Nowcasting US Business Cycles with Networks and Machine Learning

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A Stylised Stock Network Perspective of the Business Cycle

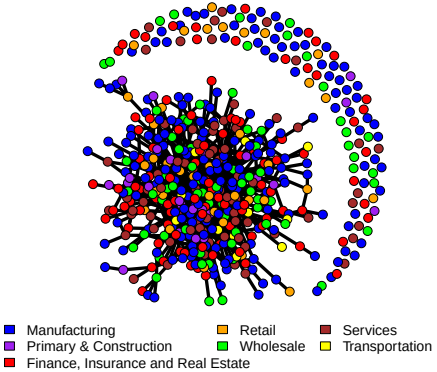


Figure: **NBER Recession Periods**
00:Q1 to 19:Q1, 12m, 5%, n≥5 caus.(#9)

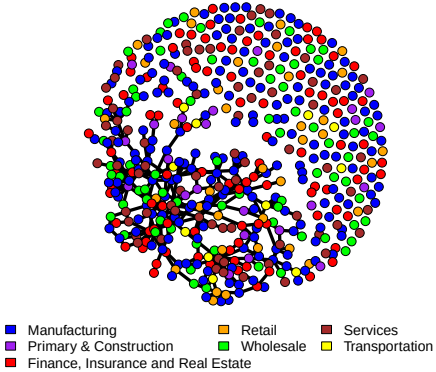
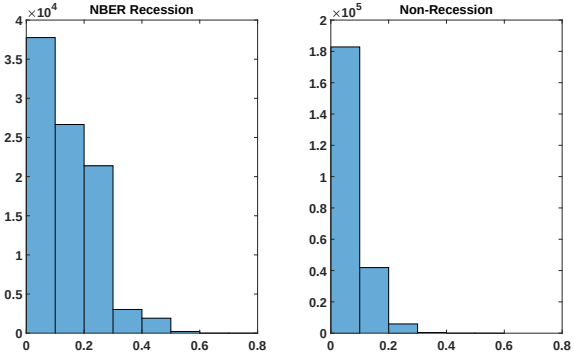


Figure: **NBER Non-Recession Periods**
00:Q1 to 19:Q1, 12m, 5%, n≥7 caus.(#68)

The figures display averaged quarterly Granger Causality networks of the S&P 500 from 2000:Q1 to 2019:Q1 on a 12 month rolling window bandwidth and a 5% significance level. 68 non-recession periods and 9 recession periods. The natural benchmark threshold for the averaging would be 50% causalities over the full time-span for the non-recession and the recession periods. However, we can even reduce the number of relations in the case of non-recession periods to 7 without seeing the connectedness as in the recession periods.

Normalised Connectedness During Phases of the Business Cycle



Note: The graph illustrates normalised quarterly connectedness from 2000:Q1 to 2019:Q1 on a 12 month rolling window bandwidth and a 5% significance level. Connectedness in specific nodes in NBER recession periods are more persistent than in non-recession periods, where connectedness might be more idiosyncratic.

Project outline

Objective:
- Nowcasting of business cycle turning points.
  - Negative growth periods (2-state model)
  - High, low and negative growth periods (3-state model)
  - [NBER recessions]

Setup:
- S&P 500 pairwise (Granger) stock networks & Naive Bayes classifier.

Advantages:
- Financial markets provide information about future developments.
- **Data** in **real-time, not revised** and **no subjective component**.
- Networks can capture **non-linearities in the economy.**
- Dimension reduction techniques **reveal cyclical patterns**.
- Pooling: More **robust to every cycle is different** critique.

Findings:
- **Information stemming from the real sector** is identified ex-post to be the driver.

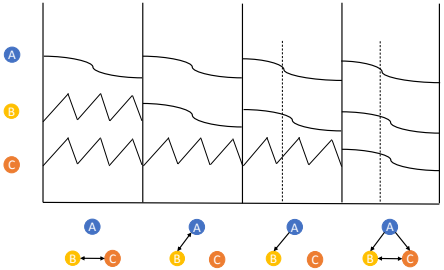
Assumptions:

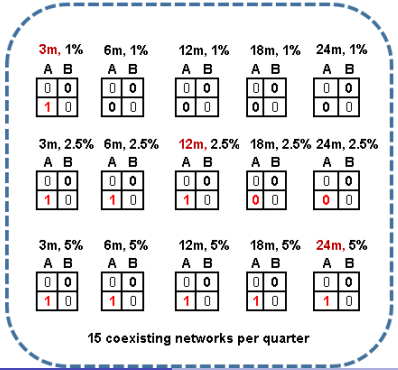
1. **Stock returns relate to economic fundamentals** and **expectations** about near term profits (captures business cycles).
   - Forward looking and real-time measure as assessed by markets.
   - Stable relation between business cycles and stock market.
     (Demand declines, businesses reduce expenses, downsize workforce; when this becomes economy-wide would lead to contraction)
2. **Stock network is stable.**
   - Networks are stable in times of crisis and can be used for prediction. *(Heiberger, 2014, 2018)*.
3. **Stock network captures how shocks propagate through the economy**
   - Connectedness increases between financial intermediates prior financial crisis *(Bilio et al., 2012; Diebold and Yilmaz, 2014)*.
   - Liquidity in stock markets is drying up as a precursor to the crisis in the real economy *(Næs et al, 2011)*.

Model description:

Step 1: **Stock Networks**

- Daily firm level return index for S&P 500 constituents.
- Based on pairwise Granger-causalities (directionality).
- Lower frequency representation (daily to quarterly).
- 15 networks per quarter (3, 6, 12, 18, 24m) x (1, 2.5, 5%).

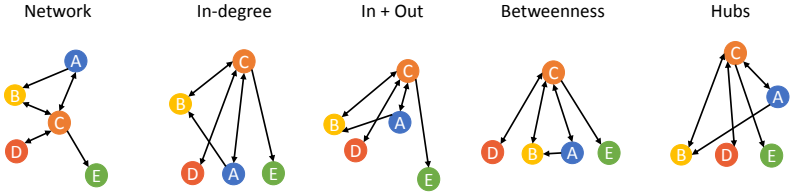




Model description:

Step 2: **Measuring economy-wide shock propagation**

- Calculate network topology measures (over time; aggregates & node-level).



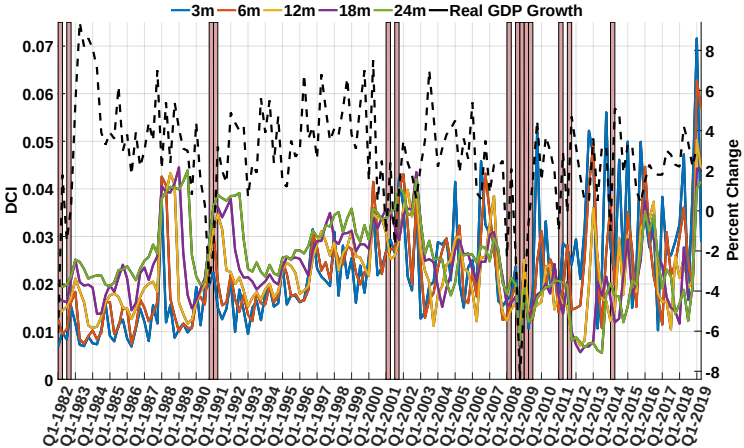
Step 3: **Feature selection**

- Data cleaning and normalisation (75,885 $\rightarrow$ 61,111)
- RFE-SVM (2-fold crossval., min 10) with correlation bias reduction.
- Identify (stable) cyclical patterns in the economy. (15-300 features).

Step 4: **Naive Bayes Classifier**

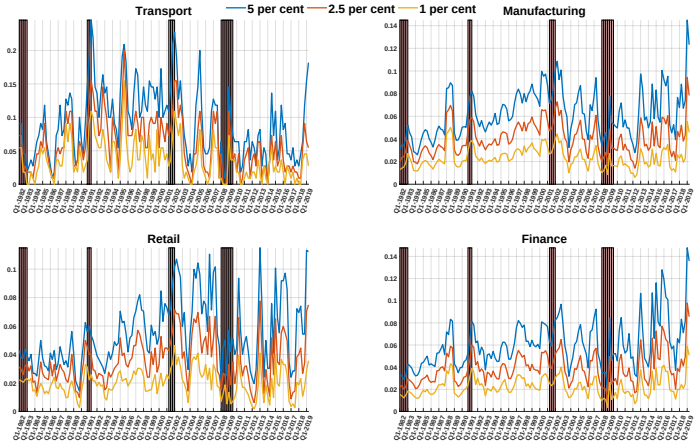
- Train until t-1. Nowcast t given stock networks.
- Robustification: Exclude weak growth periods (pos, but close to zero)

Aggregate: Dynamic Causality Index (DCI) Not informative!



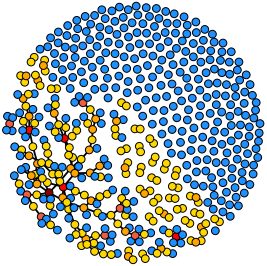
Note: *The graph displays the dynamic causality index (DCI) for the S&P500 for different lengths of rolling window bandwidths. All DCIs are derived from networks that showed significance at the 1% level. Red bars indicate negative growth periods.*

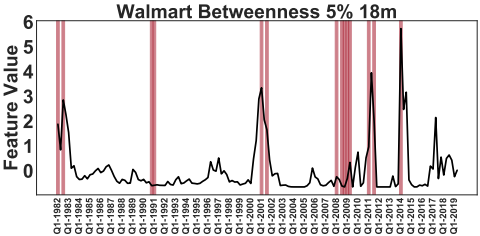
(Within-) Sector: Dynamic Causality Index Still not informative!

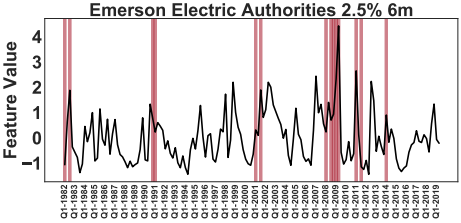


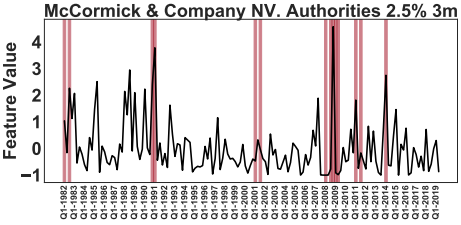
Note: *The graph displays the dynamic causality index (DCI) for the S&P500 for significance levels of rolling window bandwidths. All DCIs are derived from networks with a 12m rolling window bandwidth. Red bars indicate NBER recession periods.*

Node-level Measures: Economy-wide shock propagation





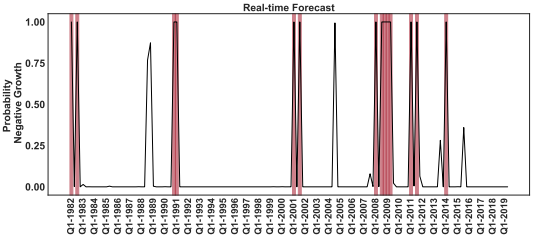


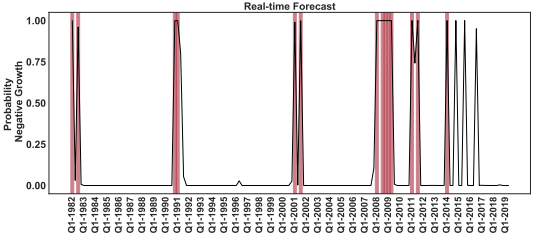


Naive Bayes Classifier a weak method? Depends!

- **Performs well as forecasting tool**
  (Davig and Hall, 2019; Heiberger, 2018)
  - NB outperforms logistic reg and Survey of Professional Forecasters.
  - *NB and logistic reg asymptotically equivalent under certain distributional assumptions*, **not true for business cycle data.**
  - **NB has a larger asymptotic errorrate, but converges to the error rate faster than logistic reg, resulting in more accurate recession forecast with limited data.**

Figure: Nowcast US 2019:Q2 (**Left:** Benchmark **Right:** Alternative)

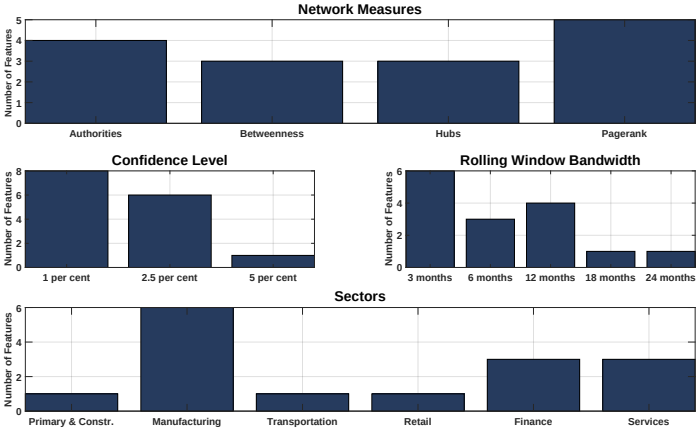




Ex-post validation: Features Negative Growth (#15)

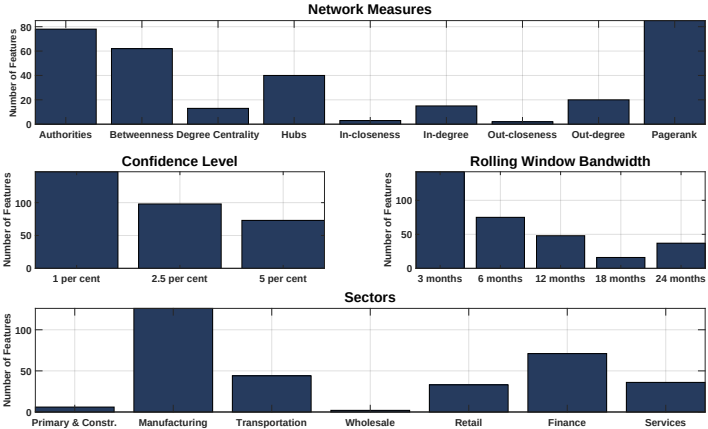
- **Walmart:**
  - **Retail**, Fortune 500: 2018 largest company by revenue.
  - **Betweenness Centrality:** connectedness to other nodes that are not connected to each other. (Node serves as a bridge).
- **Emerson Electric:**
  - **Engineering services**: Multinational corporation that operates in industrial, commercial, and consumer markets.
  - **Authorities** represents a company that is linked by many different hubs.
- **McCormick & Company:**
  - **Manufacturing**: Largest spice producer in the world.
  - **Authorities** represents a company that is linked by many different hubs.
- **Vulcan Materials:**
  - **Production and distribution construction material**: operates in 19 states.
  - **Hubs** have a significantly larger number of links in comparison with other nodes in the network.

Ex-post validation: Features (#15) Negative Growth



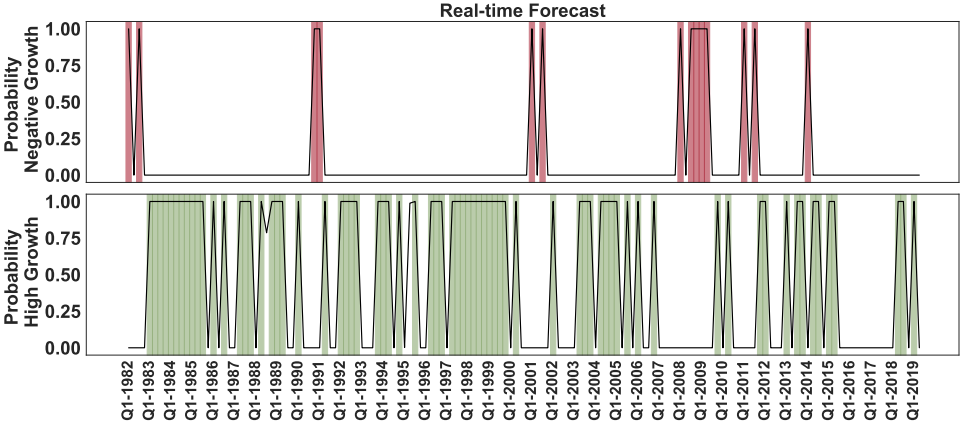
Note: *Each subplot shows the properties of the selected features. The subplots are independent, but show the same dataset and sum each to the number of features.*

Ex-post validation: Features (#318) High, Low and Negative Growth



Note: *Each subplot shows properties of the selected features. The subplots are independent, but show the same dataset and sum each to the number of features.*

High, Low and Negative Growth Probabilities



Note: *The graph shows the trinary state model probabilities for high, low and negative growth periods. Red and green bars indicate historical periods with negative and high growth.*

Euro area: Some preliminary results

Nowcast: 2019 Q1

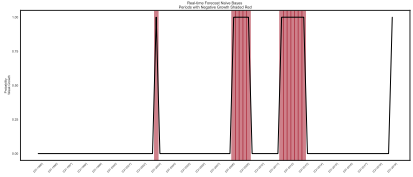


Figure: Negative Growth

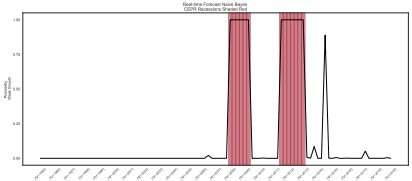


Figure: CEPR Recession

- **Negative Growth:**
  - **EA GDP growth** in **2019Q1: 0.4%**. What happened?
  - Miss-specification (Features represent solely German companies).
  - **German GDP growth (quarterly): 2019Q1: 0.4%; 2019Q2: -0.1%**
  - Possible solution: Extract country specific features separately and pool.
- **CEPR:**
  - Problem of short series. Overfitting likely.

Preliminary conclusions

i) **Networks & ML can nowcast the business cycle**

- **Forward looking** behavior of financial market information.
- Almost no revisions and timely available data.
- However, raw return data from S&P 500 companies is not informative. (Noisy firm-specific (idiosyncratic) shocks.)
- Economy-wide downturn (upswing) contains cyclical information. (Network can capture **system-wide developments**.)
- Pooling: Promising to be robust to **every cycle is different**.

iii) **Ex-post validation:**

- **The real sector** is identified ex-post to be the driver.
- Negative growth periods: **manufacturing (medium-term)**
- NBER recessions/High, low and negative growth periods: **manufacturing (short-term)**

Thank you.

Reserve Slides. / Technical Appendix.

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Reserve Slides. / Technical Appendix.

How can Big Data & Machine Learning improve our understanding of business cycles?

Methodology should be understood as an **accessory or complementary** tool.

1. **Get timely & clean signals from Big Data sources**
   - Financial market connectedness *(investor expectations).*
   - Vacancy postings *(regional and sector-specific business expec.).*
   - Credit card payments *(regional consumption).*
2. **New perspectives for evaluating conventional data**
   - Efficiently selecting informative regressors.
   - Accounting for non-linearities.
   - Different frequencies.

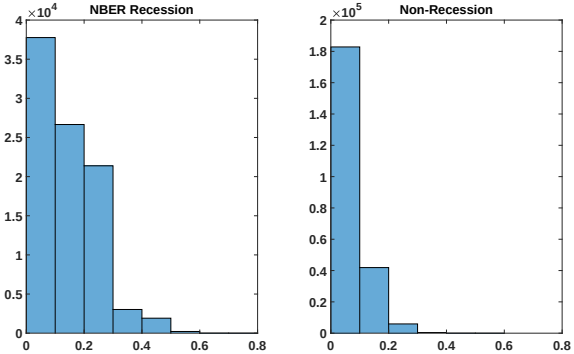
Data description

Sector	#Nr. of Companies
Primary and Construction	24
Manufacturing	191
Transportation	71
Wholesale	11
Retail	35
Finance	97
Services	71

TABLE – Sectoral composition in the S&P 500

**Note:* The table displays the sectoral composition of the S&P 500 (snapshot 2018:Q3) according to SIC classification as described in the paper.

Normalised Connectedness During Phases of the Business Cycle



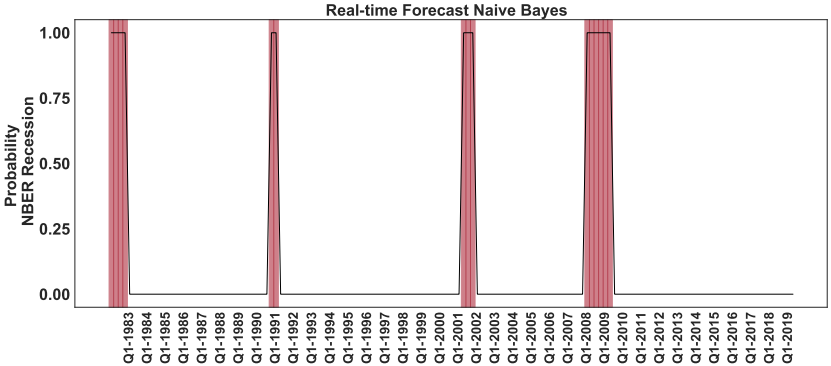
Note: The graph illustrates normalised quarterly connectedness from 1982:Q1 to 2019:Q1 on a 12 month rolling window bandwidth and a 5% significance level. Connectedness in specific nodes in NBER recession periods are more persistent than in non-recession periods, where connectedness might be more idiosyncratic.

Ex-post validation: Features (#15) Negative Growth

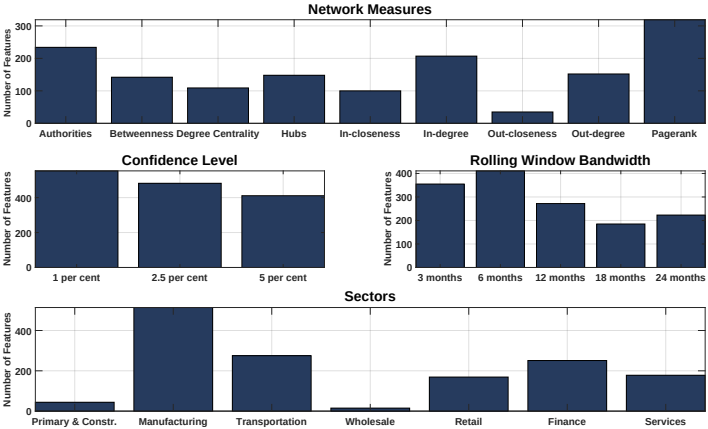
Company	Sector	Measure	Significance	Window
E TRADE FINANCIAL	Finance, Insurance and Real Estate	Pagerank	1%	24m
WALMART	Retail	Betweenness	5%	18m
H&R BLOCK	Services	Hubs	2.5%	12m
BECTON DICKINSON	Manufacturing	Authorities	1%	12m
NEXTERA ENERGY	Transportation	Pagerank	1%	12m
H&R BLOCK	Services	Hubs	1%	12m
ROBERT HALF INTL.	Services	Pagerank	1%	6m
EMERSON ELECTRIC	Manufacturing	Authorities	2.5%	6m
VULCAN MATERIALS	Primary & Construction	Hubs	1%	6m
MCCORMICK & COMPANY NV.	Manufacturing	Authorities	2.5%	3m
SNAP-ON	Manufacturing	Pagerank	2.5%	3m
NVIDIA	Manufacturing	Pagerank	2.5%	3m
M&T BANK	Finance, Insurance and Real Estate	Betweenness	2.5%	3m
MCCORMICK & COMPANY NV.	Manufacturing	Authorities	1%	3m
REGIONS FINL.NEW	Finance, Insurance and Real Estate	Betweenness	1%	3m

TABLE – Selected Features United States, Negative Growth

Probabilities: NBER Recession Overfitted?



Ex-post validation: NBER Recession Periods Artificial?



Note: *Each subplot shows the distribution of specific properties of the selected features. The subplots are independent, but show the same dataset and sum each to the number of features.*

Sensitivity: Euro area (effectively a version of Germany)

Nowcast: 2019 Q1

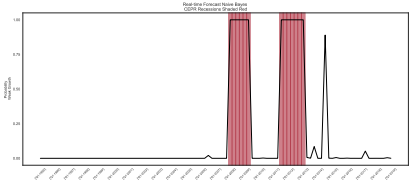


Figure: CEPR Recession

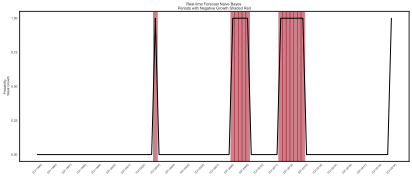
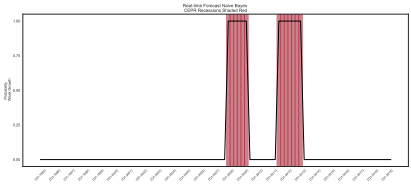
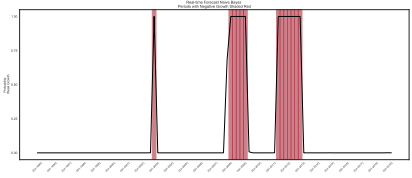


Figure: Negative Growth

Nowcast: 2019 Q2

- Sensitivity: Training the NB including close to zero growth rates eliminates reactivity.





Digression: Naive Bayes in a nutshell

$$P(Class_j|x) = \frac{P(x|Class_j) \times P(Class_j)}{P(x)} \quad Class_j \in \{Recession, NoRecession\} \quad (1)$$

- Posterior: $P(Class_j|x)$ post. probability of Class j given predictor x.
- Likelihood: $P(x|Class_j)$. The probability of the predictor given a Class j (computed from the training set).
- Prior: $P(Class_j)$. The probability of Class j (what we know about the class distribution before we consider x).
- Evidence: $P(x)$. Denominator is effectively constant.

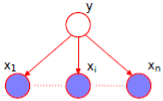
Independence assumption

$$P(x|Class_j) = P(x_1|Class_j) \times P(x_1|Class_j) \times ... \times P(x_k|Class_j) \quad (2)$$

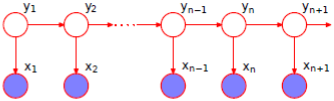
Posterior probability of Class j given a new instance x'
can be obtained by substituting the independence assumption

$$P(Class_j|x') = P(x'_1|Class_j) \times P(x'_2|Class_j) \times ... \times P(x'_k|Class_j) \times P(Class_j) \quad (3)$$

Digression: Naive Bayes vs Markov Switching



Naive Bayes



Hidden Markov Model

Source: manuscript A. Passerini

Hid. Markov Model:

- *Assumes a relationship between y_t and y_{t-1}. Probability of a particular state is dependent only on the previous state.*
- *Turning points are treated as hidden states.*

Naive Bayes:

- Assumes no relationship, y are i.i.d..
- Previous state y_{t-1} as feature $\rightarrow$ "reversed Markov chain".
- Each feature is conditional indep. of every other feature.
- Turning points are treated as data.

Target variables

The **binary** outcome for NBER recession periods is:

$$(\textit{NBER Recessions} \rightarrow \textbf{NBER}) = \begin{cases} 1 & \textbf{Recession} & \text{if NBER Recession} = 1 \\ 0 & \textbf{No recession} & \text{if NBER Recession} \neq 1 \end{cases} \tag{4}$$

or Positive versus Negative GDP growth, which is given by:

$$(\textit{QGDP} \rightarrow \textbf{Negative}) = \begin{cases} 1 & \textbf{Negative} & \text{if QGDP} < 0 \\ 0 & \textbf{Non-Negative} & \text{if QGDP} \geq 0 \end{cases} \tag{5}$$

Alternatively, for the **trinary** outcome we specify equation (6) for Negative Growth if the rate is smaller than 0, normal between 0 and 2, and Positive Growth above 2 per cent:

$$(\textit{QGDP} \rightarrow \textbf{High, Low and Negative}) = \begin{cases} 2 & \textbf{High} & \text{if QGDP} > 2 \\ 1 & \textbf{Neg.} & \text{if QGDP} < 0 \\ 0 & \textbf{Low} & \text{if QGDP} \leq 2 \text{ and QGDP} \geq 0 \end{cases} \tag{6}$$

Network topology to feature matrix

i) Delete features with too low variance (75,885 $\rightarrow$ 61,111)
ii) Normalize remaining series
iii) Collect them in a Matrix

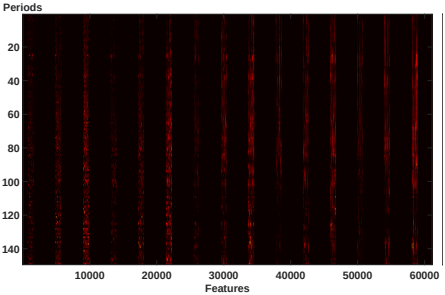


Figure: Non-normalized

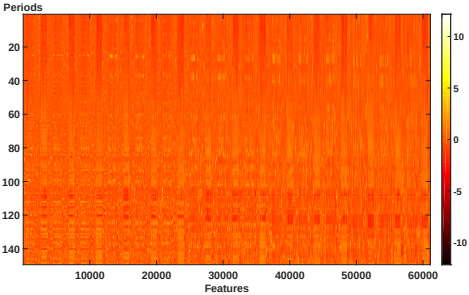


Figure: Normalized