Case study: data-driven pricing

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The problem

- A retail client wanted to improve their strategy for pricing apparel.
- In the past, they would start with a base price (usually set by executives) and mark-down whatever wasn't sold towards the end of the season.
- As such, plotting price over time would usually give something like:
- TO DO: INCLUDE FAKE PLOT, PRICE VS WEEK, LINEARLY DECREASING, BIG DROP AT END

The problem cont.

- However, this heuristic pricing led to high variance in sell-through rates at the end of the season:
- TO DO: INCLUDE FAKE PLOT, ALMOST UNIFORM DISTRIBUTION IN SELL-THROUGH (S19 OF APPAREL PRICING DECK)
- Popular products would sell out too quickly, while unpopular products would never sell out and turn into excess inventory at the end of the season.
- A better strategy would have been to raise prices on popular products (or discount them less aggressively), and vice versa for unpopular products.

Using data to improve pricing

- On a weekly basis, the data-driven pricing model took in inputs such as last week's sales and the week (e.g. if it's the week of Thanksgiving) and outputted recommended prices
- The model roughly said to maximize profit (Π) by changing price (P)...

$$max_P \Pi = PQ_s - CQ_0$$

- ...where quantity sold is a function of price, demand (D), and elasticity (ϵ), which is a fancy term for the responsiveness of buyers to price

$$Q = DP^{\epsilon}$$

Two data-mining tasks

1. Estimate elasticity, or how responsive buyers are to price
2. TO DO: INCLUDE FAKE PLOT OF QUANTITY VERSUS PRICE WITH FITTED LINE
3. Predict demand
4. TO DO: SHOW A TIME SERIES OF DEMAND WITH DOTTED LINES TO INDICATE POSSIBLE 'FORECASTS'