Incorporating macro-economic leading indicators in inventory management

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Motivation

When will the next economic crisis hit? Where? For how long?

Traditional univariate forecasting techniques do not incorporate context information
Research Question

Long term sales forecasting are formulated using

- Historical data patterns (level, trend, seasonality, ...)
- Promotions
- Judgemental adjustments:
  - Collaborative input from clients
  - Newspapers and industry magazines
  - Rumors in the corridors

Judgemental input is known to be biased and inconsistent (Fildes and Goodwin 2007, Trapero et al. 2013)

- Information of exogenous leading indicators
  - Capturing market sentiment in external big data (Russom et al. 2011)
Research Question

- Can macro-economic indicators improve sales forecasts?

- What is the real impact on the supply chain inventory?
Experiment design

Incorporating leading indicator information

- Tactical level
- Plant level
- Top-down level

Evaluation: MAPE and MdAPE
Models

Benchmark models
- Naive model
- Holt-Winters model
- Exponential Smoothing

LASSO model

\[ \hat{Y}_i = \beta_0 + \sum_{k=1}^{S} \beta_k D_k + \sum_{j=1}^{P} \beta_i x_{ij} \]  

(1)

Cost function:

\[ \sum_{i=1}^{n} \left( y_i - \beta_0 - \sum_{p=1}^{P} \beta_p x_{ip} \right)^2 + \lambda \sum_{p=1}^{P} |\beta_p| \]  

(2)
LASSO

Least Absolute Shrinkage Selection Operator (Tibshirani, 1996)

- Shrinkage and variable selection
- Selecting $\lambda$ through cross-validation

![Graph showing LASSO coefficients over various $L_1$ norms](image-url)
Working paper:

- MAPE improvement 18.8% on 1-12 months ahead
- Set of 67,851 indicators
- Unconditional Forecasting
- Final model: 10-15 indicators selected
  - Employment in automobile
  - National passenger car registrations
  - Consumer Prices Index for solid fuel prices
Sales data of 5 plants of a global manufacturer

- Train period: 2005 - 2012
- Test period: 2013 - 2014
- Forecast horizon $h=1..6$
- Rolling origin evaluation
Empirical results: forecasting accuracy

<table>
<thead>
<tr>
<th>Method</th>
<th>MAPE</th>
<th>MdAPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naive</td>
<td>19.0</td>
<td>12.8</td>
</tr>
<tr>
<td>Holt-Winters</td>
<td>20.1</td>
<td>13.2</td>
</tr>
<tr>
<td>Exponential smoothing</td>
<td>13.5</td>
<td>9.8</td>
</tr>
<tr>
<td>LASSO</td>
<td>16.7</td>
<td>15.9</td>
</tr>
</tbody>
</table>

Lower level

![Graph showing empirical results](image)
Empirical results: forecasting accuracy

Higher level

<table>
<thead>
<tr>
<th>Forecast Horizon</th>
<th>MAPE</th>
<th>MdAPE</th>
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<tbody>
<tr>
<td>1</td>
<td>6.1</td>
<td>5.5</td>
</tr>
<tr>
<td>2</td>
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<td>8</td>
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</tbody>
</table>

Exponential smoothing
LASSO

Motivation
Experiment design
Models
Data
Forecasting
Uncertainty
Inventory
Conclusion

ISIR 2016
Ghent University, Lancaster Centre for Forecasting, Solventure
Reconciliation hierarchical forecasting

The hierarchy is captured in the summing matrix

Reconciliation incorporates $1/MSE$ of each forecast

\[
\begin{bmatrix}
\hat{Y}_{Tot} \\
\hat{Y}_A \\
\hat{Y}_B \\
\hat{Y}_C \\
\hat{Y}_D \\
\hat{Y}_E
\end{bmatrix} =
\begin{bmatrix}
1 & 1 & 1 & 1 & 1 \\
1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
\hat{Y}_{A,r} \\
\hat{Y}_{B,r} \\
\hat{Y}_{C,r} \\
\hat{Y}_{D,r} \\
\hat{Y}_{E,r}
\end{bmatrix},
\] (3)
Empirical results: forecasting accuracy

Reconciled lower level

<table>
<thead>
<tr>
<th>Model</th>
<th>MAPE</th>
<th>MdAPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exponential smoothing</td>
<td>13.5</td>
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<tr>
<td>LASSO</td>
<td>16.7</td>
<td>15.9</td>
</tr>
<tr>
<td>Hierarchical LASSO</td>
<td>14.5</td>
<td>10.5</td>
</tr>
</tbody>
</table>
Uncertainty: iterative vs direct forecasting

Reformulated LASSO model for each horizon allows for empirical estimation of $\sigma_h$

Direct forecasting: independent across horizons
Iterative forecasting: covariances inflate variance
Inventory simulation

Simulation parameters

- Production standoff $t+6$
- Service level: 0.9, 0.95, 0.99
- Inventory policy: Make to stock
Average inventory per service level

![Graph showing average inventory per service level with different models: Naive, Holt-Winters, ETS, Lasso, HierLasso. The graph displays the relationship between average inventory and fill rate, with service level markers at 0.90, 0.95, and 0.99.]
LASSO has an improved forecasting accuracy on long-term

On short horizons, LASSO leads to service level and inventory improvements
Questions?

Thank you for your attention!

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