrate the regression model. The calibration period should immediately precede the start of the investment period. Once an investment period is over, we will re-calibrate our coefficients using the most recent one-year window available. To optimize our portfolios, we must generate 5,000 scenarios, as outlined in Section **??**. Each each scenario must simulate the 1-week returns of all 20 assets. You do not need to measure transaction costs for this project.

At the end of the out-of-sample test we must analyze our results. We should plot the portfolio value through time. We can also use an area plot to show the changes per period in the composition of our portfolios (i.e. to see how our optimal weights changed every time we rebalanced a portfolio). This will allow us to evaluate if our portfolios were concentrated or well-diversified. Finally, we should also compute performance metrics, such as the average rate of return or portfolio standard deviation. You are welcome to compute any other additional performance metrics to further compare the portfolios.

Deliverables

Report (85%)

Prepare a formal project report. The report should introduce the purpose of this project, explain your methodology, show a summary of our computational results, and present an analysis of these results. Finally, you should include a discussion and conclusion section.

The report should show our understanding of the stochastic processes involved and the Monte Carlo simulation method. Moreover, we should describe the optimization models implemented. The analysis of the computational experiment should also reflect our knowledge of the material seen in class. The discussion section should provide any insights we are able to derive from the results, as well as any strengths or weaknesses of the different methods and models.

The report should have a minimum of one plot to illustrate the weekly value of your portfolio and a table to show your portfolio performance metrics (e.g., average return). You are welcome to include more relevant plots and/or tables.

The report is worth 85% of the total. The distribution is the following

- Formal report structure and presentation: 10%
- Stochastic process description and Monte Carlo simulation implementation: 20%
- CVaR and robust CVaR optimization description and implementation: 20%
- Portfolio optimization out-of-sample analysis: 20%
- Discussion and conclusion: 15%

MATLAB program (15%)

Prepare a MATLAB program and functions to perform the computational experiments. Be sure to properly comment on your code to briefly explain what you are doing. Your code should be easy to read and the TA should be able to run it. The code will be evaluated on cleanliness, readability, and efficiency.

References

French, K. R. (2016). Data library. http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. [Online; accessed 20-Sep-2017].

Quandl.com (2017). Wiki – various end-of-day stock prices. [Online; accessed 07-Nov-2017].