Nowcasting Economic Activity

a comparison of nowcasting, econometrics and machine learning models

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Outline

1.1 - Project context: Now-casting.com

- now-casting.com trial at CFM
- Now-casting.com: real time forecasts (nowcasts) for quaterly GDP growth
- based on large monthly macro dataset
- mixed feelings about Nowcasting.com predictions

Project in a nutshell

- replicate dynamic factor model of Nowcasting.com
- consider other models: nowcasting, econometrics, machine learning
- compare predictive performances

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Project in a nutshell

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2.1 - US macro dataset

- quarterly series of real GDP growth
- 30 monthly series of macro variables
- "small" dataset: subset of 10 variables
- sample dates: 1992m1 - 2019m12 ($T = 318$ m /106 q)
- series made stationary by differentiation / growth rate

2.2 - dataset overview

- quarterly GDP
- business indicators: pmi, business outlook survey, business confidence index, consumer confidence index
- production and sales: industrial production, Markit GDP index, business sales, residential sales, inventories
- labor and wage: unemployment rate, employment, weekly hours, hourly earnings, consumer credit, personal income
- macro aggregates: federal debt, exports, imports
- prices: ppi, cpi
- money and credit: monetary base, bank asset and liabilities, mortgage rate
- interest rates and finance: federal funds rate, treasury bill, treasury 10 years, effective exchange rate, spot Euro/US, NYSE index, VIX

3. Nowcasting

Nowcasting

3.1 - Dynamic factor model

- model used by Now-casting.com
- GDP predicted from a small number of factors f_t
  $\hat{y}_t = \alpha + \beta f_t$
- intuition: factors f_t obtained from dimension reduction of large set of monthly features x_t
- concretely: factor values and dynamics obtained from PCA on x_t + Kalman filtering
- estimate α and β by simple OLS
- predict: $\hat{y}_{t+h} = \alpha + \beta \hat{f}_{t+h}$
  $\hat{f}_{t+h}$ obtains directly from Kalman filter

3.2 - MIDAS regression

- simple linear regression combining low and high frequency features
- $\hat{y}_{t+1} = \mu + \sum_{j=0}^{p} \gamma_i \; y_{t-j} + \sum_{i=1}^{n} \sum_{j=0}^{q} \beta_{ij} \; x_{i,t-j}$
- possible curse of dimensionality in β_{ij}
- reduce lag structure to simple polynomial:
  Amon polynomial: $\beta_{ij} \propto \exp(\theta_{i1} \; j + \theta_{i2} \; j^2)$
- only requires estimation of θ_{i1} and θ_{i2} for each feature x_i
- makes the model non-linear, requires numerical methods
- uses the small macro dataset

3.3 - Mixed frequency Bayesian VAR

- a Bayesian VAR that combines low and high frequency features
- infer high frequency values for low frequency variables from high-frequency features
- hidden states x_t are estimated by Bayesian Kalman filtering (Carter and Kohn algorithm)
- VAR is then estimated on full, high-frequency dataset x_t: $x_t = c + A_1 x_{t-1} + \cdots + A_p x_{t-p} + \varepsilon_t$
- uses the small macro dataset

4. Econometrics

Econometrics

4.1 - Vector Autoregression

- VAR model:

$$y_t = c + A_1 y_{t-1} + \cdots + A_p y_{t-p} + \varepsilon_t \qquad \varepsilon_t \sim N(0, \Sigma)$$

- stack VAR coefficients $c, A_1, \cdots, A_p$ in a single vector β
- β and Σ estimated by OLS
- uses the small macro dataset
- trained on two lags, using AIC

4.2 - Bayesian VAR

- same model:
  $y_t = c + A_1 y_{t-1} + \cdots + A_p y_{t-p} + \varepsilon_t \qquad \varepsilon_t \sim N(0, \Sigma)$
- "estimate the model" = apply Bayes rule to get the posterior distribution of β and Σ:
  $\pi(\beta, \Sigma | y) \propto f(y|\beta, \Sigma)\pi(\beta, \Sigma)$
- use a prior strategy known as the "Minnesota prior"
- Bayesian shrinkage: reduces weight of less useful coefficients
- estimation an predictions: simulation methods (Gibbs sampling algorithm)

4.3 - Time-varying Bayesian VAR

- model of the form:

$$y_t = c_t + A_{1,t}\, y_{t-1} + \cdots + A_{p,t} y_{t-p} + \varepsilon_t \qquad \varepsilon_t \sim N(0, \Sigma_t)$$

- VAR coefficients β_t and volatility Σ_t are time-varying
- hidden states following auto-regressive stochastic processes
- estimated by Bayesian Kalman filter (Carter-Kohn algorithm)

5. Machine learning

Machine learning

5.1 - LSTM

- formulated as a (non-linear) VAR model, using lagged value $x_{t-1}, x_{t-2} \cdots$ of features as input
- MSE used as loss function
- dataset is split in train/test samples (80-20%)
- MSE on test is lowest with one layer, 3 units (encoder style)
- optimizer has little impact: AdaDelta, RMSprop, Adam all yields same estimates
- dropout is applied but has little impact
- 500 epochs to train the model
- uses the small dataset

5.2 - Random forest

- formulated as a MIDAS regression to account for lagged values of all features (including quarterly GDP)
- produces a non-linear MIDAS regression
- difference with MIDAS: uses the full macro dataset: random forest efficient at determining useful features
- feature engineering (adding month or quarter) does not affect the results
- 100 base learners, maximum depth of 5 (weak learner)

5.3 - Boosting

- “Boosted VAR”
- estimated equation-by-equation by gradient boosting
- produces a non-linear Vector Autoregression
- 100 base learners, learning rate of 0.1
- uses the small macro dataset

Model recap

Model	Summary
dynamic factor model	dimensionality reduction, prediction from structural factors
MIDAS regression	linear gression on mixed frequency, parsimonious lag structure
mixed frequency BVAR	inference of high frequency values for low frequency features
vector autoregression	multivariate AR model, OLS estimation
Bayesian VAR	Minnesota prior, Bayesian shrinkage
Time-varying BVAR	dynamic coefficients, stochastic volatility
LSTM	LSTM VAR, lagged values used as input
random forest	random forest (non-linear) MIDAS regression
Boosting	gradient boosted (non-linear) VAR

Figure: Model recap

6.1 - Forecast exercise

- sequential sample: start from 1993m7 - 2017m1, then increase sequentially by one month, for 36 months (3 years)
- for each sample: produce forecasts at 1, 2, 3 and 4 quarters aheead
- forecasts are produced for GDP and all features in x_t
- for each model, sample, horizon and features, compute RMSE $= \sqrt{(x_{t+h} - \hat{x}_{t+h})^2}$
- consider the average RMSE over the different samples
- RMSE are normalised to clear scale effects
- add a number of benchmarks to the 9 models for comparison

6.2 - Results: GDP Nowcast

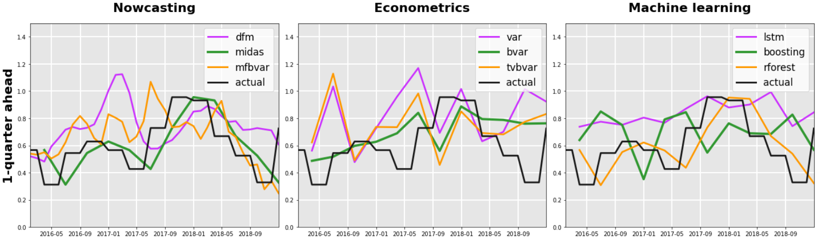


Figure: GDP nowcasts for the 9 models

6.2 - Results: GDP Nowcast

		1 quarter ahead	2 quarters ahead	3 quarters ahead	4 quarters ahead
nowcasting	dfm	0,707	0,694	0,598	0,443
	midas	0,593	0,909	0,609	1,154
	mfbvar	0,536	0,613	0,543	0,503
econometrics	var	0,885	0,808	0,697	0,729
	bvar	0,502	0,558	0,486	0,547
	tvbvar	0,784	0,732	0,740	0,706
machine learning	lstm	0,712	0,747	0,769	0,745
	random forest	0,592	0,566	0,635	0,552
	boosting	0,605	0,568	0,594	0,548
benchmarks	last value	0,593	0,697	0,775	0,749
	ridge var	0,835	0,761	0,704	0,678
	nowcasting.com	0,668	0,679	–	–
	bloomberg	1,019	–	–	–

Figure: RMSE on GDP predictions

6.2 - Results: GDP Nowcast

	3 months before	2 months before	1 month before
dfm	0,755	0,703	0,663
mfbvar	0,659	0,504	0,444
nowcasting.com	0,726	0,620	0,659
bvar benchmark	0,502	0,502	0,502

Figure: RMSE on GDP nowcasts: 1, 2 and 3 months before release

6.2 - Results: GDP Nowcast

		1 quarter ahead	2 quarters ahead	3 quarters ahead	4 quarters ahead
nowcasting	dfm	0.556	0.722	0.778	0.917
	midas	0.417	0.667	0.667	0.583
	mfbvar	0.805	0.694	0.833	0.861
econometrics	var	0.417	0.667	0.667	0.917
	bvar	0.667	0.667	0.833	0.833
	tvbvar	0.417	0.75	0.833	0.833
machine learning	lstm	0.583	0.75	0.833	0.583
	random forest	0.417	0.75	0.5	0.417
	boosting	0.583	0.583	0.75	0.167

Figure: Percentage of correct direction prediction

6.3 - Conclusions: GDP Nowcast

- BVAR and MF-BVAR dominate for both RMSE and direction
- BVAR best one quarter before release, MFBVAR best one month before
- not clear which one is best 2 months before release
- other good nowcasts models: MIDAS, random forest, naive last value predictor
- other models overfit

7.1 - Results: feature

		Business confidence index	Industrial production	Business sales	New residential sales	Unemployment rate	Weekly hours	CPI	Bank assets	Federal Funds rate
nowcasting	dfm	0,267	0,104	0,073	0,048	0,340	0,238	0,249	0,167	0,303
	mfbvar	0,341	0,165	0,099	0,037	0,398	0,216	0,322	0,140	0,252
econometrics	var	0,340	0,142	0,091	0,029	0,528	0,417	0,297	0,197	0,251
	bvar	0,311	0,125	0,078	0,031	0,309	0,245	0,249	0,190	0,216
	tvbvar	0,338	0,147	0,090	0,029	0,406	0,384	0,272	0,178	0,297
machine learning	lstm	0,320	0,127	0,056	0,042	0,462	0,338	0,211	0,189	0,265
	random forest	0,204	0,116	0,065	0,020	0,290	0,197	0,182	0,104	0,147
	boosting	0,316	0,126	0,081	0,035	0,471	0,210	0,258	0,190	0,268
benchmarks	last value	0,361	0,169	0,097	0,033	0,342	0,260	0,270	0,108	0,212
	ridge var	0,343	0,139	0,091	0,029	0,522	0,408	0,297	0,193	0,248

Figure: Feature nowcasts (1 quarter ahead)

7.1 - Results: feature

		Business confidence index	Industrial production	Business sales	New residential sales	Unemployment rate	Weekly hours	CPI	Bank assets	Federal Funds rate
nowcasting	dfm	0,299	0,106	0,077	0,043	0,359	0,232	0,277	0,186	0,290
	mfbvar	0,244	0,106	0,043	0,018	0,229	0,213	0,163	0,168	0,165
econometrics	var	0,412	0,153	0,093	0,047	0,605	0,287	0,273	0,222	0,348
	bvar	0,309	0,127	0,060	0,044	0,443	0,219	0,232	0,220	0,307
	tvbvar	0,357	0,155	0,094	0,046	0,596	0,296	0,296	0,184	0,439
machine learning	lstm	0,332	0,149	0,064	0,045	0,447	0,307	0,238	0,211	0,286
	random forest	0,375	0,146	0,083	0,039	0,379	0,267	0,277	0,126	0,305
	boosting	0,340	0,139	0,086	0,041	0,511	0,210	0,246	0,261	0,262
benchmarks	last value	0,320	0,175	0,097	0,050	0,508	0,299	0,395	0,140	0,274
	ridge var	0,393	0,153	0,090	0,047	0,587	0,272	0,271	0,221	0,347

Figure: Feature forecasts (2 quarters ahead)

7.1 - Results: feature

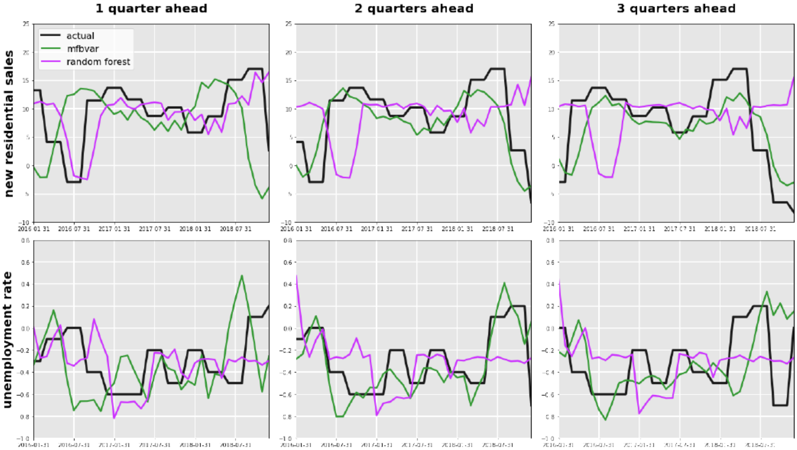


Figure: Feature forecasts (2 quarters ahead)

7.2 - Conclusions: feature forecasts

- random forest is best for feature nowcasts
- MF-BVAR best at longer horizons
- for meaningful comparison: VAR on monthly sample, optimised dataset
- still difficult to understand why MF-BVAR anticipate dynamics

factor and feature correlation

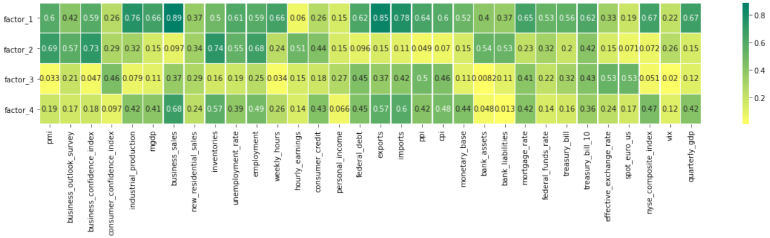


Figure: Dynamic factor models: correlations

lag structure

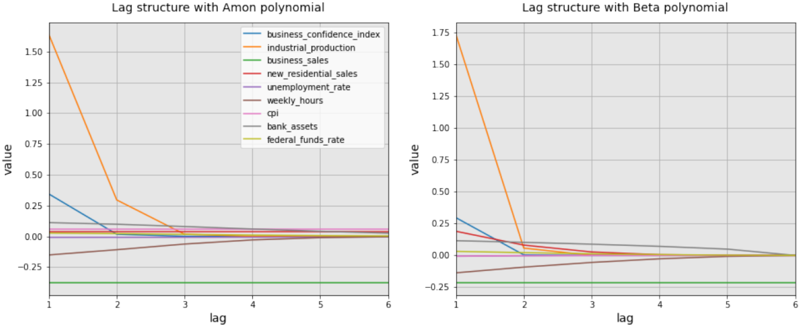
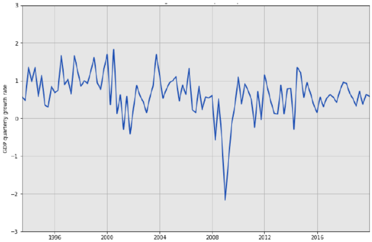
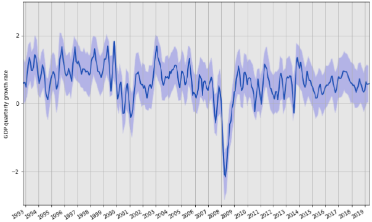


Figure: MIDAS regression: lag structure

monthly GDP



(a) Actual quarterly values



(b) Monthly estimates with 95% credibility bands

Figure: MF-BVAR: monthly GDP estimates

VAR and BVAR coefficients

	Lag 1		Lag 2	
	OLS VAR	Bayesian VAR	OLS VAR	Bayesian VAR
business confidence index	0.103	0.007	0.050	0.004
industrial production	0.095	0.044	0.042	0.003
business sales	-0.005	0.001	-0.041	-0.002
new residential sales	-0.001	0.002	0.003	0.002
unemployment rate	0.025	0.005	-0.037	-0.006
weekly hours	-0.087	-0.008	-0.058	-0.014
cpi	-0.015	-0.018	0.052	0.009
bank assets	-0.005	-0.004	0.026	0.007
federal funds rate	-0.013	0.024	0.091	-0.011
gdp	-0.082	0.046	0.056	0.159

Figure: VAR and BVAR coefficients: Minnesota effect

Stochastic volatility

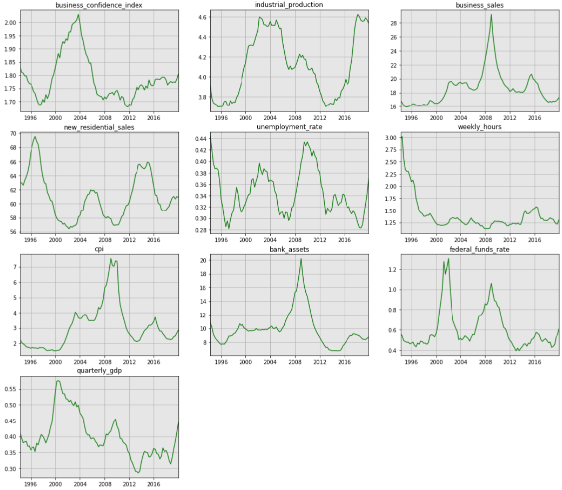


Figure: TV-BVAR: stochastic volatility

Feature importance

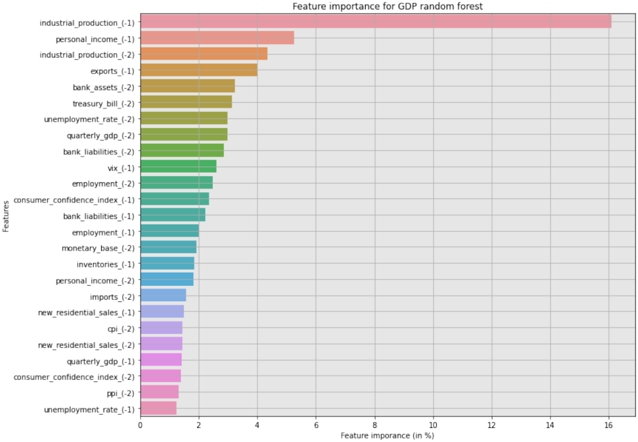


Figure: Random forest: GDP feature importance

Feature importance

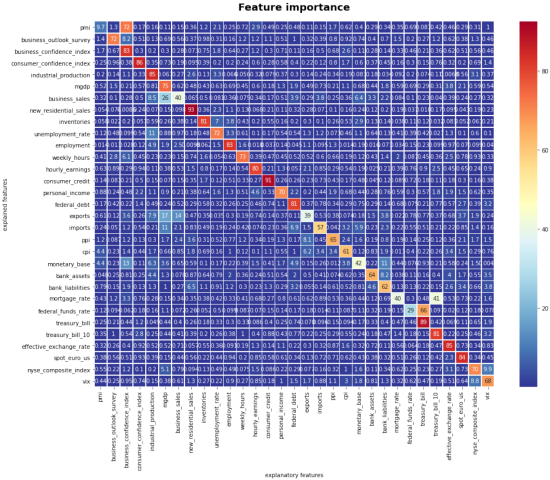


Figure: Random forest: other feature importance

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