Causal Leading Indicators Detection for Demand Forecasting

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Introduction

A main supplier to a global tire manufacturer wants to improve their current global tactical sales forecast of 12 months (Holt-Winters). Their lead times for raw materials are 4-6 months. They believe economic leading indicators can add value here. Intuitive examples of leading indicators

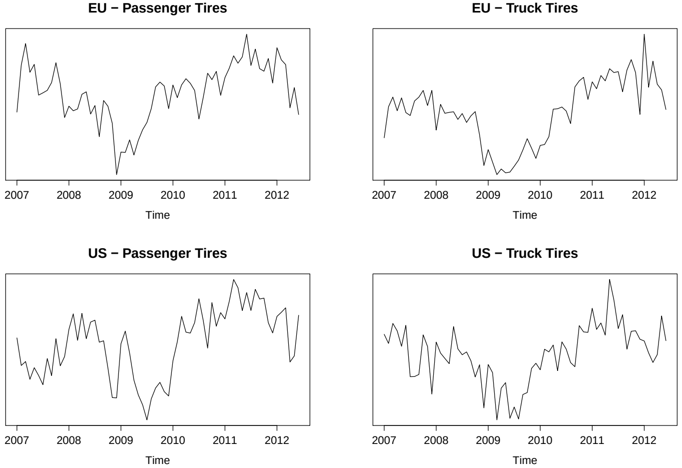
- Change in events

$$\textit{Severe Winter } (\Rightarrow \textit{Used Gas Volume} \nearrow) \Rightarrow \textit{Tire wear} \nearrow$$

- Different economic conjuncture in country

$$\textit{Economic Growth} \nearrow \Rightarrow \textit{Road Transport} \nearrow \Rightarrow \textit{Tire Production} \nearrow$$

Data Plot


EU − Passenger Tires
EU − Truck Tires
US − Passenger Tires
US − Truck Tires
2007
2008
2009
2010
2011
2012
Time

Problem Statement

Problems with including exogenous leading indicators

- Variable selection on limited data
  - 60 historical sales points (5 years)
  - 60,000 leading indicators (monthly data on FRED)
- Availability of leading indicator data
  - Leading indicators are shifted in time to detect optimal leading effect: Shift in time $<$ forecast horizon
  - Moment of publication of indicator data
- Combining univariate and exogenous information (Huang et al. , 2014) (Leitner et al. , 2011)

LASSO Regression

Least Absolute Shrinkage Selection Operator (Tibshirani, 1996)

$$\sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j x_{ij}\right)^2 + \lambda \sum_{j=1}^{p}|\beta_j|$$

Advantages (Bai and Ng, 2008) (Li and Chen, 2014) (Iturbide, 2013)

- Variable selection: LASSO shrinks coefficients to zero
- Works if sample points (n) $<$ predictor set (p)

Model problems

- Optimization of Lambda
- How to include univariate information

Including univariate information

Capturing the univariate structure (cheap information)

- Level
- Trend
- Seasonality
- Auto-Regression Process
- Moving-Average Process

Empirical Setup

Global Sales Data

- Training: 2007:01-2012:06 (66 observations)
- Test: 2012:07-2013:12 (18 observations)
- Forecast horizon 12 months ahead (for 7 rolling origin)
- 4 Monthly Time Series
  - Truck and Passenger tires
  - US - EU

Indicator Data

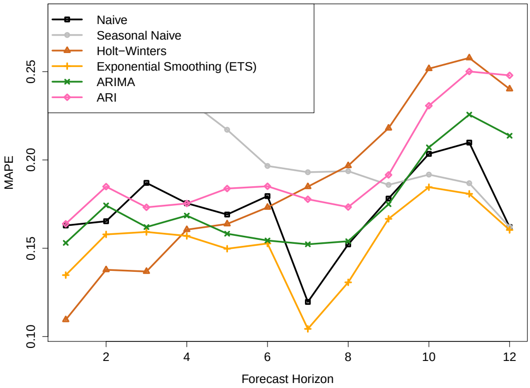
- Judgemental subset of 1,000 indicators out of 60,000
- Shifted in time up to 12 months ahead resulting in 13,000 variables

Benchmark Models

Univariate models:

- Naive
- Seasonal Naive
- Holt-Winters (Company benchmark)
- Exponential Smoothing (ETS)
- ARIMA
- ARI

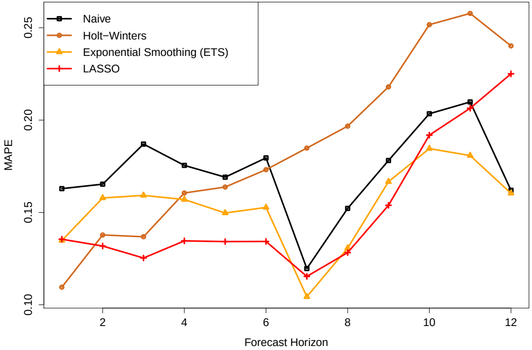
Evaluation Benchmark Models



Model	MAPE
Naive	17.205
Seasonal Naive	21.196
Holt-Winters	18.590
Exponential Smoothing (ETS)	15.323
ARIMA	17.484
ARI	19.479

LASSO Results

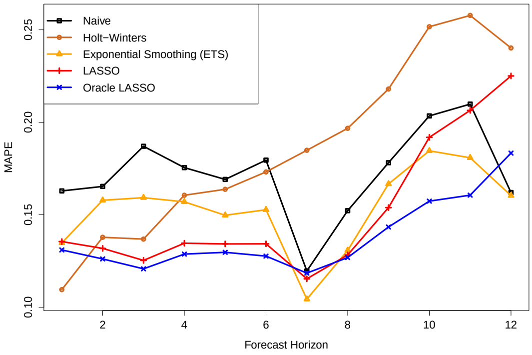
LASSO with limited sales history can improve on the company benchmark and on ETS, but deteriorates on long horizon



Model	MAPE
Naive	17.205
Holt-Winters	18.590
Exponential Smoothing (ETS)	15.323
LASSO	15.138

Data or model problem?

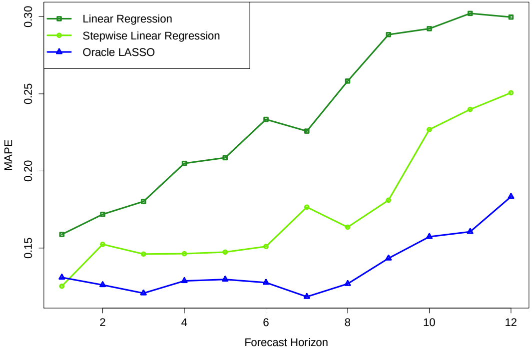
If future values of leading indicators are known (Oracle), LASSO can improve on company benchmark and ETS



Model	MAPE
Naive	17.205
Holt-Winters	18.590
Exponential Smoothing (ETS)	15.323
LASSO	15.138
Oracle LASSO	13.781

Data or model problem?

If future values of leading indicators are known (Oracle), LASSO outperforms on linear regression and stepwise linear regression



Model	MAPE
Linear Regression	23.538
Stepwise Linear Regression	17.560
Oracle LASSO	13.781

Upcoming research

Conclusion

- Improved company sales forecasting with 18.6% (Oracle: 25.9%)
- This can lead to lower inventory and better planning
- Method for gaining insight in potential driving forces of their sales

Next steps and limitations:

- Causal relationship between indicator and sales
- Different method of removing the Oracle assumption

Questions?

Thank you for your attention !

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