INDR 422/522

Fikri Karaesmen

Spring 2023

Course Introduction

Feb. 28, 2023

Course Description

- This course is an introduction to data science and prescriptive analytics in the context of operations. We take as examples typical operational problems of demand and sales forecasting, inventory management and pricing and revenue management. We review predictive analytics approaches from machine learning and statistics in the context of time-series forecasting and feature-based prediction. We then investigate prescriptive analytics approaches focusing on data-driven optimization and joint estimation and optimization. We will work with real data as much as possible and the implementations will be in Python.

Learning Outcomes

- use tools of predictive analytics for time series demand modeling and optimization
- understand and apply the concepts of model validation
- understand linear and non-linear predictive methods
- understand the data driven optimization framework for inventory and price optimization
- understand the basic stochastic dynamic programming framework, approximations and reinforcement learning tools
- combine and use predictive analytics tools for solving optimization problems from operations

Course Evaluation Methods

Method	Description	Weight %
Midterm Exam	Midterm Exam	20.00
Project	Course Project (Groups of 2 or 3)	25.00
Homework	4 Homework Assignments	25.00
Participation	Lecture attendance, in-class exercises, discussion	5.00
Final Exam	Final Exam	25.00
	Total:	100.00

For this semester exam schedule and grading scheme are subject to change.

Participation assessment: The participation expectations (physical vs. online attendance) are also subject to change pending Higher Education Council Decisions. For the online part of the course (for now until the end of March), full participation grades are based on live online attendance and participation to zoom lectures and zoom polls and other online in-class activities. The logs are taken automatically from zoom/panopto. Please let me know if you have an exceptional situation.

Homeworks

- Groups of 2 (or alone)

- We’ll provide help and examples on implementation but you will have to implement your own computation.

Participation

- To get full participation grade, you have to be present synchronously (i.e. at the lecture time) and complete the polls/ class exercises.
- We hope to get back to regular classroom teaching in April.

Blackboard page

- Please follow course blackboard page for lecture content
  - Lecture slides
  - Notes
  - Implementation videos
  - Problem Solutions
  - Resources
- Please follow announcements / e-mails: that’s our only way to reach you.

Course Schedule (subject to change)

Meeting Week	Subject
1	Time Series and ARIMA Forecasting
2	Regression-based Methods
3	Multi-feature Regression (bias-variance tradeoff)
4	Classification problems
4	Regularization (lasso and ridge reduction)
5	Advanced Regression Based Methods
6	Non-linear Methods for Prediction
7	Non-linear Methods for Prediction
8	Joint Estimation and Optimization
9	A Single-Period Inventory Problem: Data-Based Solutions
10	A Single-Period Inventory Problem: The Case with Features
11	Dynamic Capacity Allocation and Introduction to Dynamic Programming
12	Reinforcement Learning for Capacity Allocation
13	Reinforcement Learning for Capacity Allocation

Implementations

- We'll work with real data as much as possible
  - sometimes we'll combine real data with synthetic data for optimization purposes
- We will provide documentation and videos for implementation examples.
- Python scripts using ML libraries
  - Most of the time nothing requiring advanced knowledge or expertise in python programming
  - If you have advanced skills, you can easily do better especially in terms of input and output.

Books

- Two books that are available as free texts on line:
  - Hyndman and Athanasapoulos, *Forecasting: Principles and Practices,* https://otexts.com/fpp2/
  - James, Witten, Hastie, Thibshirani, *An Introduction to Statistical Learning 2nd ed.*, https://www.statlearning.com/
- We'll mostly follow James et al.

Warnings

- Please don’t ask me technical software questions (how to download jupyter notebook or how to use google colab, why is my interface not working, I cannot download this library on my laptop etc.)
- Same for data manipulation: I’ll prepare most of my data on a spreadsheet but if you are able to manipulate data within python you can make your life simpler
- It would be great to have a platform to share best practices (in terms of data manipulation, graphics, appropriate libraries etc.)

Reminders

- There are excellent resources in predictive analytics
  - including the two recommended textbooks but also others
- There is no good book yet on Prescriptive Analytics that specializes in operations (inventory, capacity, price optimization)
  - Most of the developments are very recent
  - Please try to follow the lectures and read the papers
- We'll look at Reinforcement Learning and DP approximations in a special setting (most books treat the general setting which is more complicated)

Some other concerns

- My expertise and therefore the emphasis of this course is not necessarily on the algorithmic side of predictive methods
  - But more on understanding the structure of the methods and the resulting estimates.
- The methods/algorithms improve at a furious pace
  - we will not be talking about the most recent methods but if you are able to understand them you can use them for optimization and decision-making purposes following the framework.

Prerequisites and other requirements

- Some prerequisites:
  - INDR 262: Linear Optimization (constrained optimization models)
  - ENGR 200: Probability and Random Variables (manipulating random variables, conditional probability)
  - INDR 252: Applied Statistics (hypothesis tests, regression, estimation)
- And to a certain extent:
  - INDR 343: Stochastic Models and INDR 372 Production Planning (or some basic knowledge on forecasting and inventory and capacity management)
- I do not have much time to review topics from these courses, but I will use them as needed. Please make sure to review them.

Positioning

- This course includes an overview of predictive ML methods but the end goal is to use them in the context of optimization.
  - This means there is some overlap with ENGR 421/521
- The predictive tools apply to many contexts but we'll maintain a focus on demand uncertainty especially on time-series data
  - This means there is some overlap with INDR 372
  - And maybe with courses in Econometrics
- We'll look at stochastic dynamic programming in a limited context (simple discrete-time models) in the context of revenue management.
  - There is some overlap with INDR 564 and INDR 475/575
  - But in these applications, we can have an entry point to approximation schemes fpr reinforcement learning

Prescriptive Analytics

- This is likely to be the right perspective for Industrial Engineering and Operations Research
  - Combine predictive analytics with optimization to solve decision problems involving uncertainties
  - Joint estimation (prediction through ML) and optimization (OR tools) is a new and exciting framework

Operational Problems

- Designing inventories, capacities, prices to minimize costs or maximize profits.
- There are many uncertainties, demand, yield, demand response to price etc.
- This requires looking at formulation that minimize an expected cost or maximizes an expected profit.
  - Or some more advanced risk measures taking into account the structure of the uncertainty.
- This might be an appropriate framework to apply tools from supervised learning because typically there are regular short-term repeated decisions to make in a changing environment.
  - The tools that we discuss may not necessarily be appropriate for long-term strategic decisions

A typical operational problem

- A standard optimization problem in operations looks like

$$\min_{\mathbf{z}} E[c(\mathbf{Y}, \mathbf{z})]$$

  where $\mathbf{z}$ is a decision variable and $\mathbf{Y}$ is a random variable. In addition, there could be constraints on the decision variable (i.e. $\mathbf{z} \in \mathcal{Z}$).
- To consider a concrete problem we can consider inventory planning at two stores with random demands (Y_1, Y_2) and the decisions could be the order quantities (z_1, z_2) that minimize the expected cost. This problem becomes interesting if inventory transshipments can take place between the stores.
  - We then need to consider the simultaneous decisions for (z_1, z_2), taking into account the correlation structure of (Y_1, Y_2).

A typical operational problem

- If we start with the assumption that the probability distribution of $\mathbf{Y}$ is known, then we have optimization frameworks (e.g. stochastic programming) to address such problems even at large scale.

- Some smaller scale problems can be solved analytically (the single-period random demand newsvendor problem is an example).

$$\min_q c_u E[(D-q)^+] + c_o E[(q-D)^+]$$

where D is the random demand, q is the order quantity and c_u and c_o are the underage and overage costs.

A typical operational problem

- In practice (reality), the probability distribution of $\mathbf{Y}$ is not known with certainty but we may have some past observations on hand for $\mathbf{Y}$: $(\mathbf{y_1}, \mathbf{y_2}, \ldots \mathbf{y_n})$.
- We may have observed demands of (28,43) at the two stores on day 1, (52, 25) on day 2 and so on.
- We then have options to "fit" a joint probability distribution using the observations or use the demand observations as scenarios that become inputs to the optimization problem.
  - For instance, we may fit a bivariate normal distribution to the data that specifies, the means, the standard deviations and the correlation.
  - A little more on this later.

A typical operational problem

- Machine learning (in the supervised learning framework) starts with data $(\mathbf{y_1}, \mathbf{x_1}), (\mathbf{y_2}, \mathbf{x_2})...(\mathbf{y_n}, \mathbf{x_n})$ and focuses on the prediction problem of $\mathbf{Y}|\mathbf{X}$
- and proposes a number of effective tools.
- On the other hand, prescriptive analytics focuses on:

$$\min_{\mathbf{z}} E[c(\mathbf{Y}|\mathbf{X} = \mathbf{x}, \mathbf{z})]$$

- and of course also on finding the minimizer $\mathbf{z}^*$.
- Note that the typical ML-based problem is also an optimization problem where some error function is minimized.
- Prescriptive analytics therefore considers such nested optimization problems one for estimation, the other on operational cost minimization.

Remark

- Recall that we started by defining a standard problem:

$$\min_{\mathbf{z}} E[c(\mathbf{Y}, \mathbf{z})]$$

where $\mathbf{z}$ is a decision variable and $\mathbf{Y}$ is a random variable.

- Please note that

$$E[c(\mathbf{Y}, \mathbf{z})] \neq c(E[\mathbf{Y}], \mathbf{z})$$

- If the two were equal, then we could leverage ML methods to estimate $E[\mathbf{Y}|\mathbf{X}]$ and would solve a deterministic optimization problem.

Example:

- Let Y be a uniformly distributed random variable in $(0,1)$ and $c(y) = y^2$.

$$E[c(Y)] = E[Y^2] = \int_0^1 y^2 \, dy = \frac{1}{3}.$$

whereas:

$$c(E[Y]) = E[Y]^2 = \left(\frac{1}{2}\right)^2 = \frac{1}{4}.$$

The Newsvendor Problem

- A single-period random demand inventory problem (the newsvendor problem). We have to order a quantity in advance of the demand realization.
- No opportunity to reorder during the sales season, unsatisfied demand is lost
- Unsold items are salvaged at a value below their purchasing cost.
- Since demand is not known with certainty, there will be a mismatch between the supply and demand.
- Assume that we somehow know the distribution of random demand D. We can the maximize the expected profit:

$$\max_{q} E\left[-cq + p\min(q, D) + s(q - D)^{+}\right]$$

p: sales price, c: purchase cost, s: salvage value and p>c>s.

The Newsvendor Problem

- In practice, we might have data that are past observations of realized demand $d_1, d_2, \ldots, d_n$.
- We then have two basic alternatives i) fit a probability distribution to the data and obtain the corresponding random variable D ii) Use the sample as our 'world' and perform empirical optimization. This is called sample average approximation (and empirical risk minimization in ML).
- We assign a weight that equals $1/n$ to each observation and solve the following deterministic problem

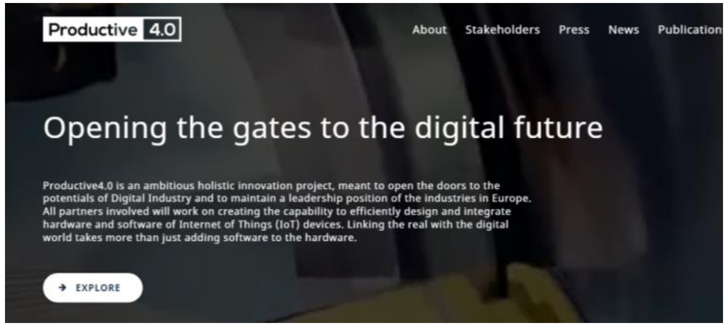
$$\max_q \; -cq + \frac{\sum_{i=1}^n p \min(q, d_i) + s(q - d_i)^+}{n}$$

- Note that the solution of the above problem finds the optimal order quantity that would maximize the average profit for the sample.

A Case Study: Semi-Conductor Production Planning under Random Yield

- A lot sizing problem with random yield: a well-established problem with a large literature
  - Karlin (1958), Henig and Gerchak (1990),Yano and Lee (1995) …Okyay, Karaesmen, Özekici (2014)
- ECSEL - Productive 4.0: European project focusing on the electronics industry and semi-conductor manufacturing
  - Yield uncertainty is still an issue especially for new products
  - In parallel work, we investigate methods for an improving yield rate (Diefenbach, Karaesmen, Schwarz, Stolletz (2022))
- Yield rate is known to depend on a number of design features and on many signals that have to with the environment.

https://productive40.eu/



Framework for our study

- Proposing and evaluating methods for data-driven lot sizing with random yield and random demand
- Feature based data is not available from our partner in Productive 4.0 project
- But a publicly available data set from a semiconductor plant comprises more than 500 features and the corresponding yield
  - Does not completely support the model that corresponds to the problem but can be modified to do so
- Developing methods and evaluating potential gains from data-driven optimization on (almost) real data

The Lot-Sizing Problem of the Manufacturer

- A contract specifies the number of chips to deliver to a customer by a deadline.
- How much to produce to match the contracted quantity
    - Alternatively, when to start production given processing times

- The yield rate is taken into account in this planning
- Apart from possibly non-standard penalty conditions, this corresponds well to the classical problem of random proportional yield.

The Lot-Sizing Problem: the Model

- Proportional (multiplicative) yield

- Find the order quantity Q to meet uncertain demand D by time T
- When you order Q units, the number of non-defective items that is received is QY where Y is a random variable that takes values in $[0, 1]$.
- Let us take the newsvendor objective:

$$\min_{Q} bE[(D - QY)^{+}] + hE[(QY - D)^{+}]$$

  where b and h are the unit underage and overage costs.
- D and Y are not necessarily independent.

The Lot-Sizing Problem: the Model with features

- In reality, D and Y may depend on some features $\mathbf{X}$ and $\mathbf{W}$.
- Given that $\mathbf{X} = (x_1, x_2, ..., x_n)$ and $\mathbf{W} = (w_1, w_2, ..., w_n)$, we would then solve:

$$\min_{Q} bE[(D|(\mathbf{X}, \mathbf{W}) - QY|(\mathbf{X}, \mathbf{W}))^+] + hE[(QY|(\mathbf{X}, \mathbf{W}) - D|(\mathbf{X}, \mathbf{W}))^+]$$

The Model with features: SECOM data

Date	Pass/Fail	f1	f2	f3	f4	…..	f589	f590
19/07/2008	1	3030.93	2564	2187.733	1411.127		NaN	NaN
19/07/2008	1	3095.78	2465.14	2230.422	1463.661		0.006	208.2045
19/07/2008	0	2932.61	2559.94	2186.411	1698.017		0.0148	82.8602
19/07/2008	1	2988.72	2479.9	2199.033	909.7926		0.0044	73.8432
19/07/2008	1	3032.24	2502.87	2233.367	1326.52		0.0044	73.8432
19/07/2008	1	2946.25	2432.84	2233.367	1326.52		0.0052	44.0077
19/07/2008	1	3030.27	2430.12	2230.422	1463.661		0.0052	44.0077
19/07/2008	1	3058.88	2690.15	2248.9	1004.469		0.0063	95.031
19/07/2008	1	2967.68	2600.47	2248.9	1004.469		0.0045	111.6525
19/07/2008	1	3016.11	2428.37	2248.9	1004.469		0.0073	90.2294
19/07/2008	0	2994.05	2548.21	2195.122	1046.147		0.0071	57.8122
19/07/2008	0	2928.84	2479.4	2196.211	1605.758		0.0081	75.5077
20/07/2008	1	2920.07	2507.4	2195.122	1046.147		0.0034	52.2039
21/07/2008	1	3051.44	2529.27	2184.433	877.6266		0.0034	52.2039
21/07/2008	0	2963.97	2629.48	2224.622	947.7739		0.0084	142.908
22/07/2008	1	2988.31	2546.26	2224.622	947.7739		0.0045	100.2745
22/07/2008	1	3028.02	2560.87	2270.256	1258.456		0.0042	82.0989
22/07/2008	1	3032.73	2517.79	2270.256	1258.456		0.0042	82.0989
22/07/2008	1	3040.34	2501.16	2207.389	962.5317		0.0042	82.0989

1567 observations for yield outcome with 590 associated features,
https://archive.ics.uci.edu/ml/datasets/SECOM

Some of the things to do

- Use predictive methods to obtain a yield prediction as a function of the features
  - Model reduction: find those features that improve predictions and eliminate others
- Extract information about yield probability distribution to use in the optimization formulation
  - Predicting the average yield rate is not enough because defaulting a contract because of insufficient quantity is much more expensive than overproduction.
- Assess the benefits of using feature information to make the lot-size decision.