Demand Forecasting for Future Fashion Products

Methodology

Natural Language Processing (NLP)
- We use sentence embedding to turn product descriptions into numerical vectors.
- SWIVEL was chosen over USE or BERT for increased scalability without sacrificing performance.

Bottom-Up
K-Nearest Neighbors (KNN) matches new products to similar products from the past.

We use the six nearest neighbors' sales to estimate sales for the new product. Six was found to be the optimum number of neighbors through the elbow method.

Top-Down

We use Weighted K-means Clustering to group all products into six distinct profiles based only on their sales trends. Six was found through a voting process between four metrics.

Then, we use Random Forest to classify products into one of these profiles utilizing their unique NLP embeddings.

Ensemble

The Bottom-Up approach captures the idiosyncratic trends from the products' style and attributes. The Top-Down approach captures general trends, which are highly correlated with markdown schedules. Combining the two approaches results in a model that outperforms either individually.

The models are combined using weighted mean and Savitzky-Golay filtering. The weights are found by cross-validation.

Location-Level Buy Forecast

Using Random Forest, we predict the demand for a product by location, and create prediction intervals based on the 5th and 95th percentile tree predictions.

Since our model often under-forecasts, we can tune the interval width to tighten the range and improve usability. We separate out a second training set to tune the prediction interval percentiles in order to prevent overfitting.

Aggregating up our location-level buy forecasts, we obtain an overall omni-channel buy forecast for each product.

Business Impact

Innovated novel methodology for demand forecasting, pioneering a new class of forecasting at Macy’s.

Models can be reinterpreted for different use cases:
1. Top-Down Method → product popularity estimator
2. NLP+KNN → product matching tool for recommendation systems

Future Considerations

Incorporate New Data Sources
- Predicted Fashion Trends
- Stockouts

Consider New Scopes of Products
- Aggregate allocation forecast across regions or climates
- Partition products based on their intended lifecycle

New Methodologies
- Time-series Approaches
- Tensor Completion

Dashboard Prototype

By prototyping a dashboard that would be used by our stakeholders, we offer an interface where they can interact with our model and tangibly see results, all without ever needing to dive into the data science.

We handpicked some metrics and visualizations to give the user a general understanding of what data the model relies on to make decisions, with feature importance being especially useful to provide interpretability.

Product-Trend Matching

Results

We implement a model pipeline that takes a product description as input and produces a product-level demand forecast across 450 stores and 90 categories.

The Product-Trend Matching and the COM Buy Forecast perform well. However, the store-level buy forecast performance suffers due to data skew and low granularity. These errors propagate through the store-level allocation forecast.

Product-Trend Matching

<table>
<thead>
<tr>
<th>Forecasting</th>
<th>Buy Allocation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Store</td>
<td>.COM</td>
</tr>
<tr>
<td>Root Mean</td>
<td>7.23</td>
</tr>
<tr>
<td>Squared Error</td>
<td>0.027</td>
</tr>
<tr>
<td>Prediction Interval Capture Percentage</td>
<td>35%</td>
</tr>
</tbody>
</table>

Data Source

- Product Descriptions, Product Sales
- Store Popularity, Demographics
- Time, COVID-19, Weather, Consumer Price Index

Data Summary

- 450 Stores + macy's.com
- 4 Years of Data
- 20K products
- 30 Store/Time Features
- 86 million observations

Problem Statement

"Currently, Macy’s, Inc. uses a manual process for deciding product allocations to their stores across the U.S. Our goal is to make this process more data-informed -- to forecast the demand for new fashion products at the product-color-store-month level in order to inform the Merchandise Planning and Allocation team at Macy’s, Inc."