UNIVERSITEIT GENT

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The value of external information: including leading indicators in sales forecasting

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Research seminar
May 25, 2016 - St. Petersburg

Business problem

A global tire manufacturer wants to improve its tactical sales forecasting with external data, obtaining insight in the main relevant leading indicators

Motivation long-term forecasting

- Global supply chains need long-term forecasting for decision making (procurement, production scheduling and capacity planning)
- External data is often available (public & expert sources)
- Incorporating field knowledge via judgement: inconsistent & bias
- Combining univariate and exogenous information (Huang et al. , 2014) (Leitner et al. , 2011)

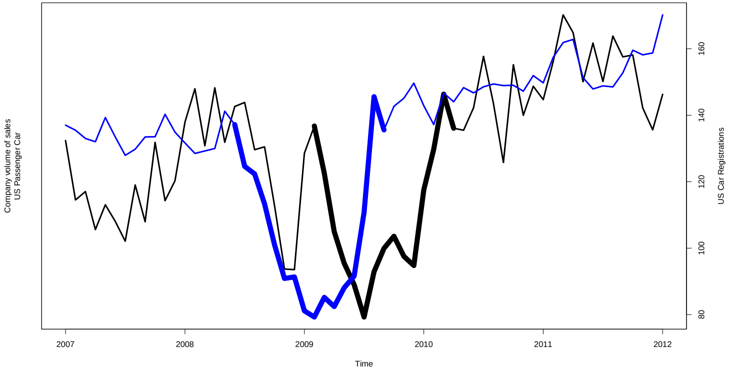
Belief in external leading indicators

National economic conjuncture is a leading for tire sales:

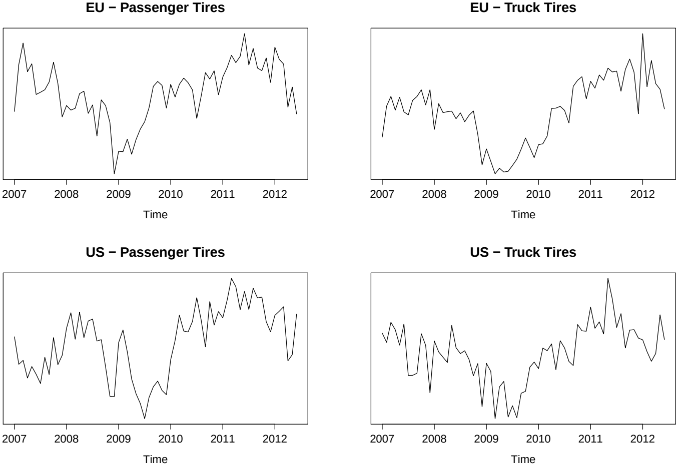
$$Economic\ Growth \nearrow \Rightarrow Road\ Transport \nearrow \Rightarrow Tire\ Production \nearrow$$

Leading Indicator Example: Tires for passenger cars (US)

The amount of newly registered cars (blue) is a leading indicator to the sudden drop (bold) in car tire sales (US) during the economic crisis of 2009-2010.



Insight in case study data



Methodology: the curses of leading indicators

Curse of dimensionality

- Short fat data problem
- $p > n$: much more predictors than training sample

Curse of optimal leading effect

- Leading indicators exhibit leading information in advance
- $pl \gg n$: detecting optimal lead expands dimensionality

Curse of missing future information

- Indicators only exhibit information up to a certain point in time
- Clear need for unconditional forecasting

Methodology: 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)

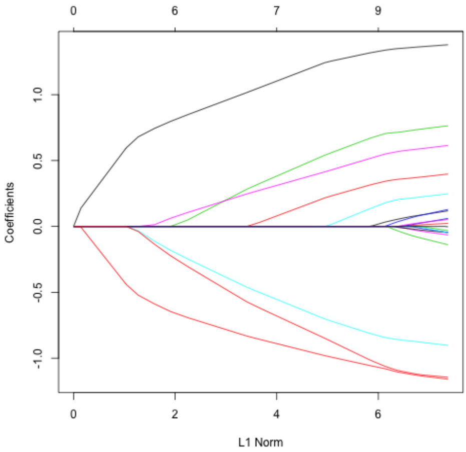
- Works with p $>$ n
- Shrinking coefficients
- Variable selection

Model problems

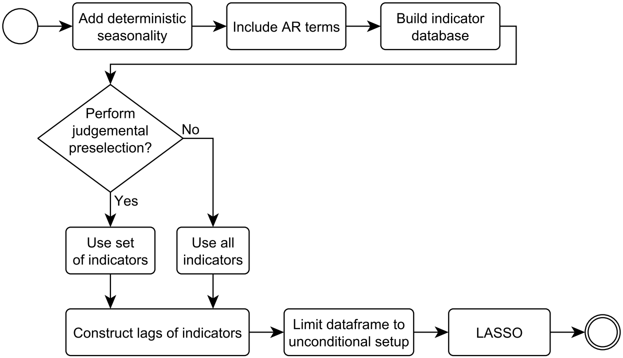
- Include univariate information
- Choosing and optimising Lambda

Methodology: LASSO regression

LASSO shrinks coefficients to zero and selects predictors



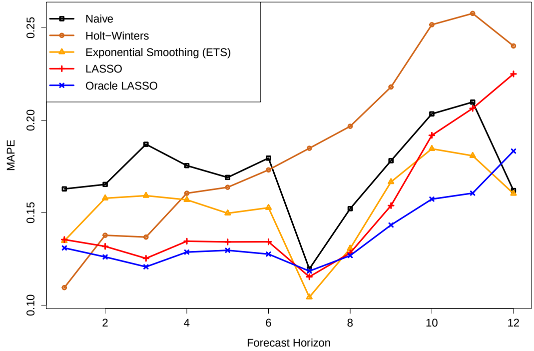
Methodology



Forecast horizon	1	5	12
Lags	1-12	5-12	12
Number of variables	814,212	542,808	67,851

Forecasting results

LASSO can improve on company benchmark and ETS, but deteriorates over long horizons



Model	MAPE
Naive	17.2
Holt-Winters	18.6
Exponential Smoothing (ETS)	15.3
LASSO	15.2
Oracle LASSO	13.8

Final model contains:

- Relevant indicators
- Leading effect
- 8-15 variables