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Applied Data Science

DSC680 (SUMMER)

**Analyzing Marketing Lift of a Targeted Local Campaign**

**Potential Audience Questions**

1. **How was the data split between the training and test sets?**
2. The data was split using a date range in the time series data. The training data ranges from the oldest available date to 15 weeks prior to the most recently available date. This provides a 10/90 split to provide model with a robust training set to better learn seasonal patterns present in the data.
3. **Why were ARIMA, SARIMA, and Exponential Smoothing chosen as the models for comparison?**
4. These models were chosen because of their ability to deal with time-series data. SARIMA was always the focus of the project, and the other two models were only a point of reference.
5. **How did the advertising campaign affect the order patterns during the test period.**
6. Using the SARIMA model’s predictions as a baseline we can compare the predicted orders against actual orders to calculate lift (advertising campaign’s effect on orders). The campaign started on the week of 4/15/24, from the weeks of 4/15/24 to 5/27/26, we can estimate that the campaign generated 31 incremental orders.
7. **Can you explain the significance of the MAE and MSE metrics in evaluating model performance?**
8. The Mean Absolute Error (MAE) of 25.11 indicates the average difference between the predicted and actual orders. MAE helps us understand the average prediction error and is on the same scale as the data making it easy to understand. Mean Square Error (MSE) functions similarly to MAE however the measure is squared. By squaring the errors, MSE penalizes larger errors more significantly than smaller ones. This means that MSE is more sensitive to outliers. When comparing multiple models the model with the lower MSE is generally considered more accurate.
9. **Why did the Exponential Smoothing model show a lower MAE but potentially overestimate orders?**
10. The model has a low MAE which looks good initially but had a higher MSE which indicates that the model was more prone to error. Since the test period had the presence of advertising, a smaller MAE actually makes sense along with the higher MSE. We expect orders to be higher during the test period due to advertising so the low MAE in combination with the high MSE indicates that the model is overestimating orders.
11. **How do you plan to incorporate the advertising campaign data into future models?**
12. We can leverage the current SARIMA model for the current campaign since we observe a low MSE, indicating good model fit. For future models I would recommend that additional campaign variables be included, and the model transitioned to a SARIMAX to leverage campaign variables to improve performance.
13. **What steps were taken to ensure the models are not overfitting the training data?**
14. The approach used in this project was to have a large robust training data, use a validation set, and hyperparameter tuning.
    1. The training data consisted of three years’ worth of historical orders for the targeted zips. The robustness of the training data allows the model to learn established seasonal patterns as well as diminish the impact of anomalies.
    2. The data was split into training and test sets. The model’s performance was evaluated on the test set and performance measures like MSE and MAE were used.
    3. A grid search was performed to identify the optimal set of parameters that balanced model complexity and performance. This helps prevent the model from becoming too complex and overfitting the training data.
15. **How reliable are the model predictions for future periods without advertising campaigns?**
16. The model’s predictions do have the potential to be very reliable for future periods.

However, this depends on several factors, including the consistency and completeness of the data fed into the model.

* 1. The baseline model is trained on a robust dataset that includes three years of historical order data which helps it learn the underlying patterns and trends.
  2. When predicting future order volumes under ordinary circumstances (without advertising), it is important to ensure that the training data used excludes periods influenced by marketing campaigns
  3. We will need to handle any gaps in the data to ensure the model continues to give accurate predictions. We can do this by inputting any excluded weeks using the baseline model’s predictions.

1. **What other external factors might influence order patterns and how are they accounted for in the models?**
2. External factors that might influence orders include both economic and competitive factors. If a new competitor is introduced to the market or if the market is in a downturn, both could negatively impact orders. We do not have the capacity to include these factors in our current model. Our best approach is to continuously feed new data to the model to train on to learn recent trends that may be influenced by factors outside of our control.
3. **How will the calculated marketing lift be used to inform future advertising strategies?**
4. Marketing lift (effect of advertising on orders) will be used to calculate a return on investment. If the campaign proves to be profitable in the form of incremental orders, then similar campaigns can be launched in similar markets with the expectation of achieving similar profitable results.