Inventory management with leading indicator augmented hierarchical forecasts

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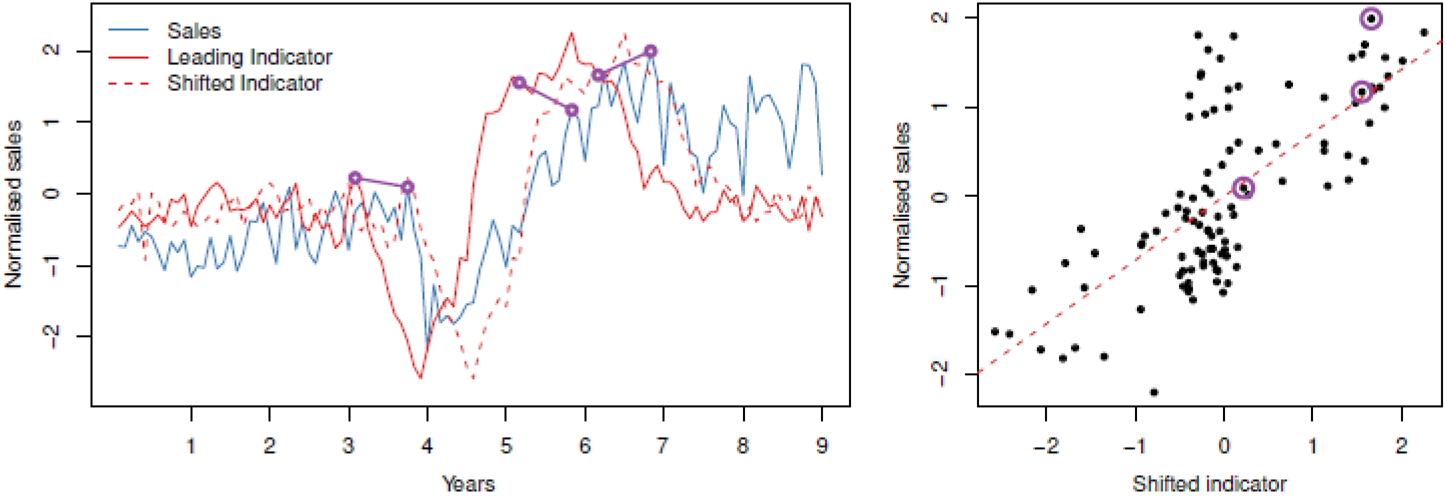
Motivation for leading indicators

Introduction

B2B raw materials for tire manufacturing:

- Leading indicator: purchases of two and four-wheel vehicles (Sweden)
- Vehicle sales lead tire sales, and lead B2B material sales



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Motivation for leading indicators

Challenges

Connection target variable – explanatory variable (indicator):

- Spurious correlation possible (trend, seasonality, …)
  - => Include autoregressive & seasonal dummy inputs
  - => Incorporate differencing

Lead order of the explanatory variable (indicator):

- Incorporate lead order of 1 – 12 months
- Limit us of lead order conditional in time

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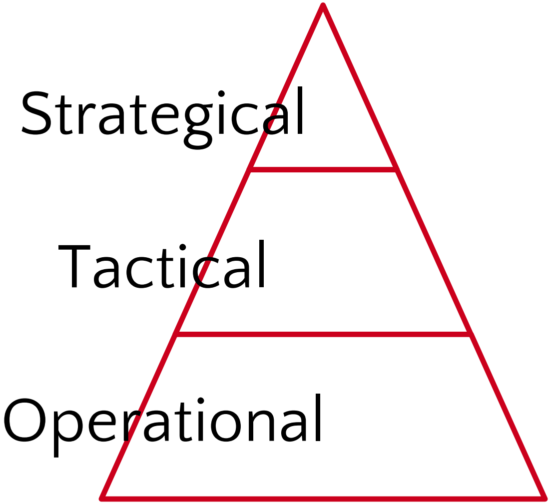
Leading indicators for tactical sales forecasting

Introduction

Different business decision horizons



New production plant, investment planning

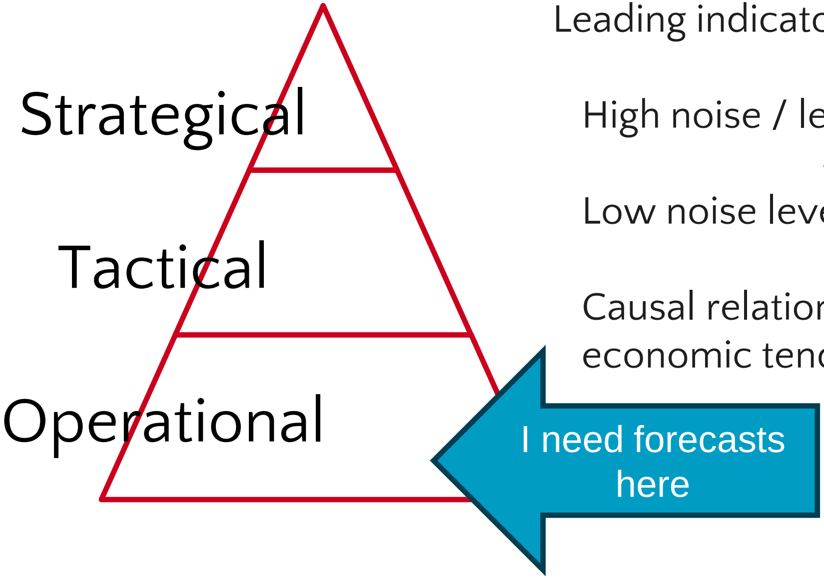
Capacity planning, resource planning

Daily operations, production planning, SKU level

Leading indicators for tactical sales forecasting

Introduction

Different business decision horizons



Leading indicators on operational level?

High noise / level ratio on product level

<–>

Low noise level on macro-economic indicators

Causal relationship between 1 product & macro-economic tendency ?

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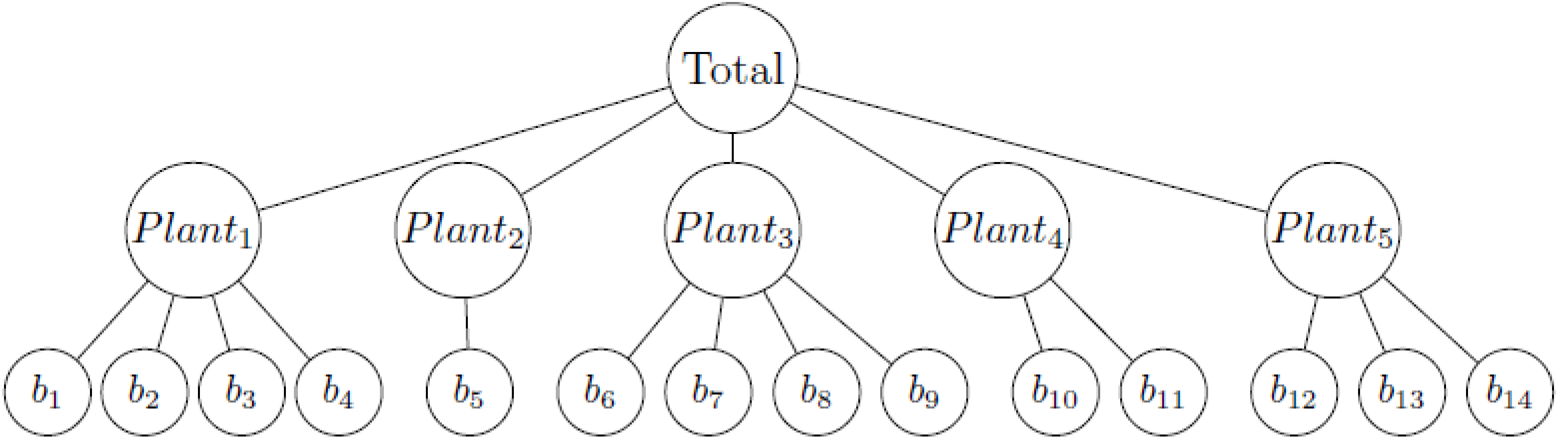
Optimal level for leading indicators

Introduction

Different hierarchical levels could benefit from leading indicators in B2B sales



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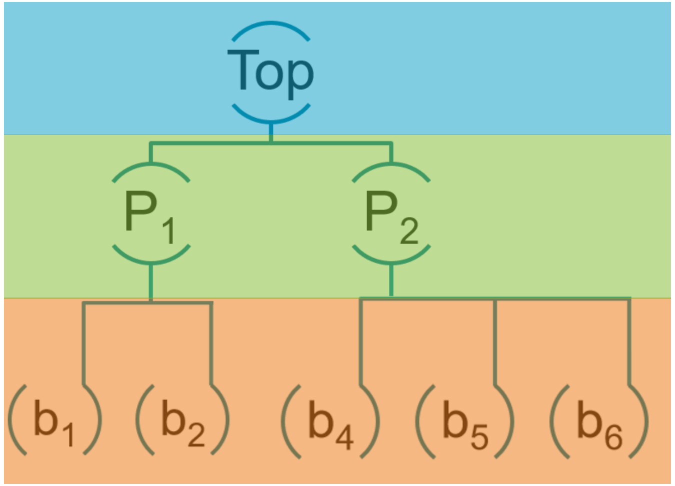
Research Questions

1. Do leading indicators improve forecasting accuracy and operational inventory management ?
    1. **How to best select & model the leading indicators ?**
       (statistical learning vs machine learning models)
    2. **What is the best level to include relevant indicators ?**
2. Does the improvement comes from hierarchical alignment or from the leading indicator information ?

Model Specification

Hierarchical structure



E = Exponential Smoothing (ETS) base model at the this level
- Univariate (trends, seasonality, ..)

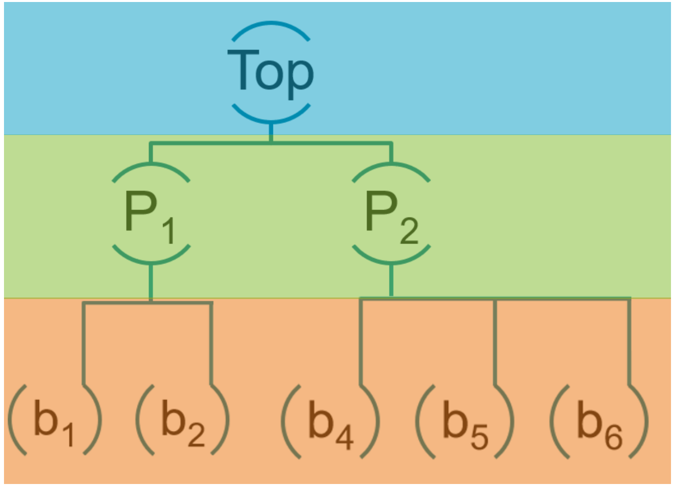
L = LASSO methodology at the this level
- Transparent output
- Identify most important leading indicators

G = LGBM with all indicators at this level
- Model nonlinear interactions
- Multicollinearity is not a problem
- Computational intensive & not transparant

Eg. LEE = Hierarchical reconciliation of forecasts
Lasso on Top; ETS on low and mid level

Model Specification

Hierarchical structure



The multi-period forecasts $\hat{\boldsymbol{y}}_{t+h}$ on different levels might be incoherent

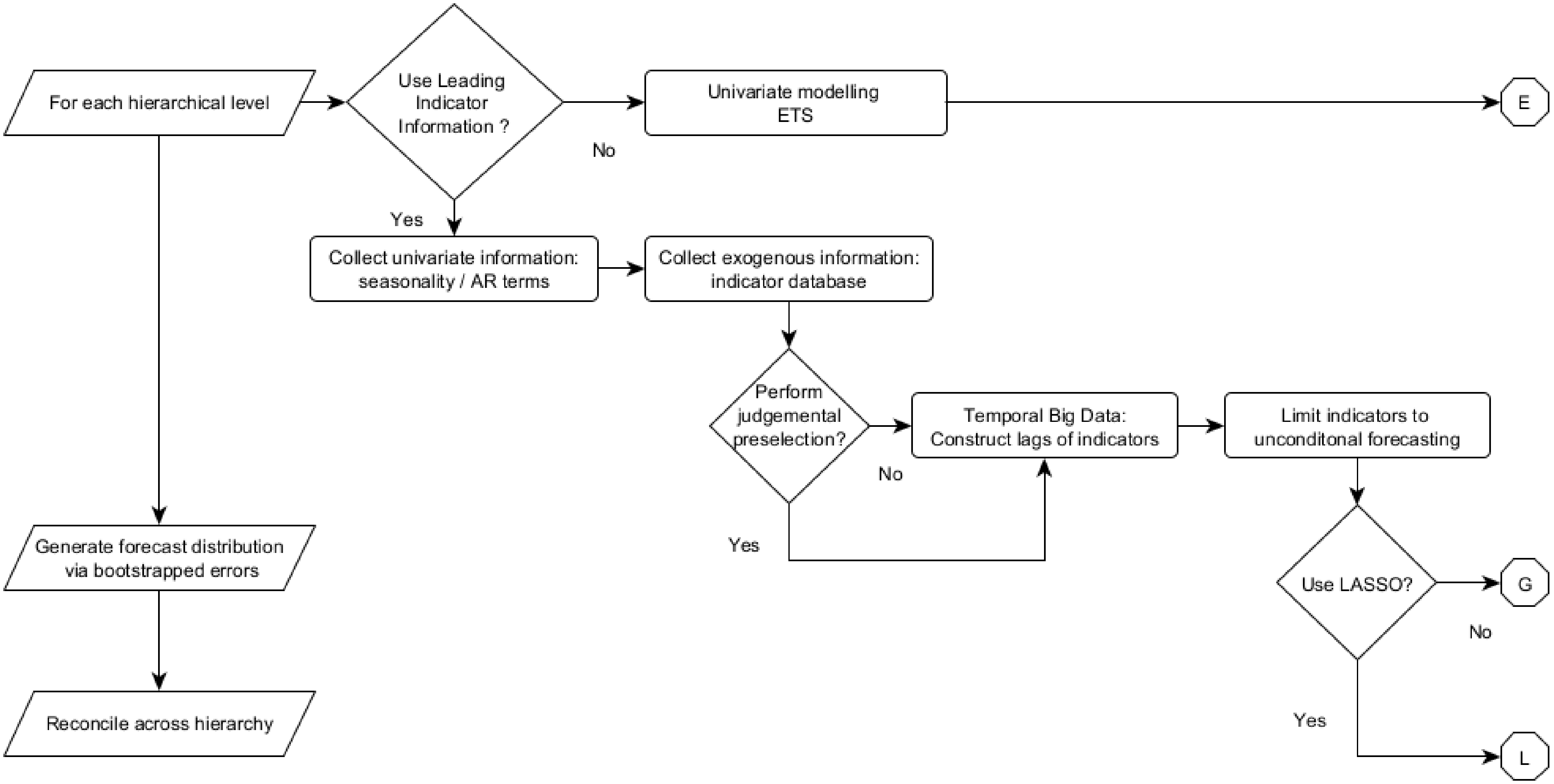
Therefore, we reconcile these forecasts to make them coherent via:

$$\tilde{\boldsymbol{y}}_{t+h} = \boldsymbol{S}\boldsymbol{G}\hat{\boldsymbol{y}}_{t+h}$$

with

$$\boldsymbol{G}_h = (\boldsymbol{S}'\boldsymbol{W}_h^{-1}\boldsymbol{S})^{-1}\boldsymbol{S}'\boldsymbol{W}_h^{-1}$$

We obtain probabilistic forecasts via bootstrapping forecast traces based on Panagiotelis et al. (2024)


For each hierarchical level
Use Leading Indicator Information ?
No
Univariate modelling ETS
E
Yes
Collect univariate information: seasonality / AR terms
Collect exogenous information: indicator database
Perform judgemental preselection?
No
Temporal Big Data: Construct lags of indicators
Limit indicators to unconditonal forecasting
Yes
Use LASSO?
G
No
Yes
L
Generate forecast distribution via bootstrapped errors
Reconcile across hierarchy

— Data

B2B Company dataset

- Hierarchy of 5 business units and 14 stock-keeping-units
- 1000+ "interesting" leading indicators selected
- Data 2005:2016

Experimental setup

- No forecasting of leading indicators → lag effect 1:12 months + unconditional setup
- Sales forecast horizon h = 1:12 months
- Experiment of 13 rolling origins

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Results

Error metrics

$$s^p = \frac{1}{r-1}\sum_{t=1}^{r-1}\left(|y_{t+1} - y_t|\right)^p,$$

Bias and accuracy

$$\mathrm{RMSsE}_h = \frac{1}{o}\sqrt{\sum_{i=1}^{o}\frac{\left(y_{i+h} - \hat{y}_{i+h}\right)^2}{s^2}},$$

$$\mathrm{AMsE}_h = \frac{1}{o}\left|\sum_{i=1}^{o}\frac{y_{i+h} - \hat{y}_{i+h})}{s^1}\right|,$$

$$\mathrm{sPIN}_h = \frac{1}{o}\sum_{i=1}^{o}\frac{w_i}{s^1},$$

$$w_i = \begin{cases}(y_i - \hat{Q}_i)\alpha, & \text{if } y_i \geq \hat{Q}_i\\ (\hat{Q}_i - y_i)(1-\alpha), & \text{if } y_i < \hat{Q}_i\end{cases}$$

Results

Error metrics

Non – cummulative metrics:

$$e_t = y_t - \hat{y}_t$$

Cummulative metric over lead times:

$$ce_{Lt} = \sum_{i=1}^{L} y_{t+i-1} - \sum_{i=1}^{L} \hat{y}_{t+i-1}$$

Results

Root Mean Scaled Squared Error

Forecasting performance at the SKU-level

Method		Non-cumulative t+3	Non-cumulative t+6	Non-cumulative t+12	Cumulative t+3	Cumulative t+6	Cumulative t+12
		RMSsE					
B	E	0.824	0.874	0.930	2.048	3.931	8.005
	L	0.837	0.873	0.985	1.962	3.473	7.632
	G	2.772	2.860	2.922	8.274	17.063	34.863
H	EEE	0.815	0.868	0.937	2.007	3.999	7.928
	LLL	0.912	0.969	1.076	2.188	4.161	8.422
	GGG	1.218	1.202	1.163	3.211	6.040	10.802
LU	LLE	0.879	0.931	1.019	2.024	3.920	7.979
	LEE	0.817	0.849	0.891	1.936	3.620	6.817
	LLG	1.022	1.035	1.063	2.511	4.675	8.239
	LGG	1.154	1.148	1.134	2.996	5.655	10.106

Results

Root Mean Scaled Squared Error

Forecasting performance at the SKU-level

Method	Non-cumulative t+3	Non-cumulative t+6	Non-cumulative t+12	Cumulative t+3	Cumulative t+6	Cumulative t+12
RMSsE						
LEE	0.817	0.849	0.891	1.936	3.620	6.817
GEE	0.810	0.856	0.914	1.981	3.877	7.589
AMsE						
LEE	1.307	1.354	1.419	3.121	5.794	10.890
GEE	1.291	1.361	1.451	3.180	6.230	12.213
sPIN						
LEE	0.167	0.181	0.217	0.434	0.864	1.771
GEE	0.173	0.193	0.231	0.439	0.922	1.988

Inventory evaluation

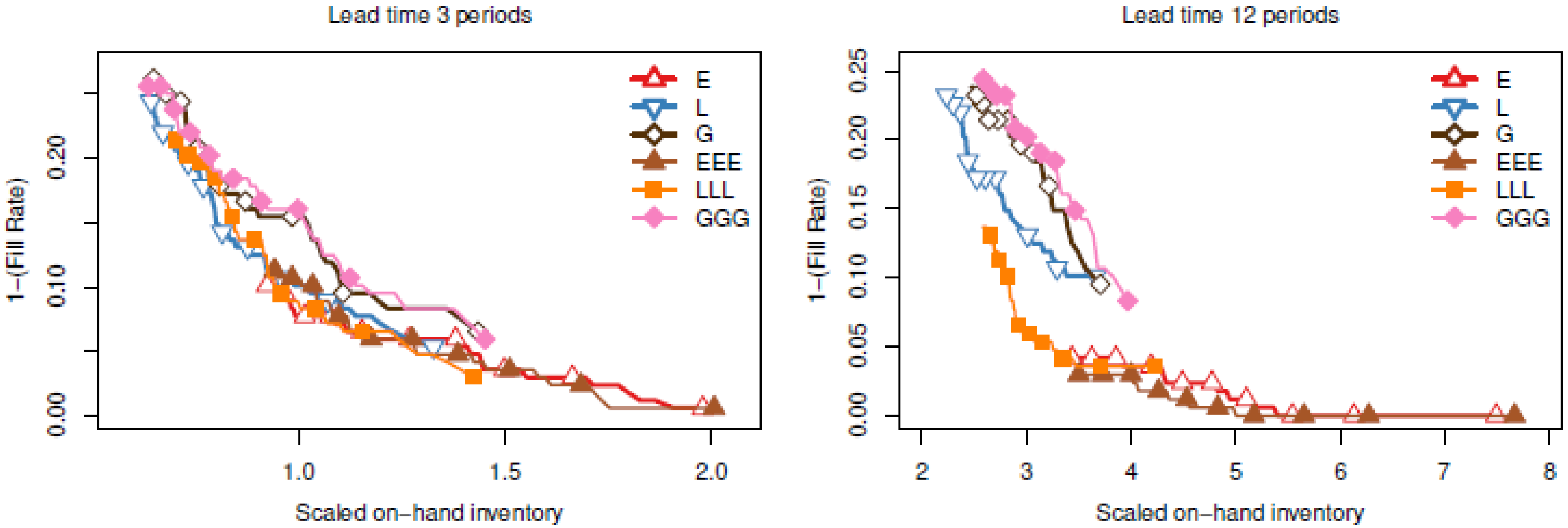
- Order up-to inventory policy with lost sales
- Review lead time 3, 6, 12
- Different target fill rates: 90 – 99.9 %
- 108 periods as burn-in sample before the test set

Results

Inventory Performance

$$\mathrm{FR}_\alpha = \frac{1}{o}\sum_{i=1}^{o}\frac{d_i(\alpha)}{y_i}$$

The effect of hierarchical reconcilation



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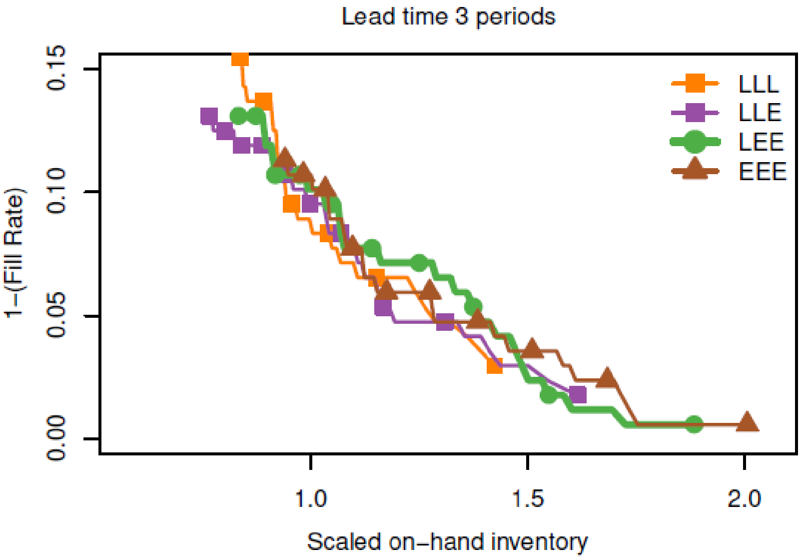
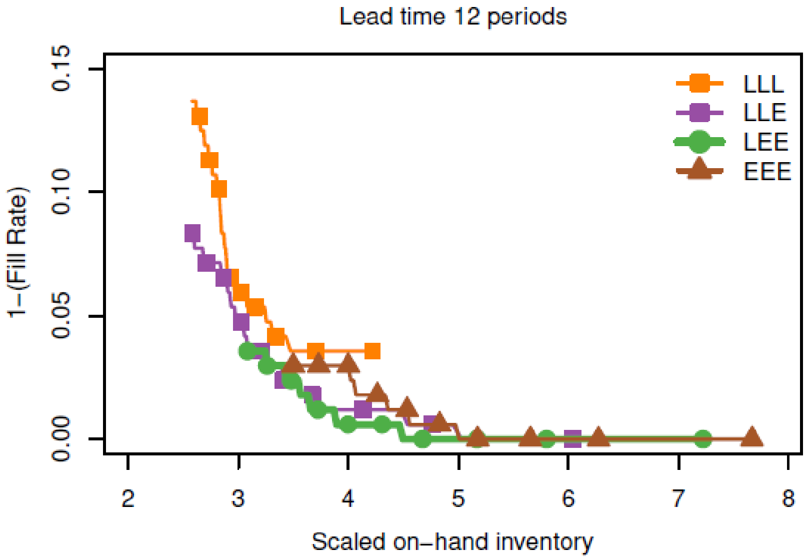
Results

Inventory Performance

The optimal hierarchical level of identifying leading indicators
- LEE leads to higher fill rates





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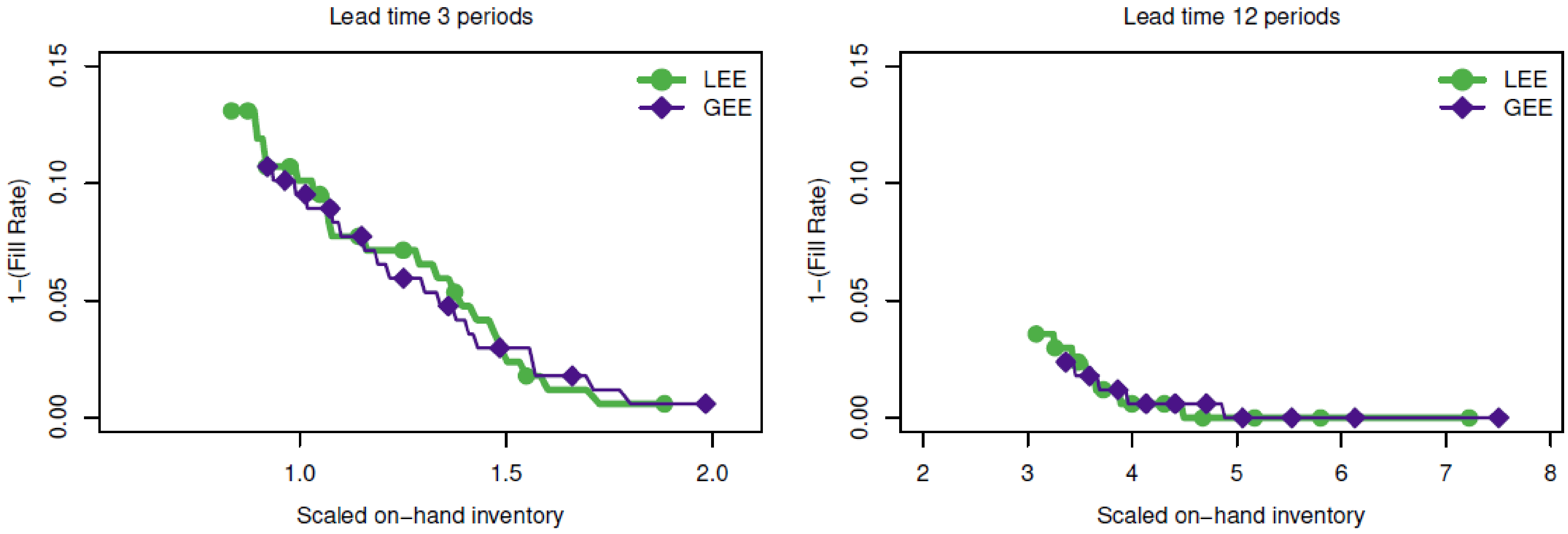
Results

Inventory Performance

Horizon	Lasso	LightGBM	Common
1	23.2	226.5	2.0
2	31.4	219.7	3.6
3	32.0	224.4	3.4
4	30.7	220.1	3.4
5	36.5	214.5	4.2
6	33.5	214.8	5.8
7	34.5	204.2	5.5
8	35.4	194.2	7.0
9	36.8	185.8	7.6
10	37.3	168.5	9.6
11	33.2	155.4	9.1
12	30.3	138.4	12.8

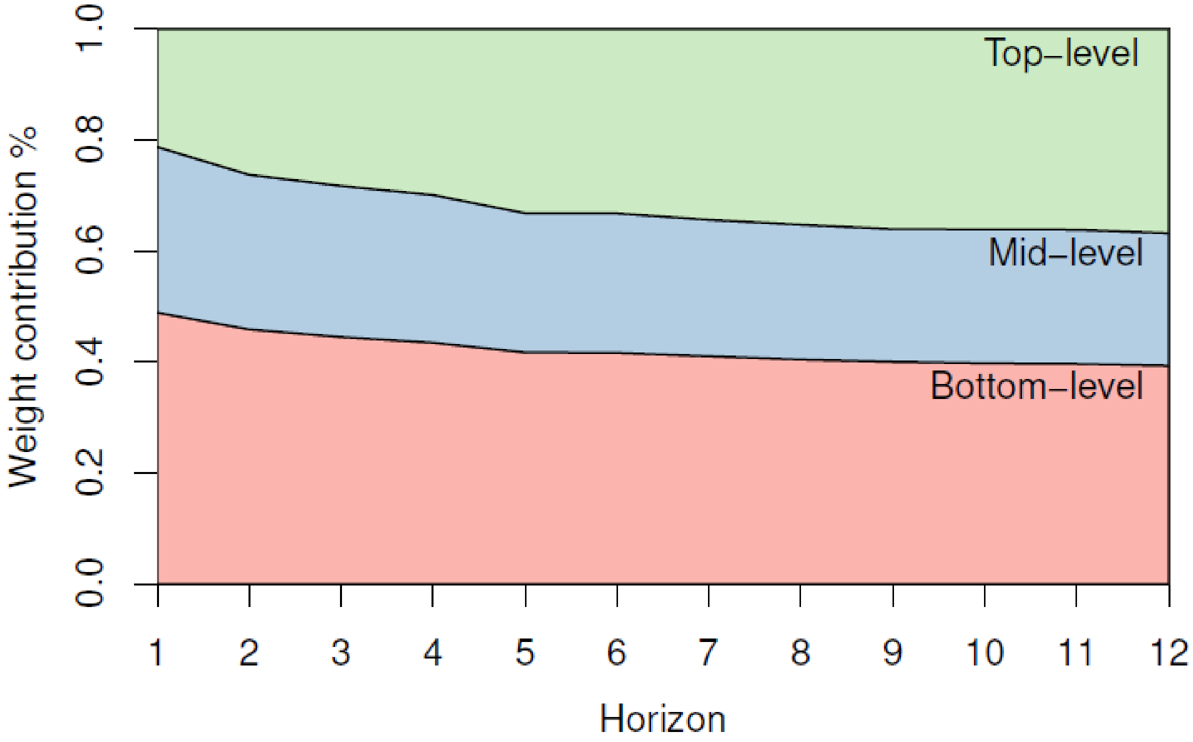
Hierarchial forecast modelling with leading indicators: LASSO vs LGBM



Results

Model insights

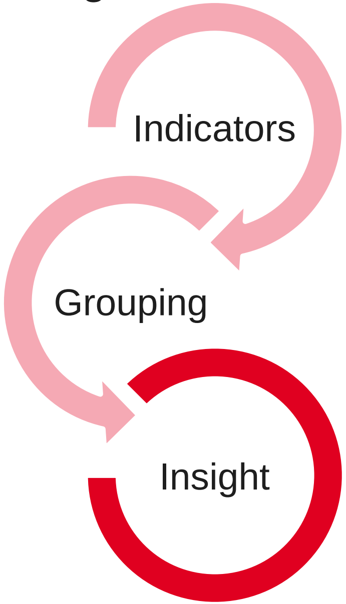
Contribution of each hierarchical level in the final forecast

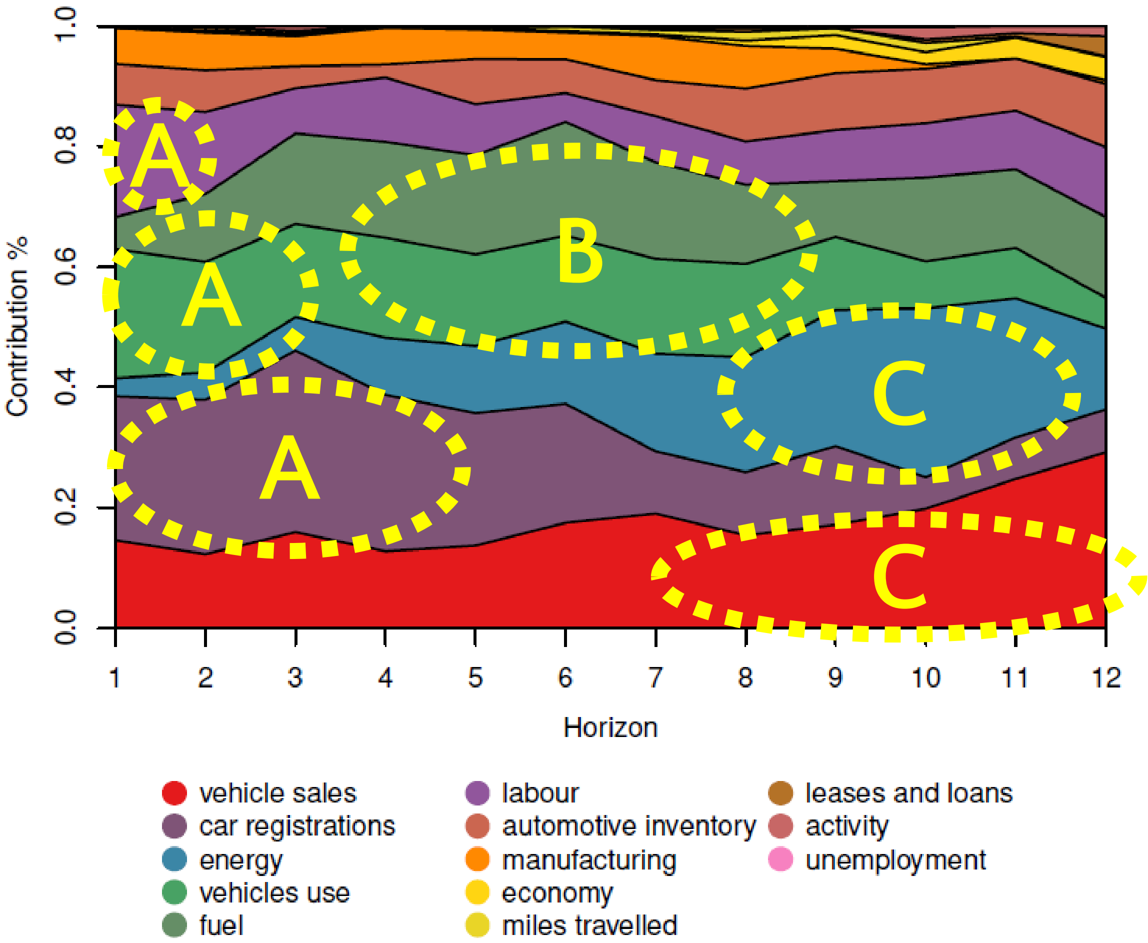


Results

Model insights

Insight in the relevant leading indicators





Conclusion

- The diversity of information across the hierarchical levels maximises the benefits
  - **Leading indicators on the bottom level do not work well**
  - **Combining leading indicators on top + univariate infloration on lower levels works**

- Leading indicator information contributes major on the top level, however the choice of modelling is of secondary importance
  - **LASSO provides managerial insight and requires less indicators**

- The improved sales forecasting effect can be carried on to stock-keeping-unit (SKU) level via hierarchical reconciliation

- The improvement originates from a three-fold play between
  - Leading indicator information
  - Hierarchical reconciliation
  - Empirical forecast distributions

Thank you for your attention

Questions ?

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