Suggested Order Quantities

AB InBev manager: Bruno Raposo
Faculty advisor: Negin Golrezaei
PhD mentor: Andreea Georgescu

Problem Statement
- US small independent stores brought more than 20% of AB InBev’s net revenue in 2018.
- Order placement involves a sales rep who spends time counting inventory and visiting the store.
- Suggesting order quantities can unlock cost savings by reducing physical visits as well as better exploiting business opportunities e.g. upselling or assortment considerations in a ~$5B market.

<table>
<thead>
<tr>
<th>Store</th>
<th>Date</th>
<th>Product</th>
<th>Quantity</th>
</tr>
</thead>
<tbody>
<tr>
<td>X</td>
<td>07/01/19</td>
<td>BUD324</td>
<td>2</td>
</tr>
<tr>
<td>X</td>
<td>07/01/19</td>
<td>BDL025</td>
<td>0</td>
</tr>
<tr>
<td>X</td>
<td>07/01/19</td>
<td>STA034</td>
<td>1</td>
</tr>
</tbody>
</table>

Goal
- Predict

Data
- High quality
  - “Sell-to”: From distributors to retailers
  - “Sell-Out”: From retailers to consumers
- Low quality
- Main data challenges
  - High granularity and noise - Store-SKU-week level
  - Critical data availability - No inventory data
  - Partial information - only a fraction of sell-out recorded
- Tracking products
  - “Matching issue”: tracking products from the distributor (sell-in) to the end-consumer (sell-out)
- SKU BUD004
- Unit sales
- Single BUD 12oz bottle

Main challenges:
- High # of historical SKUs
  - Some SKUs are hardly ever ordered, while some almost always.
- Erratic replenishment patterns
  - Order frequency is not fixed. Stores have different sizes and varying replenishment patterns.
- Many gross outliers
  - Some orders do not fit into the store's replenishment pattern (e.g. small order after an unexpected stock-out situation)

Data Processing
- Time series approach
  - ARIMA/LSTM type models
- Model selection

Selected features
- Recent replenished quantities
  - Rolling mean of # units replenished when actually ordered with or without including null values
- Recent replenishment timing patterns
  - # consecutive replenishments without including a given SKU
  - Normalized lead time
- Sales trends and inventory status
  - Last period sell-out normalized by rolling mean of sell-out
  - Stock consumption indicator
- Next week’s sales information
  - Weather forecast
  - Binary incoming special event variable

Stock-consumption indicator
- What fraction of my inventory did I consume since last replenishment?

Impact & results
- Linear Regression trained at the store/SKU level for 8 SKUs with good matching results between sell-in and sell-out

Main takeaways
- Extreme granularity of task requires accurate sales and inventory information, enabling an optimization approach towards profit maximization.
- Acquisition of POS data is costly and remains approximate.
- Prediction task could focus on a more aggregated level, leaning towards recommendations at the store-SKU level.

Scope
- 60 small “indy” stores in the New York area
- On-premise stores
- Off-premise stores

Project
- Kickoff: 06/12
- Data Acquisition: 06/21
- Mid-summer presentation: 07/12
- Problem re-scaling: 08/09
- MIT Final presentation: 08/23
- Field trip: 09/01/19

MBAn Capstone project
AB InBev, Summer 2019, NYC