Course Project
Automotive Operations Optimization
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Case Study:

My course project is centered on a general case of optimizing an automotive company's operations. The motivation came from an article highlighting how General Motors used statistical modeling, research, and domain knowledge to optimize their vehicle production across multiple car brands in multiple countries. The end result is production of the right mix of vehicles that maximizes revenue for the company.

This document will go through my personal analytics solution to this problem. The solution will involve using endogenous and exogenous factors to model demand by carline and trim and model competitive incentive actions. The results from these models will be used as inputs into an overarching optimization model that is bounded by our unique production capacity constraints. My result will be a recommendation of which vehicles to produce in the short term to put our brand in the best position to out sell the competition.

Outlined below are my considerations of the data needed, the techniques that will be used, and the possible concerns for solving this problem. Overall, my goal is to clearly show my thought process in building a state-of-the-art analytics solutions from data to final prescriptive action.

Summary:

My analytics solution unfolds in multiple pieces but each follow the general given, use, to format.

- Given: at least 10 years of historical sales data by carline and trim for ourselves and the competition, tagged with timing (month / year), geography (country / region / market), marketing spend by channel, vehicle MSRP, incentive spending by type (lease / APR, customer, dealership) and carline, previous month's inventory levels, weather indicators, economic stability indicators (unemployment rate, election year flag, GDP, exchange rates)

- Use: Flexible and non-parametric model such as Random Forest or Gradient Boosting
- To: predict the demand for all carlines bounded by the unique factors included in the model

Result: Accurate demand by carline trim based on unique seasonality, marketing spend, incentive actions, weather, and over-arching economic status.

- Given: at least 10 years of competitive inventory, competitive marketing spending, competitive incentive spending, new model launch cadence data, customer profiles of competitive makes the demand results from our model plus weather indicators, economic stability indicators (unemployment rate, election year flag, GDP, exchange rates)
- Use: Flexible and non-parametric model such as Random Forest or Gradient Boosting
- To: predict the transaction price of competitive vehicles in the next month

Result: Accurate transaction price forecasts by competitive carline based on unique seasonality, marketing spend, incentive actions, weather, and over-arching economic status.

- Given: inputs from demand models, transaction price model, current inventory levels and production constraints
- Use: Optimization Model with Simulation (switching out our own “controllables” like incentives with different values to test results)
- To: Determine the best production levels and pricing for each vehicle line across geography, seasonality, exogenous economic factors, internal constraints and forecasted competitive actions

Result: Optimal “go to market” strategy for the vehicles we have on ground and optimal strategy in ordering supply of new vehicles in the future

Data:

This analytical solution requires a lot of data. Mapping out and acquiring this data in itself would be a huge task for a company to complete – teams would need to work to fill in each piece of information needed, clean and normalize it, set up the structure to connect the datasets together and then store it in a database. Some of this heap of data can be purchased, other parts of the solution will need a creative framing of the problem to acquire the data.

Here is some of the sources that we could use:

- Transaction Price: Captives or actual "desking" platform companies can sell samples of transaction price deals
- Incentive Spend: web scrape competitive websites, purchase data from dealer software companies, factor based model
- Marketing Spend: purchase from marketing firms
- Inventory Levels: purchase data from ports on vehicle arrival and subtract out sales by vehicle
- Customer Profile: purchase registration data from credit firm – can also use this to infer transaction price and MSRP
- Exogenous: purchase or collect data from government websites (weather, economic factors etc.)

I think all this data is available but will require significant investment to acquire. Data is available from many sources, having the financial backing to purchase the amount of data needed in crucial. Further, some data might not be available. Our team may need to invest in the collection of data to fill in the pieces of the solution. For example developing a year's worth of web scraping or inventory sampling on competitive websites could be a great investment if the inventory data is not available or sparse. Each dataset would need to be ranked by priority and then "filled in" with a matching investment to purchase or collect the data.

Models in Models in Models:

Given years of investment in great data to answer our problem – our goal is not to optimize the current automotive landscape, but the short term future. Depending on the brand, producing a car can take 4-6 months. Incentive levels can also vary seasonally with the summer selling season and the holidays. Economic changes like possible interest rates increases can cause customers to put off their vehicle purchase. Changes in transaction price today (via additional incentives) will take at least a few weeks to set in, and the same goes for increases or decreases in marketing spend.

These constraints require us to look forward with the data we have and predict the near future. This means the data used to the overall "demand" model will likely have inputs from other models underneath it. A feature for the demand model could be an output from an inventory model, say a probability if the inventory levels will increase or decrease for a certain brand. Outside factors like weather and seasonality can also be modeled as inputs into our large demand and transaction price models. This infrastructure of models and supporting data will take significant time and brainpower to solve. What was originally a three model solution – one for demand, one for transaction price, and an optimization model to solve for the best outputs, each can have layers of other predictive models feeding the inputs into the other models. Each of them built with their own select features and techniques.

Reality Check:

Developing this solution seems impossible with the sheer amount of financial, time, brainpower, and discipline needed to see the full solution until the end. It is unclear with all the uncertainty in the data, and in the models used to build of features for other models in the solution, if the end product will even provide appropriate value to cover the investments made.

Viewing this problem from an overall Operation Research objective, which is to enhance the operations efficiency across the entire organization, the value begins at engaging each business unit to contribute their piece of the final puzzle. Having an accurate competitive inventory forecast, just one piece of the larger transaction price model, can help the sales planning and supply chain teams immediately. Product teams could use the inventory forecast to predict when new competitive models are due to arrive, and pieces of the transaction price model can be used to gauge pricing.

An important part of this solution is not to invest heavily and reap results at the end of many years of hard work. Building this data and modeling infrastructure can help with operations analytics as we progress to the larger optimization goal. Each business unit we work with to contribute their piece of the optimization framework will benefit from focusing on their data and thinking about which problems can be solved with this data. Framing this analytics problem in this manner will ensure we are building value at “every step” of the way towards our final goal. The end result might not even be a fully-fledged optimization model with inputs from a robust demand and transaction price model, but an engaged operations teams with their own path towards better decision making and analysis. Best case scenario would be building value throughout the project and then delivering on the overall optimization model to sway enterprise level decisions.

<u>Optimization:</u>

Given that we have developed a robust infrastructure of data, models and the results our demand and transaction price forecast, we can now develop an optimization model to guide production and pricing decisions. The optimization model will seek to maximize revenue, constrained by production capacity, cost to ship vehicles to different regions, overall industry demand, our demand by carline, and current inventory capacity on ground. The variables in this case would be the amount of vehicles to produce and the variable price to sell current vehicles for (can adjust MSRP using incentive spend). Aiming to maximize revenue will guard against recommending to price vehicles at zero to maximize sales, or only produce all sports cars and large SUVs to maximize transaction price. Based on domain knowledge, the team could also impose additional constraints based on the production of new carlines or the near coming of a new model year. For instance, requiring production quota for a new model year sedan coming next month. In totality, the model will recommend how many vehicles to produce, where to send them regionally, what price the current vehicles should be sold at to maximize potential revenue.

Another potential enhancement would be develop a probability based optimization model, instead of one with a “hard margin”. All of our inputs and constraints have uncertainty and random noise. Framing the optimization problem to take on probabilistic constraints could be beneficial to grounding the model in reality. Further, the inputs into the model could also be adjusted to probabilities, say giving a range of possible demand for carlines. Scenario modeling could be built to iterate the optimization model over the worst case, most confident case, and best case demand and transaction price levels. An optimization model could be used to optimize the production and pricing across all scenarios, or be driven by industry insight and domain knowledge.

The framework of our optimization model can also be used to study the effects of the business. Using the model and simulation can help us determine the price elasticity of our vehicles and our current customers. Trying out different constraints for pricing will show which cars benefit the most from added marketing and incentive investment (most likely sedans), and which carlines would actually not degrade from small price increases (usually sports cars and large SUVs).

After years of investment in data and analytics, our complete solution could be the basis to drive the company’s decisions optimally, no matter the competitive action, industry effects, internal constraints or economic changes. Our model ecosystem will ensure we are taking the right actions, or at least we are most likely (probabilistic) taking the right actions to maximize revenue for our company.