**Project Overview**

**Project Importance**
- Luxury retailers make little revenue from ready-to-wear clothes.

**Project Scope**
- Our project was forecasting demand for women's handbags in their European stores.
- Specifically, we created a model to predict demand for handbags that are part of the new seasonal collection, meaning they have no historical sales.

Below is the criteria on which we filtered the data.

<table>
<thead>
<tr>
<th>Women's handbags</th>
<th>Full-price items</th>
<th>Retail locations</th>
<th>Gross sales</th>
<th>New Collection</th>
</tr>
</thead>
</table>

**Project Timeline**

- **January - February**: Exploratory Data Analysis, Initial Demand Forecasting Models
- **March - April**: Feature Engineering, Constructing Panel Data
- **May - June**: Pairedness Comparison Research, Efficient Algorithm Implementation
- **July - August**: Sophisticated Demand Forecasting Models, Summer Capstone Showcase

**Data Overview**

**Raw Data**

We were given four datasets:

- **Store Data**: Information about stores, such as location and sales information.
- **Product Data**: Details about products, such as SKU and price.
- **Transactions Data**: Sales transactions, including transaction type and amount.
- **Inventory Data**: Stock levels and other inventory-related data.

**Store Clusters**

The client provided us with five store clusters, labeled A through E.

**Dissimilarities between Train and Test**

- Significant discrepancies exist between the train and test sets, which makes accurate predictions difficult for the test set.
- We inspected the number of SKUs made per subclass for the two datasets to assess the dissimilarity.
- Below is a plot showing that some subclasses are prevalent in the test set but absent from the train set.

**Top 6 subclasses in the test season**

- **Feature Engineering**

- **Historical Features**

- **Sales for that category for season-1**
- **Sales for that category for season-2**

- **Stock made for that category for season-1**
- **Stock made for that category for season-2**

- **Sales per store for season-1**
- **Sales per store for season-2**

- **Store popularity**

**Product and Store Features**

- Aggregated style and color features were created to decrease dissimilarity between the train and test sets.
- Consider a granular five-digit color code for a green bag, where the first three digits indicate that it is green, the next digit indicates the brightness of the shade, and the final digit signifies the exact hue of green.
- By reducing this feature to an aggregated three-digit code, we are able to find more similarities between the train and test set.

**Data Processing**

**Clustering Data using k-Prototypes**

- We applied clustering to our data using k-prototypes, which integrated k-means and k modes algorithms to cluster both continuous and categorical variables.
- We selected the number of clusters by validating on the model's overall performance.

**Reducing Proportion of Null Values**

- We imputed missing values in the dataframe using analytical techniques.
- Using our analytical expertise, for example, we inspected the data and replaced null values with zero for binary features.
- We used ETL techniques to create an aggregated feature, and by merging datasets on this aggregated feature, the number of null values was dramatically reduced.

**Dummifying Data and Deleting a Degree of Freedom**

- We dummed the categorical variables and, when doing so, we deleted the extra degree of freedom.
- This approach decreased the complexity of the data and increased the performance of our model.

**Feature Engineering**

**Historical Features**

- We created historical features by lagging the last two seasons of data.

**Product and Store Features**

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**Model and Results**

**Model Selection: Random Forest**

- We tried three models: Elastic Net, CART, and Random Forest.
- We evaluated these three models on mean absolute error (MAE) and mean absolute percentage error (MAPE).
- We selected the Random Forest model not only because it has the best performance, but also because it is interpretable.

**Feature Importance**

- Below are the most significant features in our model.

**Performance Compared to Benchmark**

- In order to confirm the client’s valuation of our model, we compared its performance to the benchmark, which is the amount of stock made by the client per SKU for each season.
- We assess the performance of our model and the benchmark using MAE and price MAE, which is MAE weighted by SKU price.

**Recommendation: Potential Demand**

- Sales are a proxy for demand since stock-outs could have caused fewer sales or lower sales.
- We trained a Random Forest model to predict sales for which there were no stock-outs and then predicted sales for weeks in which there were stock-outs.
- Below is the MAE for the Fall-Winter 2016 season, for which we predict that demand is 90.0% higher than sales. The MAE of this model is 0.461 and MAPE is 27.3%.

**Impact**

- Our Capstone project resulted in a better performing forecasting model in comparison to the client’s model. This superior performance is a result of our data insights, feature engineering, and model selection.
- Ultimately, better forecasting improves the organization’s profitability and customer satisfaction.

- Fewer missed sales: accurately forecasting demand will ensure that inventory is in the right place at the right time.
- Lower working capital: the client can operate with less inventory because of confidence in demand projection.
- Improved customer service: with a deeper understanding of customer demand and unique store selling behaviors, the client can effectively deploy inventory to provide higher sell-through rates, improved on-time availability, and fewer stockouts.