Describe analytics models and data that could be used to make good recommendations to the retailer. How much shelf space should the company have, to maximize their sales or their profit? Of course, there are some restrictions – for each product type, the retailer imposed a minimum amount of shelf space required, and a maximum amount that can be devoted; and of course, the physical size of each store means there's a total amount of shelf space that has to be used. But the key is the division of that shelf space among the product types. For the purposes of this case, I want you to ignore other factors – for example, don't worry about promotions for certain products, and don't consider the fact that some companies pay stores to get more shelf space. Just think about the basic question asked by the retailer, and how you could use analytics to address it. As part of your answer, I'd like you to think about how to measure the effects. How will you estimate the extra sales the company might get with different amounts of shelf space – and, for that matter, how will you determine whether the effect really exists at all? Maybe the retailer's hypotheses are not all true – can you use analytics to check? Think about the problem and your approach. Then talk about it with other learners and share and combine your ideas. And then, put your approaches up on the discussion forum, and give feedback and suggestions to each other. You can use the {given, use, to} format to guide the discussions: Given {data}, use {model} to {result}. One of the key issues in this case will be data – in this case, thinking about the data might be harder than thinking about the models.

The overall objective is to optimize shelf space allocation across products to maximize total retailer profit, subject to practical constraints like minimum/maximum space per product.
The key models and techniques that can help achieve this include:

Linear Regression Modeling: Given historical sales data, use linear regression to estimate price and shelf space elasticity

Build regression models at the product level to estimate the relationship between number of inventory/shelf facings and sales, while controlling for pricing effects. These product-level models can estimate revenue lift from increased shelf space. Useful data includes past sales, inventory, pricing and product perishability data.

We can build a regression model like:
$Sales\_ijk = \beta 0 + \beta 1 \mathit{Price\_ijk} + \mathit{\beta 2}ShelfSpace\_ijk + \varepsilon$

Where i denotes product, j denotes store, and k denotes week. So this models the sales for each product i, at each store j, for each week k as a function of that product's price and allocated shelf space that week.

The coefficients β1 and β2 indicate how sales respond to price and space changes. For example, β1=-2.5 would imply that for a 1% increase in price, sales drop by 2.5%. This is the price elasticity. We'd calculate these for all significant price and shelf space drivers.

Example product-level model: $SodaSales = 100 + -3.2\mathit{SodaPrice + 1.5}SodaShelfSpace$

Simulation Modeling:

Leverage under/overstock data along with days of supply metrics to build simulations that assess shelf replenishment needs under different facing allocation scenarios. Simulations can model the movement of inventory in/out of store under realistic constraints.

The goal of the simulation is to model inventory movements and shelf replenishment needs over time under different shelf facing scenarios for each product.
For example, for sodas:

1. Input historical daily soda sales per store
2. Input varying soda shelf facing allocation scenarios to simulate
    - Scenario 1: Current state with 5 soda facings
    - Scenario 2: Reduced to 3 facings
    - Scenario 3: Expanded to 8 facings
3. Simulate daily sales by randomly drawing from historical sales distribution
4. Simulate daily shelf replenishment orders based on facing level out of stock triggers
    - Example: Reorder when 2 or fewer facings remain
5. Track KPIs over 90-day simulation period
    - Average inventory
    - Lost sales from out of stocks
    - Order frequency
    - Days of supply remaining

By running multiple simulations under each scenario, we can compare the impact of different shelf allocations on operational metrics like product availability and inventory costs.
Key outputs would be:

- Service level for each facing scenario (e.g. 95% probability at least 1 facing in stock)
- Distribution of lost sales across simulations
- Range of variability for inventory days of supply

These outputs would quantify the shelf replenishment and shopper service level tradeoffs when reducing or expanding shelf facings for each product. The simulations can account for real-world uncertainties in demand.

Integer Programming: Given supply constraints, use integer programming to optimize shelf space allocation

Formulate an optimization model to maximize total expected profit across products by deciding optimal shelf space allocation. Enforce realistic constraints around total shelf space, individual product minimums and maximums. Leverage pricing data along with shelf-sales relationships from the regression models.

The retailer wants to:
Maximize TotalProfit = Σ(Sales_ijk * (Price_ijk - UnitCost_ijk))

Subject to constraints like: Σ ShelfSpace <= TotalSpaceAvailable min_space <= ShelfSpace_ijk <= max_space

An integer program would find the optimal shelf space values for each product at each store.

A/B Testing & Monitoring: Given optimized plan, use A/B testing across sample of stores before wide rollout

We'd take a small subset of stores and implement the model-recommended shelf plan, keeping other stores unchanged. By comparing sales data after a period, we can measure real-world impact vs just relying on models. Changes would then be rolled out further if the test stores see positive results.

Validate a subset of model-recommended shelf plans via controlled A/B testing. Track key operational metrics pre and post implementation to quantify true impact. Techniques like CUSUM analysis can identify any deterioration in revenues from initial model estimates.

The integrated use of predictive analytics, simulations, optimization and testing provides a structured data-driven approach to optimizing shelf space planning on an ongoing basis while balancing business constraints.

Additional Analysis

One additional way to augment this analysis, is by introducing inventory management or efficiency ratios, which will give a clearer view on how inventory should be allocated to store space:

Inventory Ratios:

- Days of Supply (DOS) = Current Inventory / Average Daily Sales
- Inventory Turns = Cost of Goods Sold / Average Inventory
- Out of Stocks % = # of Out-of-Stock Events / Total Replenishment Events

Analytics Models & Data:
Given historical sales, inventory, and out of stock data by product and store, use linear regression modeling to estimate the relationship between shelf space and sales for each product while controlling for pricing effects and inventory availability.
The model can incorporate inventory ratios like DOS and Out of Stocks % to account for lost sales opportunities:

$$\text{Sales} = \beta 0 + \beta 1 \mathit{Price} + \beta 2\text{ShelfSpace} + \beta 3 \mathit{DOS} + \beta 4\text{OutOfStocks}$$

Then use optimization to allocate shelf space across products to maximize total expected profit based on the shelf-space sales models. Enforce realistic constraints around total shelf space and product min/max limits.

To validate, implement a subset of model-recommended plans via A/B testing across a sample of stores. Track lift in sales and monitor inventory ratios before and after changing shelf allocations.

Conclusion

The goal is to optimize retail shelf space allocation across products to maximize total profit, subject to constraints like minimum/maximum facings per product. A structured approach can achieve this using: 1) Linear regression modeling to estimate the sales lift from increased shelf space based on historical data;

2) Simulation modeling to assess shelf replenishment needs under different allocation scenarios while enforcing realistic inventory constraints; 3) Integer programming to optimally allocate space to maximize expected profit given pricing data and estimated shelf-sales relationships; and 4) Controlled A/B testing with a sample of stores before wide rollout to validate and quantify the real-world impact of model-recommended plans. Together, these predictive analytics, simulation, optimization and testing techniques enable data-driven shelf space planning that balances business constraints and is refined over time.