Optimizing Lab Procurement with Sparse Vendor Selection

Kevin Talty[1]; John Stockdale[1]; Prof. Dimitris Bertsimas[2]; Dr. Dennis Burianek[3]; LTC(R) Bill Kindred[3]; Steven Holland[3]

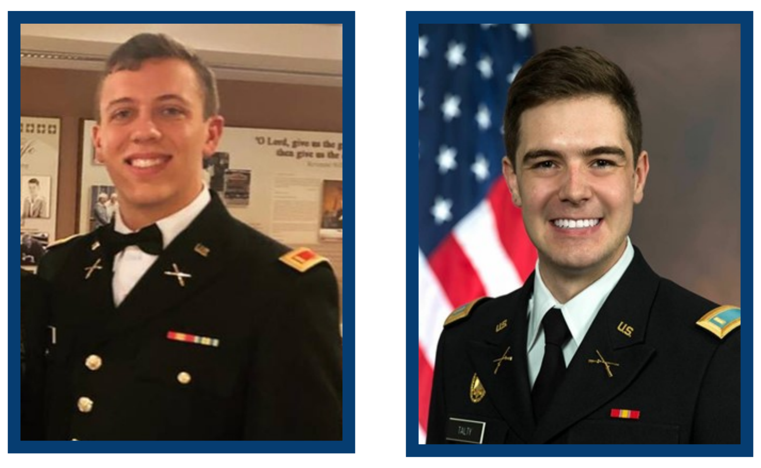
[1]MIT MBAn 2019; [2]Faculty Advisor, MIT; [3]MIT Lincoln Laboratory, Lexington, MA

MIT MANAGEMENT SLOAN SCHOOL

LINCOLN LABORATORY
MASSACHUSETTS INSTITUTE OF TECHNOLOGY

Our Mission

John Stockdale and Kevin Talty endeavor to push the limits of MIT Lincoln Laboratory. Funded by the United States Government, Lincoln Laboratory has a commitment to the nation to deliver cutting edge technology. An underlying part of this promise is that the Laboratory will do so without wasting the tax payers' dollar. Stockdale and Talty will play a part in that transaction where they will help the Laboratory improve and optimize its spending on raw materials in order to uphold this mission of the Laboratory—especially with regard to making the precious American dollar go farther.



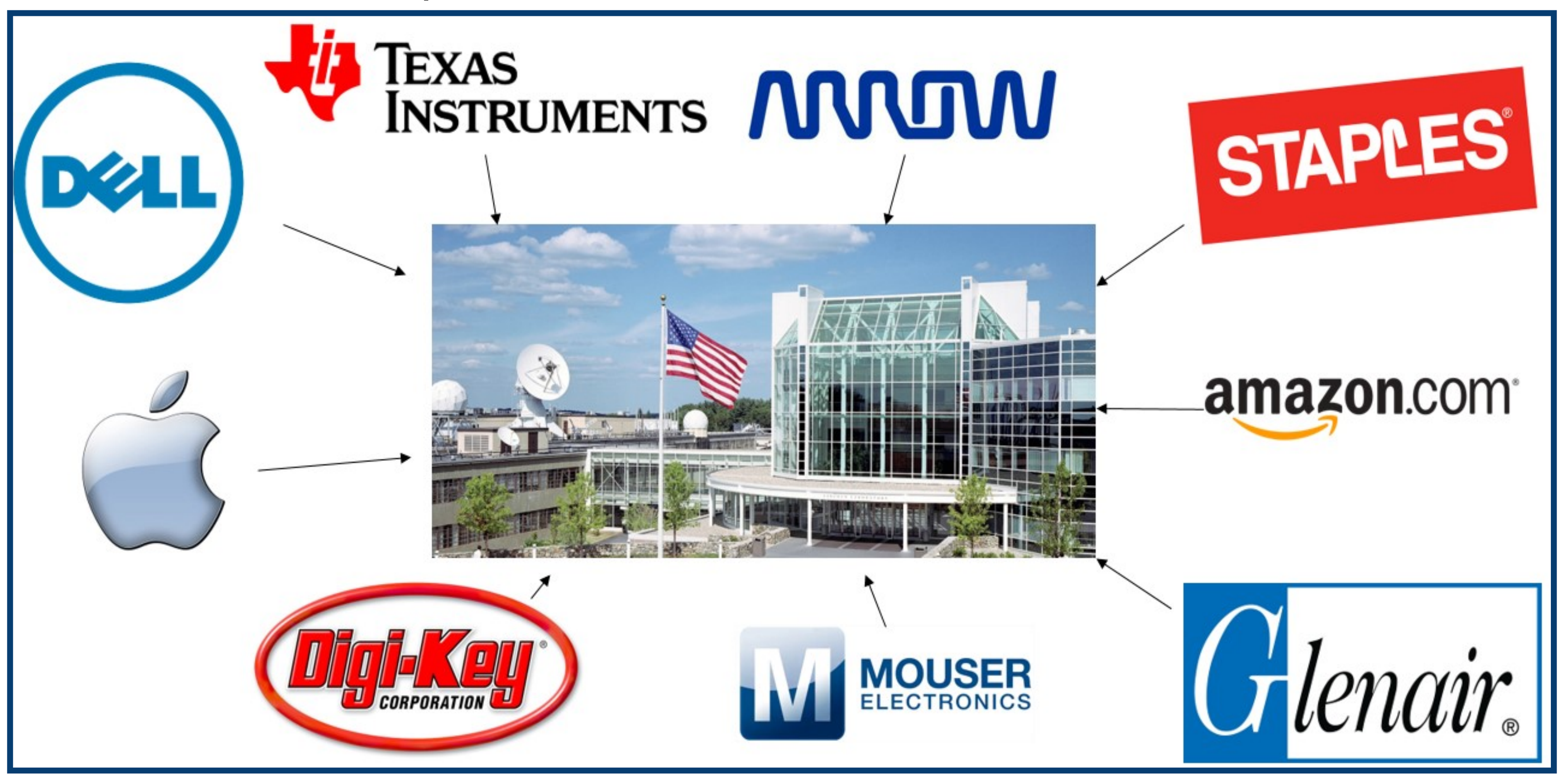
Background

What is MIT Lincoln Laboratory?

MIT Lincoln Laboratory is a Federally-Funded Research and Development Center. At a macro-level, the Laboratory is allotted money from U.S. Governmental Agencies to carry-out research and, in turn, provide cutting-edge technology back to these agencies.

Inspiration

The Laboratory purchases thousands of unique items from hundreds of vendors. There is currently no system to determine whether or not the vendor used was optimal.



The Data

Overview

Lincoln Laboratory's Contract Services Department (CSD) gave Stockdale and Talty purchase records over the last 5 years for the laboratory. This data, maintained in a Microsoft Access database, includes each purchase order sent by a Laboratory employee, the individual item breakdown within each order, and the receipt(s) for each item in each order. The final data set has approximately 600,000 rows and 72 features.

Shopping Cart Dataset: n = ~175,000

Administrative Approval

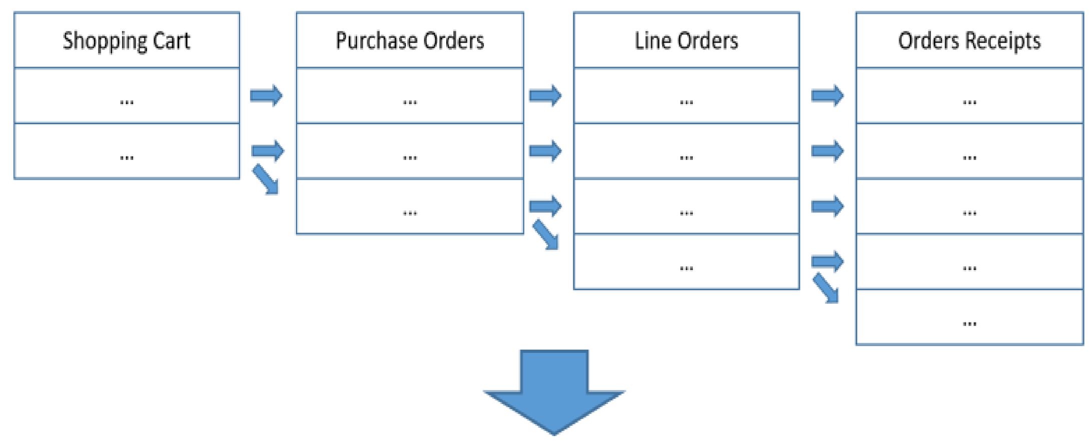
Purchase Order Dataset: n = ~150,000

Individual Item Breakdown

Line Orders Dataset: n = ~300,000

Back Orders

Order Receipts Dataset: n = ~500,000



ID	.....	Item Number	Receipt Number
12345	.....	1	1
12345	.....	1	2
12345	.....	2	1
12346	.....	1	1
12346	.....	1	2
......	.....	.....	.....

Imputation

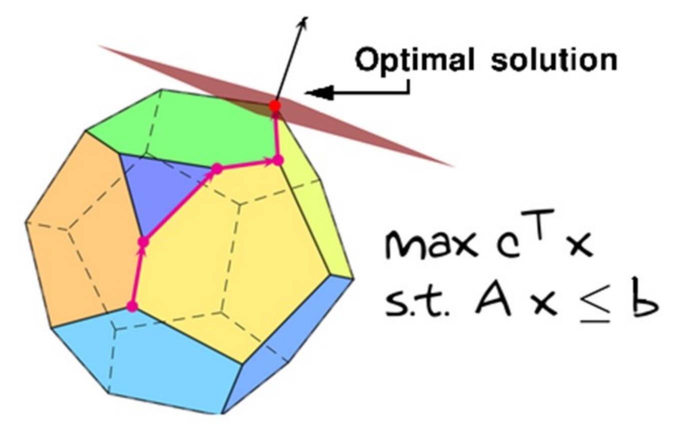
After data-wrangling, there still were numerous missing data points. We decided to use SoftImpute and an SVD missing value imputation method. We knew this would be fitting for the project because SVD performs well with sparse matrices—this worked in our case because some columns had as much as 79% of the data missing. Even more, valuable metrics such as "days late" and "ship time" had upwards of 70% of the data missing.

Timeline

- February
- Data Compiling
- Data Exploratory Analysis
- March
- April
- Data Imputation
- Optimization Implementation
- May
- June
- Optimization Hyper Parameter Search
- Analysis of purchasing method and item selection
- July
- August
- Implementation in Stockroom Trial

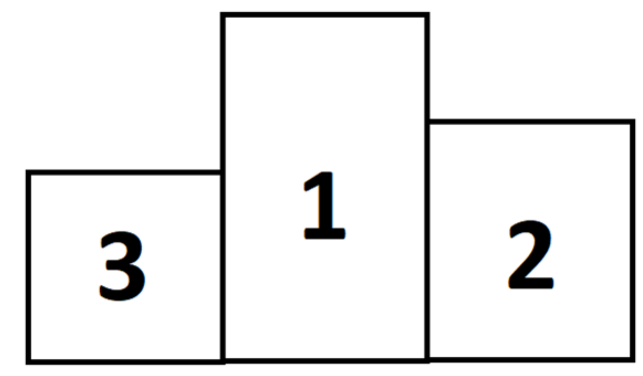
Modeling

Optimization Formulation



Create an optimization formulation to minimize a function of (cost, delay, lead time, quality)

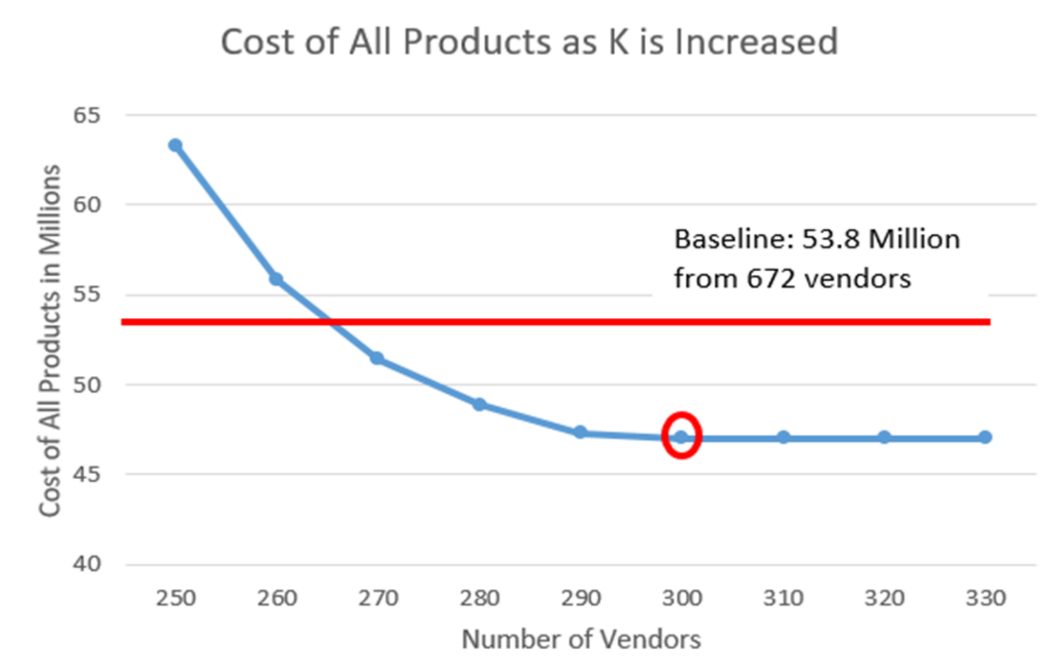
Vendor Ranking



Provide ranked list of vendors to supply each item

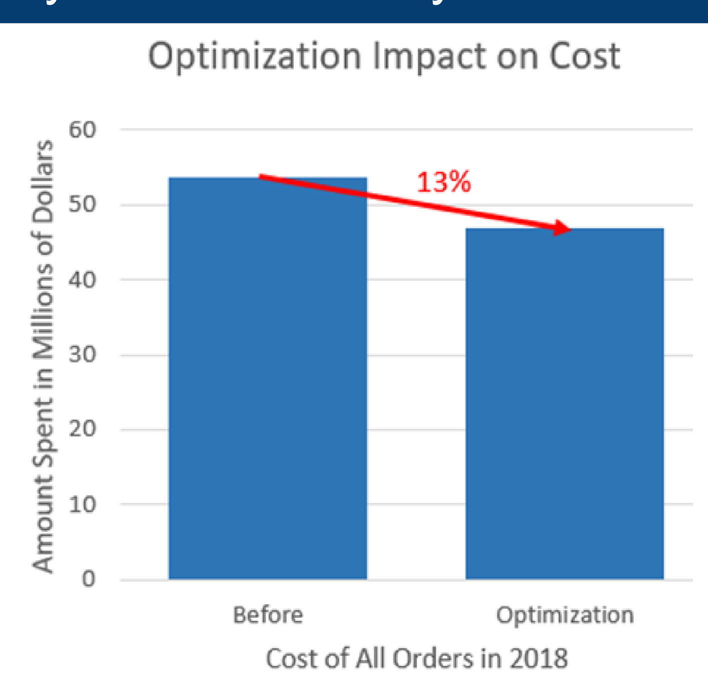
Results

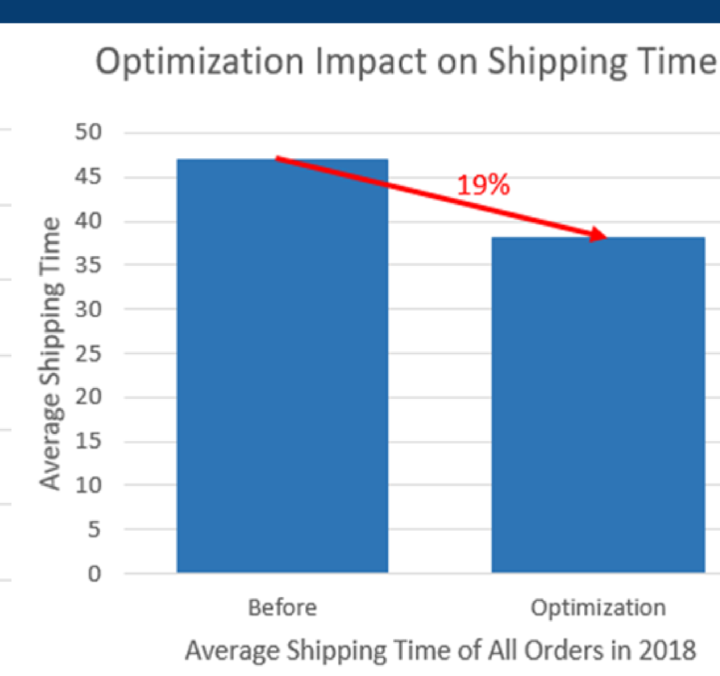
Impact of Limiting the Number of Vendors



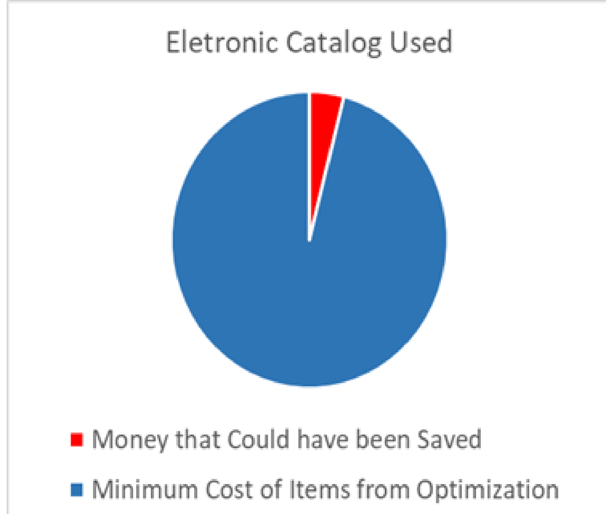
Optimal Hyper-Parameter Results

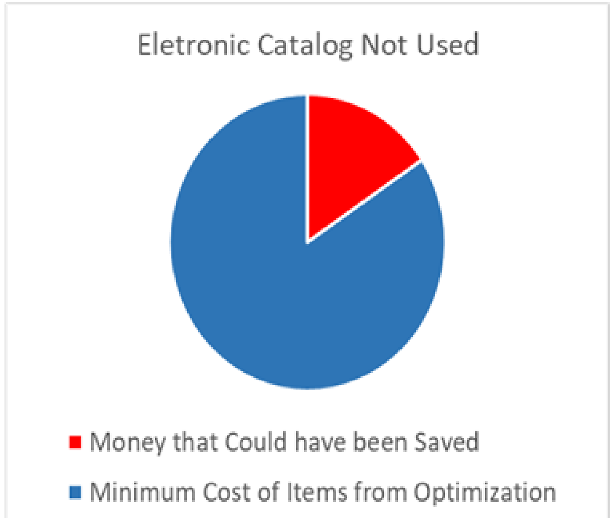
The best model was able to save 7 million dollars and take 9 days off the average shipping time of all the products purchased by the Laboratory in 2018 and only utilized 290 vendors.





Based on Item Purchasing Mechanism





Impact

To test the optimization model, a trial was run for a week of stockroom purchases in August. The optimization saved about 17,000 dollars in just one week. Over one year, that can lead to 900,000 in savings for the stockroom. This trial shows the immediate impact the optimization can have on the Laboratory.

LINCOLN LABORATORY
MASSACHUSETTS INSTITUTE OF TECHNOLOGY