Forecasting demand with internet searches and (social media shares)

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Improving forecast with search traffic data…

% Improvement
13.6% MAE
9.3% MAE
76% RMSFE
7.1% MAE
12% MAE
18% MAE
.
.
27% MAPE
.
5.6% MAPE
10.5% MAE
2.3% MAPE
10.3% MAE
5.3% RMSE
45% Corr.

Field	Target Variable	y	ST Lag	Horizon	hold-out	% Improvement
Econometric Ind.	Unemployment claims be		0	1	yes	13.6% MAE
	Consumer confidence Ind		0	1	yes	9.3% MAE
	Private consumption[4]		3	1	yes	76% RMSFE
	Housing market[5]	y	2	1	yes	7.1% MAE
	Housing market[2]		0	1	yes	12% MAE
	Retail sales[2]		0	1	yes	18% MAE
Services	Visitor arrivals to HK[2]		0	.	no	.
	Visitor arrivals[6]		3	1	yes	.
	Hotel room demand[7]		1	1	yes	27% MAPE
Cons. Goods	Car brand sales[8]		0	24	yes	.
	Car brand sales[9]		2	1	yes	5.6% MAPE
	Motor Vehicles and Parts		0	1	yes	10.5% MAE
	Car sales[9]		1	1	yes	2.3% MAPE
	Car sales[10]		0	24	yes	10.3% MAE
	Speciality-food SKUs[11]		0	.	no	5.3% RMSE
	Video game sales[12]		0	.	no	45% Corr.

1) Choi and Varian (2012), 2) Choi and Varia … , 4) Vosen and Schmidt (2011)
5) Wu and Brynjolfsson (2013), 6) Peng et al.
8) Fantazzini and Toktamysova (2015), 9) Ge
11) Boone et al. (2015), 12) Goel et al. (2010)

Forecast evaluation

Several studies use a weak benchmark i.e.

- Lack of out-of-sample evaluation (e.g. Boone et al. 2015; Goel et al. 2010)
- Lack of adequate benchmark model, i.e. Naïve (e.g. Choi and Varian 2012; Vosen and Schmidt 2011; Geva et al. 2015)

Most of identified studies only forecast 1-step ahead

- Du et al. (2015) first forecast search traffic 24 step ahead before including in their market response model.
- It is not clear what Fantazzini and Toktamysova (2015) do. I assume that they include true future values of search traffic for 24 step ahead forecast (!)

Is search traffic information leading?

No lead time required for nowcasting applications (i.e. Choi & Varian 2012; Vosen 2011)

Lag 1 to Lag 2 most commonly used. Few studies tested explicitly for lag structure

- less than 8 weeks for cars (Geva et al. 2015)
- less than three days for tourism destination (Peng et al. 2016)

Number of lags fixed in the model but is this structure consistent over a product life-cycle?

Meanwhile at Lancaster Island™…

Yes, but it matters in practice as...

life-cycles are often short

- Minimum window size often after peak sales

lead time is required

- Multi-step ahead forecasts require larger lead

we might be estimating many SKUs

- Should companies re-estimate their model because of time-varying effects?

Application to Supply Chain Forecasting

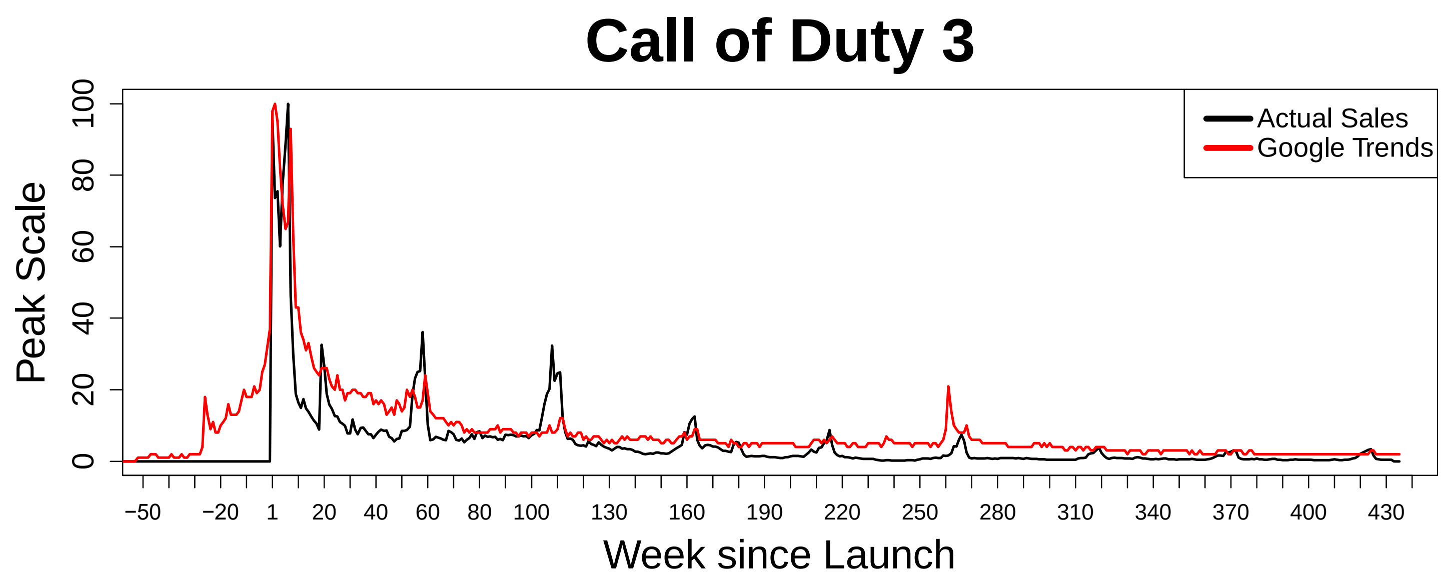
Studies with focus on the supply chain are sparse

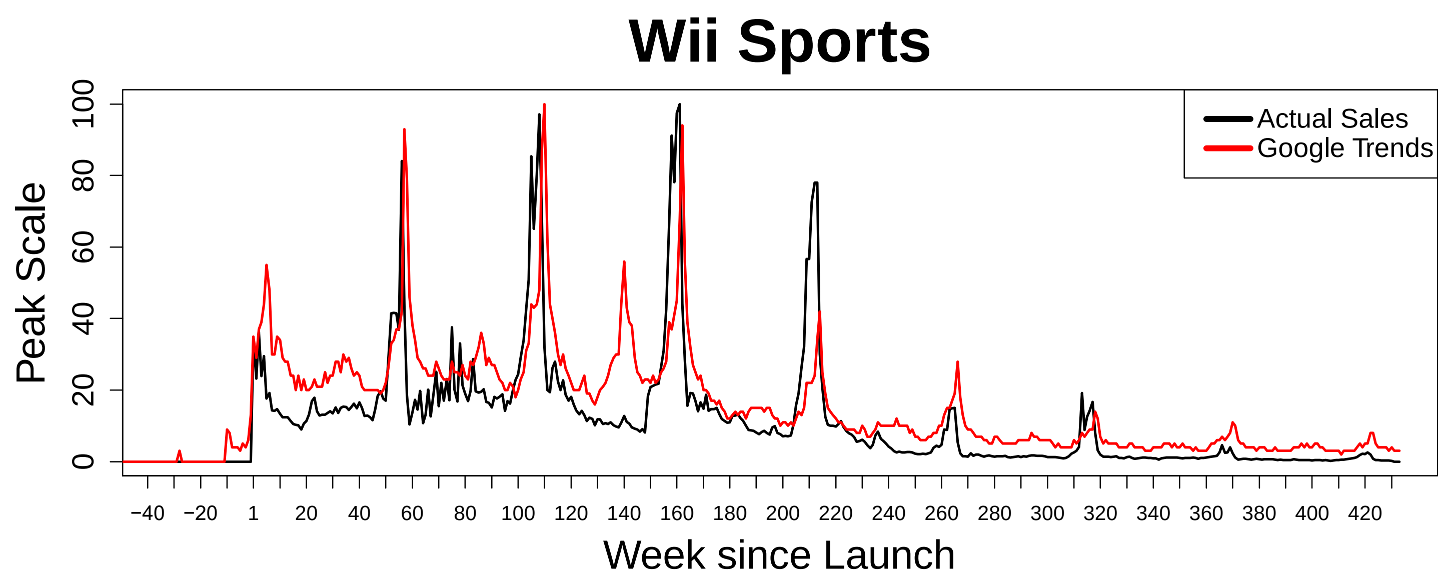
- Boone (2015) found significant better insample fit for speciality-food SKUs, but did not test for out-of-sample.
- Geva et al. (2015) found marginal 1-step ahead improvements for car sales and general higher forecasting error due to more noise.
- Goel et al. (2011) only predicted the first 4 weeks after launch. They found search traffic to be predictive but not more than other traditional explanatory variables.

No article in IJF on incorporating search traffic data (?)

Lets look at some data…

Google Trends data vs. actual sales





Experiment setting

Video game sales from VGchartz

- Global physical sales information of 98 popular game titles launched between 2005 and 2014 at a weekly frequency
- Aggregate across various gaming platforms such as PC, XBox, PS3 or Wii

Search Traffic Popularity from Google Trends

- Weekly global search traffic popularity information
- Game title used as search traffic keyword

Method

Rolling window based AR(m)X model

$$\Delta^d y_t = \alpha_0 + \sum_{i=1}^{m} \alpha_i \Delta^d y_{t\text{-}i} + \sum_{i=1+h}^{k} \beta_i \Delta^d x_{t\text{-}i} + \epsilon$$

$\Delta^d y_t = \text{sales}$ $\quad m = \text{number of AR terms}$ $\quad d = \text{number of differences}$

$\Delta^d x_t = \text{Google Trends}$ $\quad k = \text{number of lags}$ $\quad h = \text{step aheads}$

Experiment setting

Model setting: d = 1, k = {1,...,18} h = {1, 12}

Two-stage model selection process

- AR part on AIC selection
- LASSO for explanatory variable selection (Tibshirani 1996)

Re-estimation at each origin for window sizes: 20,..,N-h

Accuracy measure with AvgRelMAE (Davydenko & Fildes 2013)

- Benchmark 1 : $RelMAE_j = \frac{\text{AR(m)}}{\text{ARX(m,k)}}$
- Benchmark 2: $RelMAE_j = \frac{\text{Naïve}}{\text{ARX(m,k)}}$

Performance across series

1 step ahead

AR(m)	Naïve
0.934	0.825

<1 = better

Window Size = 24, N=98

12 steps ahead

AR(m)	Naïve
0.975	0.726

<1 = better

Window Size = 24, N=98

Results are relatively consistent throughout different window sizes

Discussion

Current results suggest **no benefit** at all in using search traffic information. What are the problems?

Can we think of other fields of applications?

- Products with longer decision process, i.e. cars
- Pre-launch forecasting (Xiong & Bhradwaj 2014, Kulkarni et al. 2012)

Task will remain challenging in practice

- Key word selection (Peng 2016; Brynjolfsson et al. 2015)
- Overfitting problem
- How is this now with time varying causality? Ignore it?

Thank you!

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Online Videos performance across series

1 step ahead

AR	Naïve
0.996	0.871

<1 = better

Window Size = 24, N=3

12 steps ahead

AR	Naïve
0.987	1.050

<1 = better

Window Size = 24, N=3

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