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Nowcasting with Payments Data and Machine Learning

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Overview

- Introduction
- Data
- Methodology
- Preliminary Results
- Conclusions

Introduction

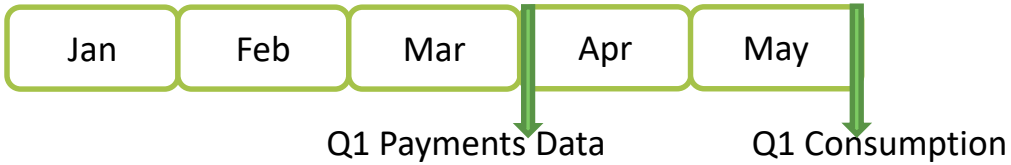
Objective

- Assess the **potential use of payments data** for prediction of various macroeconomic indicators.
- Evaluate the **capability of supervised machine learning** for improving prediction accuracy in the presence of payments data.
- Generate an **index using payments data** which can be used alongside other traditionally used features to predict GDP.

Why Nowcasting?

- **Accurate** and **timely** information about macroeconomic indicators can help policy maker to make key policy decisions.

- Official **estimates** of Key macroeconomic indicators are released with **lag. E.g.** consumption (in Canada)



- Substantial **revisions** of these indicators are frequently done (sometimes **after years** of primary release).

Nowcasting Canadian Economic Activity in an Uncertain Environment, Tony Chernis & Rodrigo Sekkel, Bank of Canada Staff Discussion Paper 2017.

Why Payments Data?

- **Capture** a broad range of the **financial activities**.
- **Gathered electronically** hence, it is available on a **timely basis.**
- Little or **no measurement** or **sampling error**.
- Multiple aggregates of payments streams are available at **different frequencies** (each-pay, daily, monthly & quarterly).

Using the payment system data to forecast the Italian GDP, V. Aprigliano et. al. Banca d'Italia, 2016
Money talks – Nowcasting real economic activity with payment systems data, Luis Dias and Andre Dias, ISI conference, 2017
Nowcasting with Payments System Data, John Galbraith and Greg Tkacz, International Journal of Forecasting, 2018.

Why Machine Learning?

- **Statistical learning** models that are shown to **efficiently** handle **large-scale** regression, classifications, clustering and reinforcement learning.

- Ideal for **nowcasting/forecasting** problems in which we are more concerned about **improving prediction accuracy**.

Big data: New tricks for econometrics, H. Varian, *The Journal of Economic Perspectives*, 2014
Machine learning at central banks, C. Chakraborty and A. Joseph, *Bank of England Working Paper-674*, 2017
Machine learning: an applied econometric approach, Mullainathan, S. and Spiess, J., *Journal of Economic Perspectives*, 2017
Macroeconomic Nowcasting and Forecasting with Big Data, B. Bok, D. Caratelli, D.Giannone, A. Sbordone, and A. Tambalotti, *Annual Review of Economics*, 2018

Preliminary Inferences:

- **Payments** data can improve prediction accuracy in the retail trade sales (**RTS**) and household consumption (**HFCE**) nowcasting.
  - In RTS RMSE reduced by **25%** & in HFCE by **37%** over basic AR model when payments data is used with OLS.

- ML-based **elastic net** can further improve the prediction accuracy.
  - In RTS RMSE reduced by **8%** & in HFCE by **20%** compared to OLS model with payments data when elastic net is used.

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Data

Features: Canadian Retail Payments Data

Payments Instrument Available form ACSS

ACSS Stream	Label, (VAL and VOL)
AFT Debit	TAPEDEB.
AFT Credit	TAPECRED.
Shared Network	SHARNET.
POS Debit	POSDEB.
POS Credit	POSCRED.
EDI	EDI.
Electronic Remittances	EREMIT.
ABM Adjustments	ABMADJ.
Online Credit Payments	ONLCRDPAY.
Online Payment Refunds	ONLPAYRFD.
Small Cheques	SMCHEQ.
Large Cheques	LGCHEQ.
Paper Remittances	PAPREMIT.
Electronic Total	ETOTAL.
Paper Total	PTOTAL.
All Payment Streams Total	ALLSTREAMS.

Automated Clearing and Settlement System (ACSS)

AFT Debit or pre-authorized debit (PAD): Commonly used for mortgage installments, utility **bills**, property taxes, credit card bills, etc.

AFT Credit or Direct Deposits (DD): Commonly used for **payroll**.

POS Debit and Credit: The debits or credit payments initiated in physical POS environments using debit cards.

Electronic Data Interchange (EDI): Involves business-to-business electronic direct credits (businesses inventory management).

Electronic Remittances (EREMIT): Bill payments to businesses.

Shared ABM Network (SHARNET): ABM cash withdrawals,

Online Payments: Payments for Online purchases using e-wallet, PayPal and electronic Person-to-Person (P2P) transactions.

Available to BoC through Payments Canada in the form of daily (value and volume) aggregates.

Targets: Official Estimates of Macro-Indicators

- Retail trade sales (**RTS**): **Delayed by 6 weeks**.

  It is a key monthly indicator of consumer purchasing patterns in Canada. The RTS is an important component of the GDP.

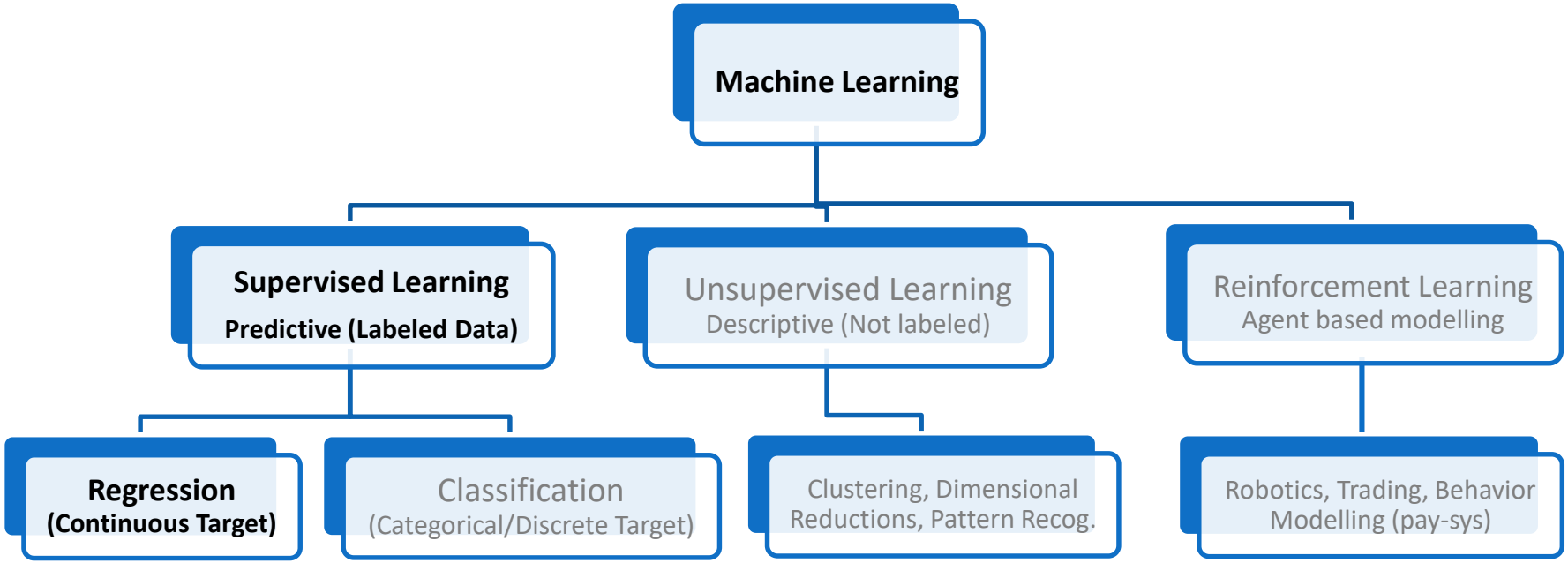
- Household final consumption expenditure (**HFCE**): **Delayed by 8 weeks**.

  It consists of the expenditure incurred by resident households on individual consumption goods and services. The HFCE It is an important component of GDP.

Publicly available through Statistics Canada.

Methodology

Machine Learning

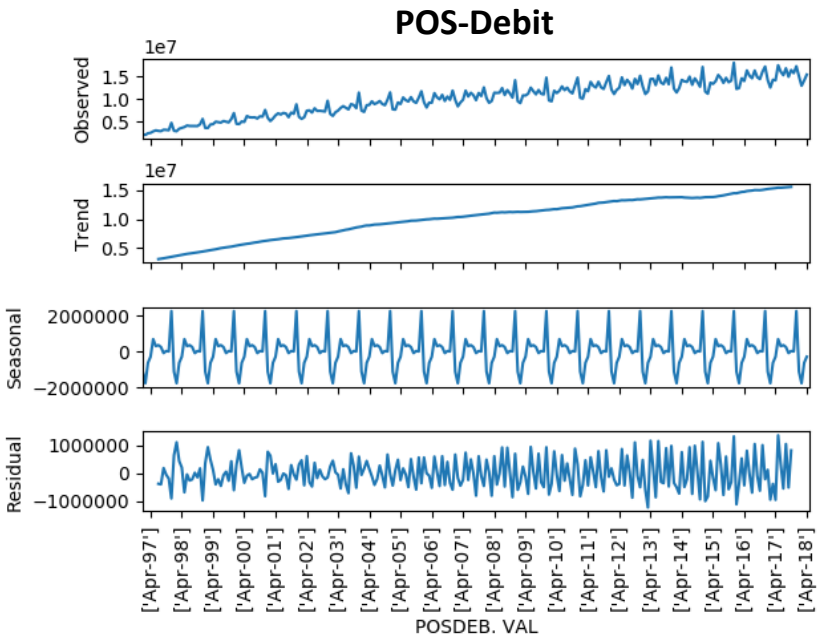


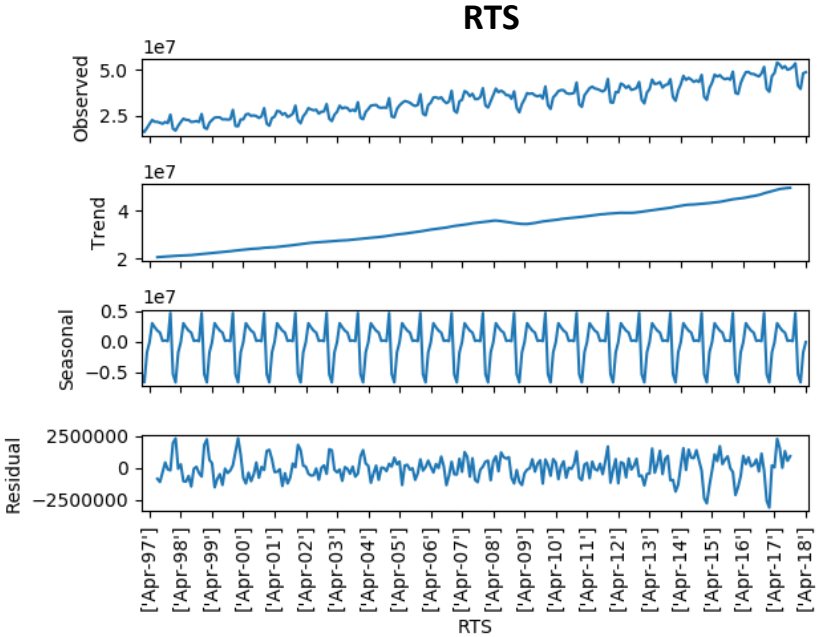
Deep Learning: Artificial Neural Networks with Multiple Hidden Layers

Supervised Machine Learning: Workflow (ML-Pipeline)

1. Adjust seasonality & trend components
2. Check correlations & feature importance
3. Features Standardizing (or normalizing)
4. Prepare training and test datasets
5. Model training and preliminary predictions
6. Model tuning, variable selection and cross-validation
7. Model parameter selection and final predictions

Features & Targets: Seasonal and Trend Adjustment

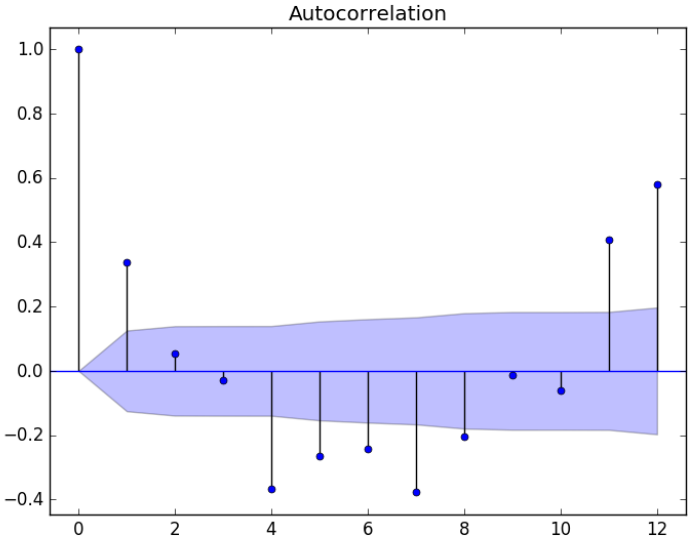




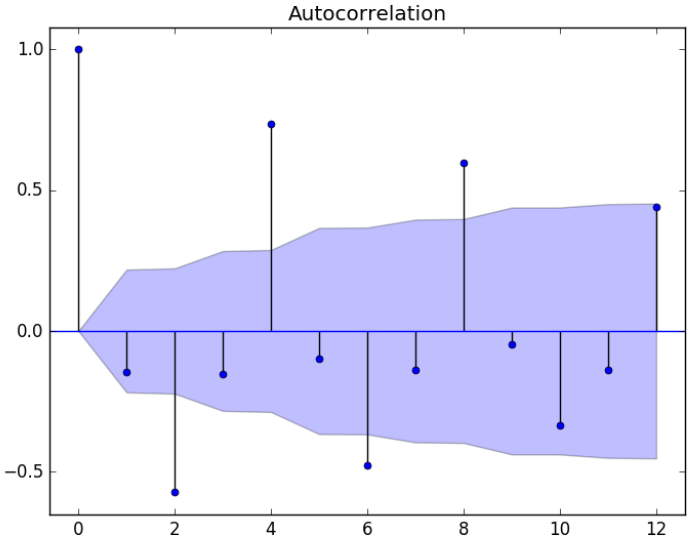
StatsModels: Seasonal Decomposition: Classical decomposition using moving averages. The seasonal component is first removed by applying a convolution filter to the data

Drawbacks: 1: first few and last few months data is loosed during this procedure.
2: it assumes that the seasonal component repeats from year to year.
3: It doesn't captures small (unusual) periods fluctuations.
More sophisticated methods are available (x13) that will be employed in future.

Autocorrelations: Targets



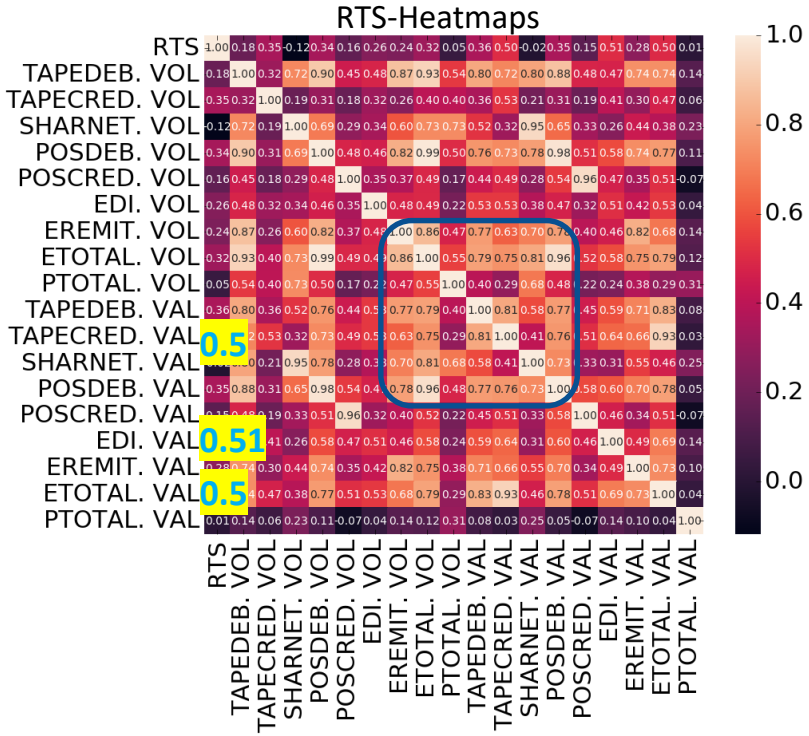
RTS
(Monthly)

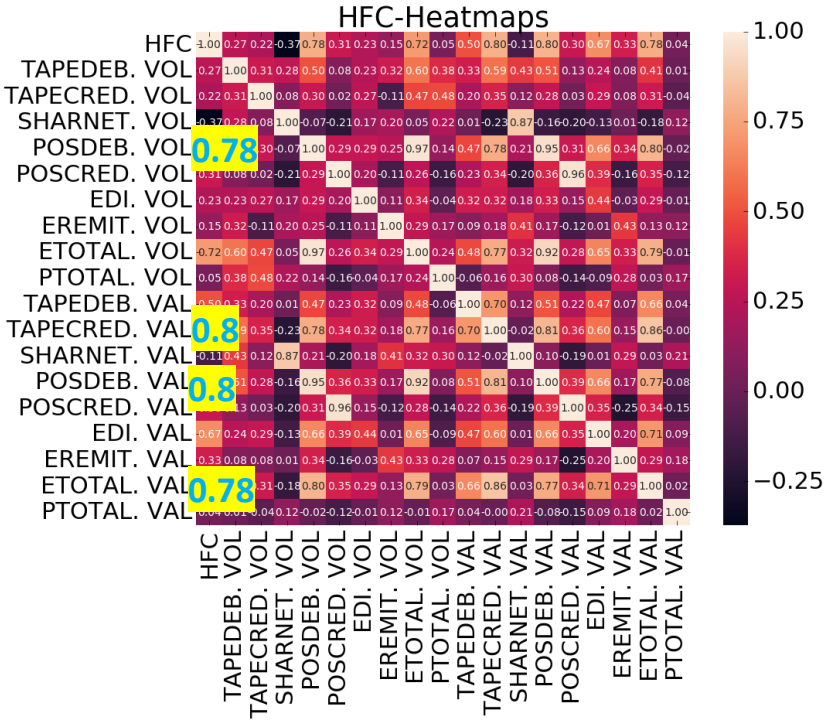


HFCE
(Quarterly)

Statsmodels: plot_acf function is used

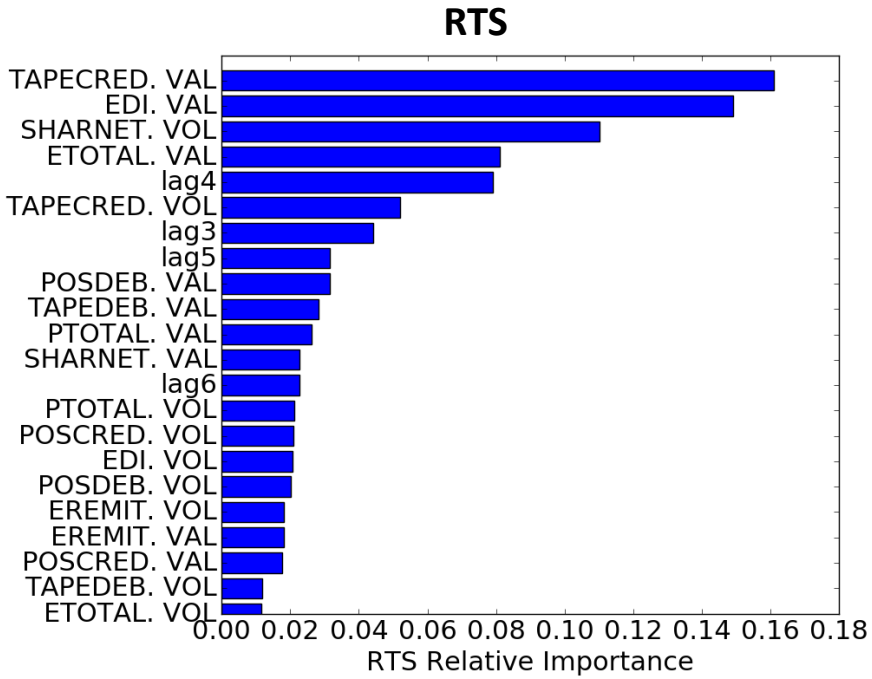
Pairwise Correlations : Heatmaps

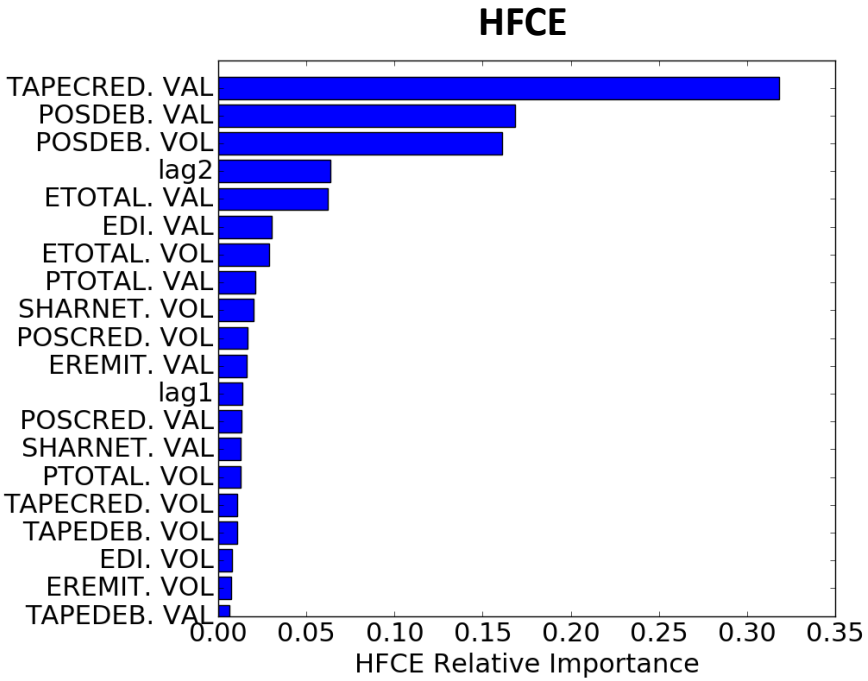




Seaborn: heatmap function is used

Feature Importance: Random Forest





Sklearn: randomForestRegressor function is used: FI is computed: how much each feature decreases the weighted impurity in a tree the impurity decrease from each feature can be averaged and the features are ranked according to this measure.

Supervised Machine Learning: Elastic Net (X: features, y: target)

- Combines the benefits of both LASSO and RIDGE Regressions.

$$\min_{\omega} \frac{1}{2N} ||y - X\omega||_2^2 + \alpha\rho||\omega||_1 + \frac{\alpha(1-\rho)}{2}||\omega||_2^2$$

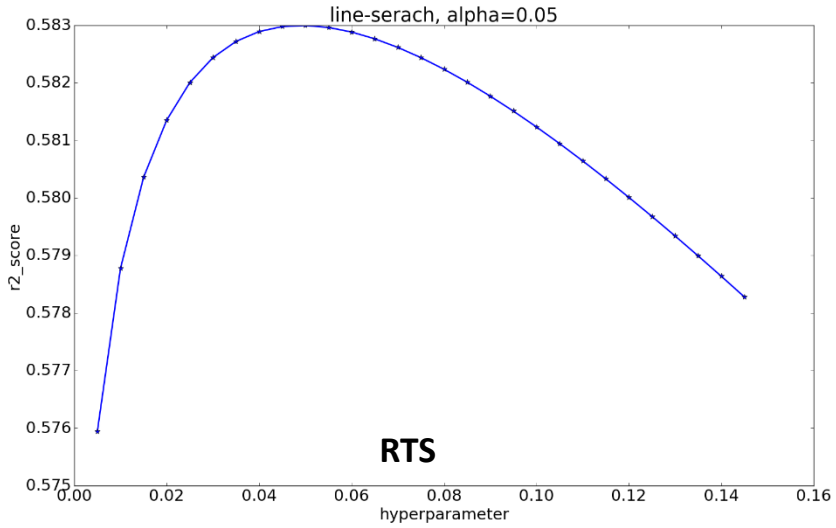
where, α and ρ are the hyperparameters, they can be tuned using cross-validation techniques.

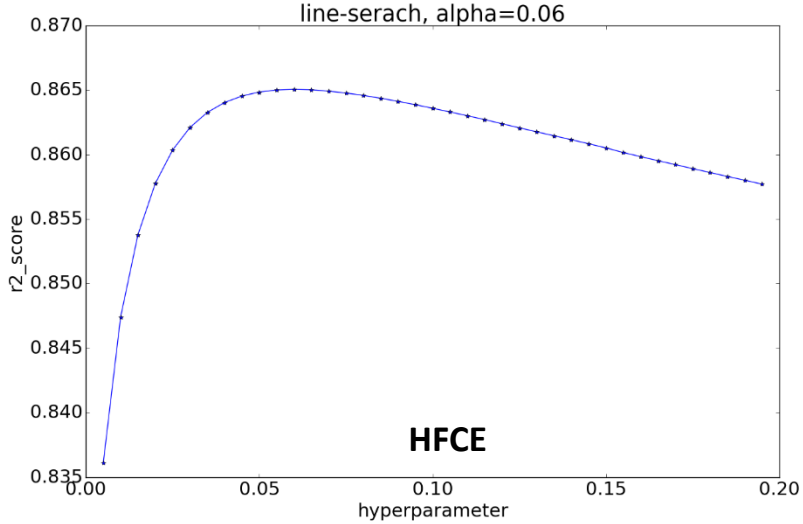
- The L_1 part of the penalty generate sparse model
- The L_2 part of the penalty helps to
  - Encourages grouping effects
  - Remove the limitation on the number of selected variables

Zou, H. and Hastie, T. "Regularization and variable selection via the elastic net", Journal of the Royal Statistical Society, 2005

Hyperparameter Tuning & Cross-Validation

- The model parameters α and ρ are tuned over validation set





$$\min_{\omega} \frac{1}{2N}||y - X\omega||_2^2 + \alpha\rho||\omega||_1 + \frac{\alpha(1-\rho)}{2}||\omega||_2^2$$

CV: Training loss vs test loss on validation sample, overfitting and underfitting?

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Preliminary Results

Case Specifications

Base Case 1	**OLS** with only lagged target
Base Case 2	**OLS** with lagged target and payments data
Main Case	**Elastic net** with lagged target and payments data, model tuning

- RTS (monthly data): Training sample: Jan-98 to Dec-13 and test sample: Jan-14 to Oct-17
- HFCE (quarterly data): Training sample: Q1-98 to Q3-12 and test sample: Q1-13 to Q3-17

For Oct-1st Nowcast

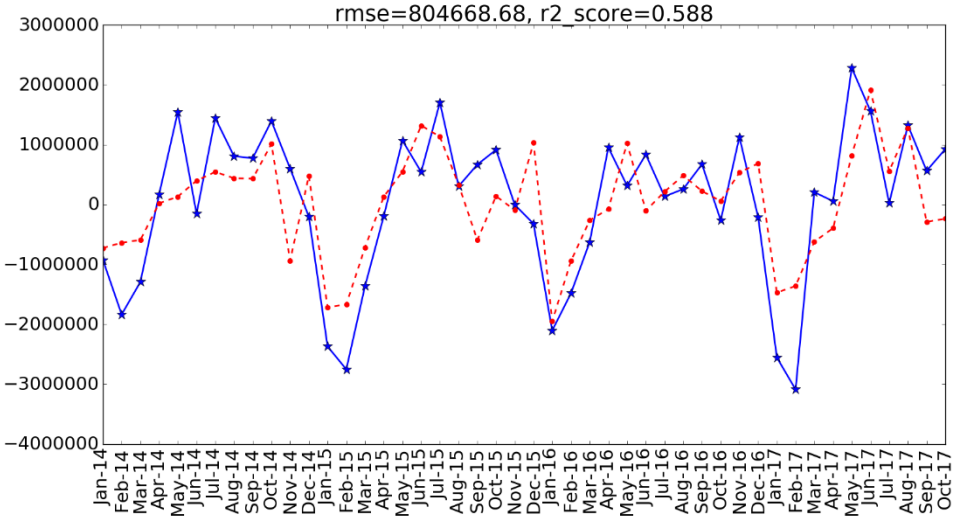
Features	Latest Availability
RTS Lags	March, April, May, June, July
ACSS Val and Vol	September
HFCE Lags	Q1, Q2
ACSS Val and Vol	Q3

RTS and HFCE: Prediction Scores

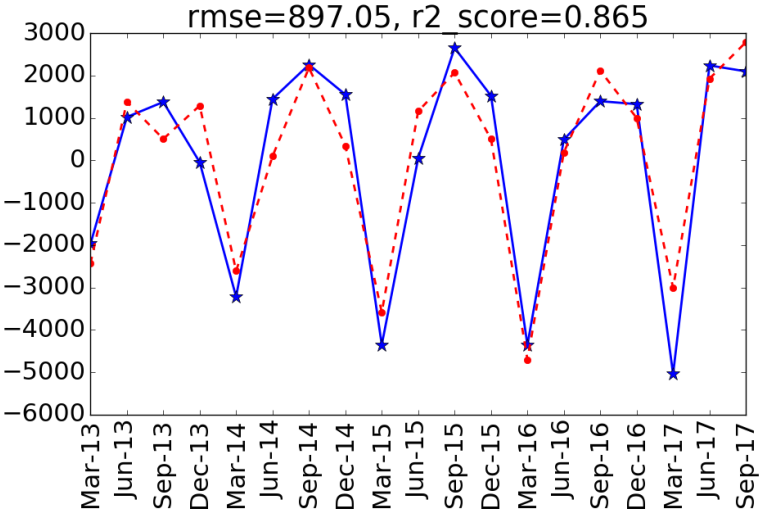
	Base Case 1		Base Case 2		Main Case	
Nowcast:	OLS with Lagged (6 lags) RTS		OLS with Lagged (6 lags) RTS & Payments data		Tuned Elastic Net with Lagged (6 lags) RTS & Payments data	
RTS	**r2-score**	0.145	**r2-score**	0.518 (257%)	**r2-score**	**0.588 (14%)**
			RMSE	25%	**RMSE**	**8%**
Nowcast:	**Base Case 1**		**Base Case 2**		**Main Case**	
	OLS with Lagged (2 lags) HFCE		OLS with Lagged (2 lags) HFCE & Payments data		Tuned Elastic Net with Lagged (2 lags) HFCE & Payments data	
HFCE	**r2-score**	0.428	**r2-score**	0.775 (81%)	**r2-score**	**0.865 (12%)**
			RMSE	37%	**RMSE**	**20%**

RTS and HFCE: Actual Vs Predicted (Main Case)

RTS

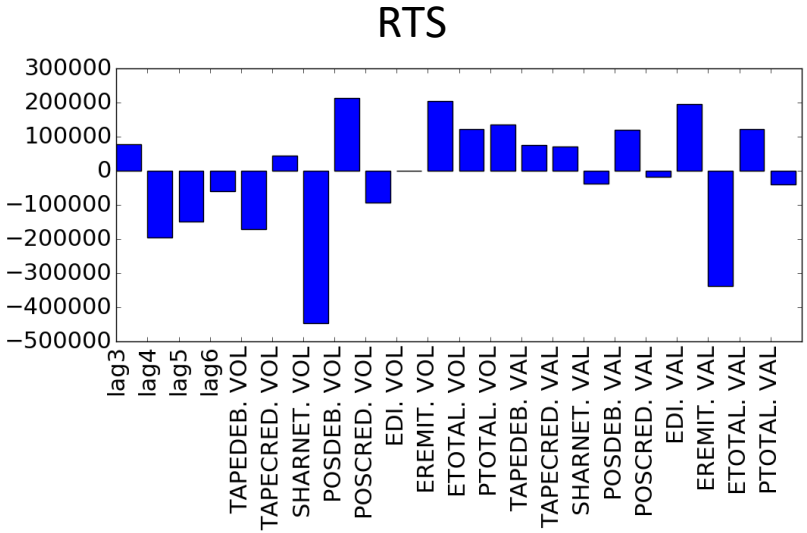


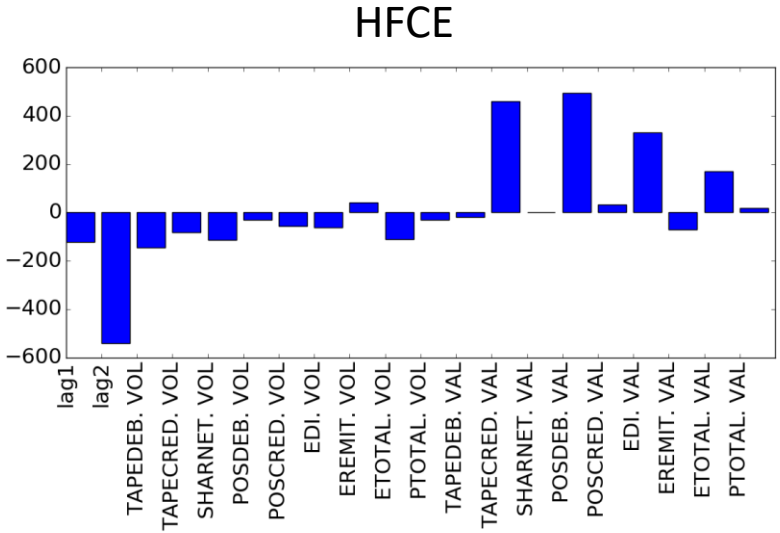
HFCE



predicted (−−) and actual (−) comparison using elastic net

RTS and HFCE: Prediction Coefficients (Main Case)

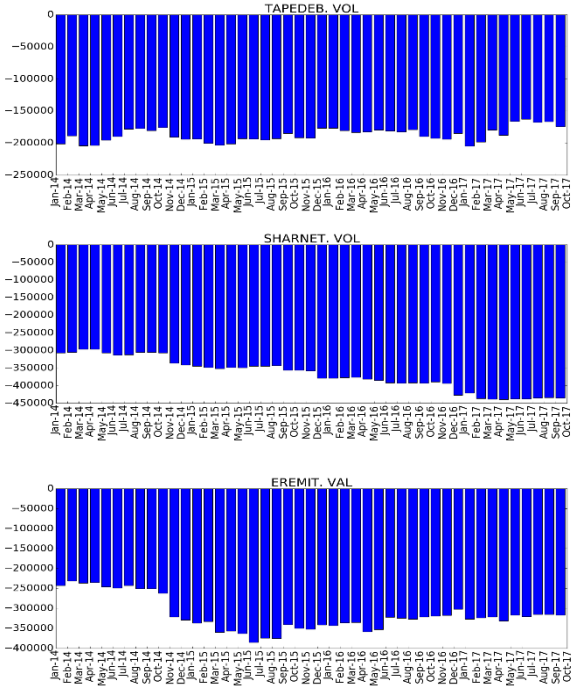




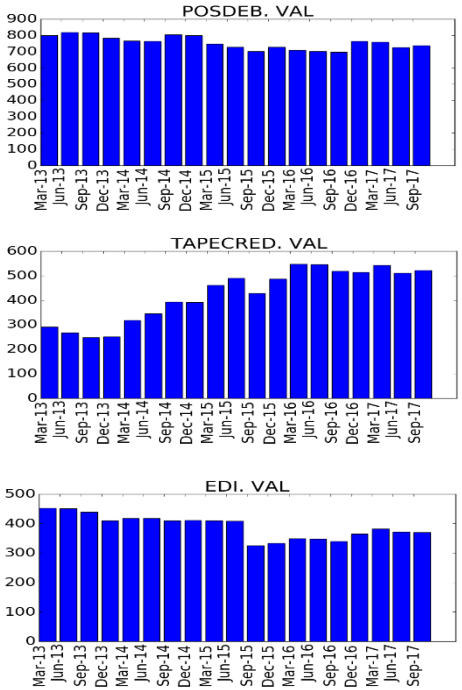
Computed after the last training session of the expanding window approach.

RTS and HFCE: Dominant Prediction Coefficients Over the Entire Training Period

RTS



HFCE



Conclusions

Conclusions

- Payments data is **useful** in improving nowcasting of RTS and HFCE.
- ML-based elastic net can **further improve** the prediction score.
- Payments data could be **useful for predicting GDP** along with other variables.

Drawbacks:

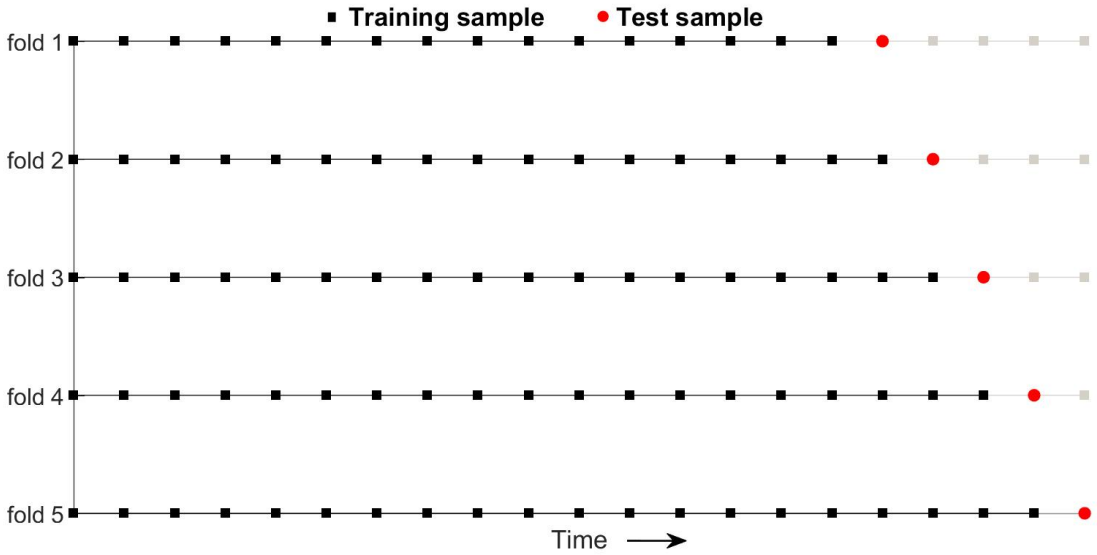
- Although **every transaction** or each day's aggregates of payments data is available, using it in monthly or quarterly aggregated forms reduces the number of samples.
- With **fewer sample points** in each stream, we cannot make use of more advanced ML approaches such as **Deep Learning (DNN)**.

Thank You!

Questions?

Model Training and Predictions: Expanding Window Approach

- Given dataset is split into: 80% training sample and 20% testing sample



Rolling window approach: Can be used to see the effects of consumer's changing priority of payments streams (eg: online vs POS etc.)