Customs revenue prediction using ensemble methods (statistical modeling vs machine learning)

Jordan Simonov and Zoran Gligorov

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Introduction

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Forecasting problem

- Finance ministries usually project the annual and monthly revenue collection targets that are expected to be met by customs administrations.
- Modern cash management requires accurate short-term forecasts not only on a monthly basis, but also on a weekly or daily basis.
- Forecasting daily collection of customs revenues.
- Possible approaches?
Table: Statistical modelling vs Machine learning

<table>
<thead>
<tr>
<th>Statistical modelling</th>
<th>Machine learning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Formalisation of relationships between variables in the form of mathematical equations.</td>
<td>Algorithm that can learn from the data without rule-based programming.</td>
</tr>
<tr>
<td>Required to assume shape of the model curve prior to performing model fitting to the data (e.g. linear, polynomial).</td>
<td>Does not need to assume underlying shape, as machine learning algorithms can learn complex patterns automatically, based on the provided data.</td>
</tr>
<tr>
<td>Predicts the output with 85% accuracy at a 90% confidence level.</td>
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</tr>
<tr>
<td>Various diagnostics of parameters are performed, such as p-value.</td>
<td>Does not perform statistical diagnostic significance tests.</td>
</tr>
<tr>
<td>Data will be split into 70%/30% to create training and testing data. Model developed on training data and tested on testing data.</td>
<td>Data will be split into 50%, 25%/25% to create training, validation, and testing data. Models developed on training and hyperparameters are tuned on validation data and are evaluated against test data.</td>
</tr>
<tr>
<td>Models can be developed on a single dataset (training data), as diagnostics are performed at both overall accuracy and individual variable level.</td>
<td>Need to be trained on two datasets (training and validation data), to ensure two-point validation.</td>
</tr>
<tr>
<td>Mostly used for research purposes.</td>
<td>Apt for implementation in a production environment.</td>
</tr>
<tr>
<td>From the school of statistics and mathematics.</td>
<td>From the school of computer science.</td>
</tr>
</tbody>
</table>

Source: Adapted according to Pratap (2017, p. 43)
Introduction
Statistical modelling
Machine learning
Ensamble learning
Conclusion
References

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Statistical modelling
# Statistical modelling

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<tr>
<td>Exponential smoothing (ETS)</td>
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<td>Trigonometric Exponential smoothing state space model with Box-Cox transformation, ARMA errors (TBATS)</td>
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## Statistical modelling

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Table: Evaluating forecast accuracy

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<th>Test set</th>
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<tr>
<td></td>
<td>RMSE</td>
<td>MAE</td>
</tr>
<tr>
<td>ETS</td>
<td>11.71</td>
<td>10.02</td>
</tr>
<tr>
<td>STL</td>
<td>3.04</td>
<td>2.33</td>
</tr>
<tr>
<td>ARIMA</td>
<td>8.7</td>
<td>5.96</td>
</tr>
<tr>
<td>TBATS</td>
<td>4.64</td>
<td>3.39</td>
</tr>
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</table>
Machine learning
Machine learning

- Linear regression (LM)
Machine learning

- Linear regression (LM)
- Classification and regression trees (CART)
Machine learning

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- Conditional inference tree (CTREE)
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<tr>
<td>LM</td>
<td>3.81</td>
<td>2.54</td>
</tr>
<tr>
<td>CART</td>
<td>4.27</td>
<td>2.72</td>
</tr>
<tr>
<td>CTREE</td>
<td>4.15</td>
<td>2.52</td>
</tr>
<tr>
<td>XGBoost</td>
<td>3.80</td>
<td>2.41</td>
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**Ensamble learning**

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**PICARD 2020**

**Customs revenue prediction using ensemble methods (statistical modeling vs machine learning)**
Evaluating forecast accuracy

**Machine learning**
- CART
- XGBoost
- LM
- CTREE
- Ensemble_ML

**Statistical modelling**
- ETS
- ARIMA
- STL
- TBATS
- Ensemble_SM

**Evaluation Metrics**
- **MAE**
- **RMSE**
By using statistical modelling and machine learning, we tested 10 different models in the R ecosystem.
By using statistical modelling and machine learning, we tested 10 different models in the R ecosystem.

Using statistical modelling, the ensemble technique reduced the RMSE error from 12.99 to 4.92, while when using machine learning, the error of 4.86 was reduced to 3.53.
Conclusion
As for both approaches, the ensemble technique has shown that it can improve prediction accuracy compared to the individual models. They can reduce the forecasting error, so to that end, we can conclude that the ensemble technique is certainly a game changer and must be an important addition to every forecaster’s toolbox. For this reason, we recommend using this technique for forecasting purposes with statistical modelling or machine learning. The choice is yours!
References