A Machine Learning Approach to Inflation Forecasting

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Outline

This presentation covers (very briefly) the following topics:

- The FRED-MD dataset
- Pre-processing for time series
- A simple forecasting setup
- Setting a baseline with AR(1)
- Regularisation methods (Lasso, Ridge, Elastic Net)
- Principal Component Regression
- VAR and its challenges with "Big Data"
- Random Forest

Introduction (1/2)

- Explore ML methods for forecasting, addressing "Big Data" challenges and the "curse of dimensionality"
- Use AR(1) as a benchmark
- Assess whether advanced (ML) methods can outperform AR(1)
- Judging forecasting accuracy is non-trivial (more on this later), but careful tuning can reveal meaningful gains

Inspired By: De Mol, Giannone, Reichlin (2008), *"Forecasting Using a Large Number of Predictors: Is Bayesian Shrinkage a Valid Alternative to Principal Components?"*, *Journal of Econometrics*.

Introduction (2/2)

- This study loosely follows the referenced paper, making simpler assumptions and using simpler techniques (e.g., no Bayesian methods)
- This exercise should be understood as rather stylized
- The focus is solely on "forecasting accuracy" of each method
- All the code is in R, and you can find each script in my GitHub repository: InflationForecast (link)
- Coding aspects are not covered here but are detailed in "UserGuide.pdf," available in the same repository

Forecasting & Data Science Terminology

- Model training — Model fitting, parameter estimation
- Training set — In-sample
- Test set — Out-of-sample
- Forecast horizon — Number of periods ahead being predicted
- Forecast origin — From where you do the forecasting from, the last known observation
- Target variable — Dependent variable being forecasted
- Features, inputs — Independent variables, regressors, predictors

Note: Key terms only (many more exist), and these are not exact equivalents.

Additional Forecasting & Data Science Terminology

- Cross-validation — Pseudo out-of-sample forecasting, backtesting (finance)
- Rolling window — Fixed-size training set shifting forward over time
- Expanding window — Growing training set while keeping earliest data
- Nowcasting — Estimating the present or near future in real-time
- Hyperparameter tuning — Optimizing model configuration to control complexity and prevent overfitting

Note: This study uses POOS forecasting, where models are evaluated by tuning hyperparameters and comparing MSFEs, using a rolling origin evaluation with an expanding window.

The FRED-MD Dataset

- A gold standard for modern macroeconomics
- Contains convenient monthly (US) macroeconomic data from 1960 to today, spanning different sectors
- This study focuses on CPI: All Items Less Food (CPIULFSL)
- Offers convenient functions for pre-processing through their R package "fbi" (link)
- Used in De Mol et al.'s paper (older version); this study uses the updated dataset (link)

Pre-Processing for Time Series (1/3)

- Many ML techniques are not designed specifically for time series
- Stationarity is crucial and can be handled easily using the `fredmd` function from the "fbi" package
- To double-check, I plot each time series before and after and their autocorrelation
- Other essential steps include handling missing values and treating outliers
- I handle missing values and outliers manually in R (but there are also tailor-made functions for that in "fbi")

Pre-Processing for Time Series (2/3)

- The time series is shortened to cover the period from January 1960 to December 2019
- Time series with too many NAs values are removed, leaving 121 variables
- I use a SMA algorithm for the remaining NA values
- For outliers, I exclude the COVID-19 period by cutting the data short
- Breaks and regime changes (e.g., financial crises) are not considered
- I always use lag 1 (e.g., AR(1)) and do not optimize lag selection using AIC or BIC
- This approach is very approximative (more on this later)

Pre-Processing for Time Series (3/3)

- I always stay in the stationary domain for computing errors, comparing models and tuning
- This changes interpretation! CPIULFSL uses the second log difference:

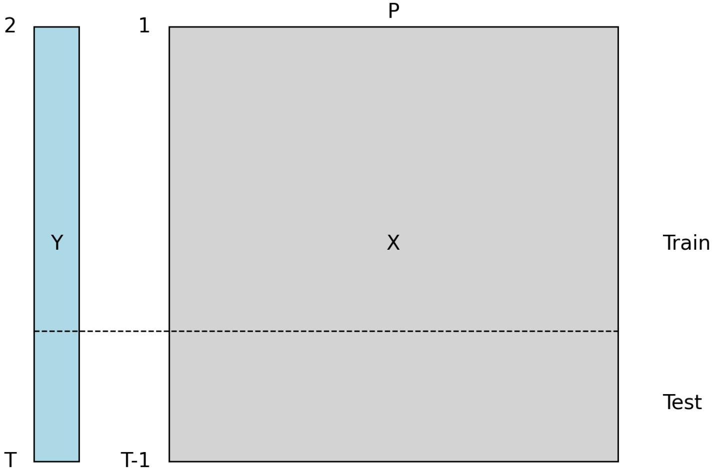
$$(\ln(x) - \ln(x-1)) - (\ln(x-1) - \ln(x-2))$$

- This forecasts "inflation acceleration", not inflation or raw prices
- E.g., industrial production uses first log difference (more intuitive)
- Optimizing for $\Delta^2 \ln(CPIULFSL) \neq$ optimizing for CPIULFSL
- For that you need to "recover" forecasts via inverse transformation

A Simple Forecasting Setup (Example)

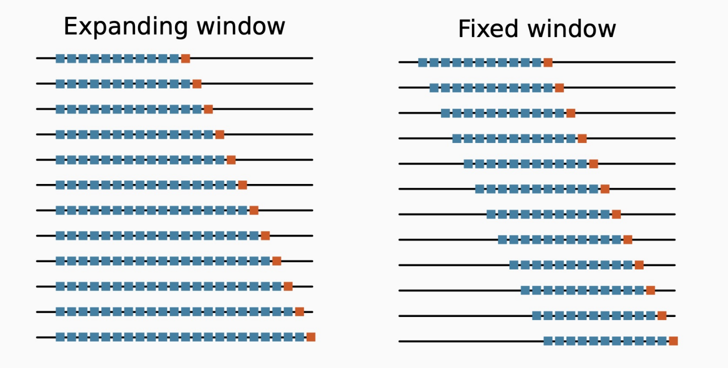
- The data is manually lagged, with Y_t as the dependent variable and X_{t-1} as the predictor
- The data is split into $\approx 70\%$ training and 30% testing
- The (training) data is standardized at each iteration
- The model is re-trained each time
- An input is used for each prediction (lagged X prevents look-ahead bias)
- After (de-standardizing) each prediction, the corresponding test observation is added to the training set
- This process repeats, predicting one Y_{test} value at a time, until all test data points are predicted

Matrix Representation



First month of Y and last month of X are excluded

Rolling Origin Evaluation

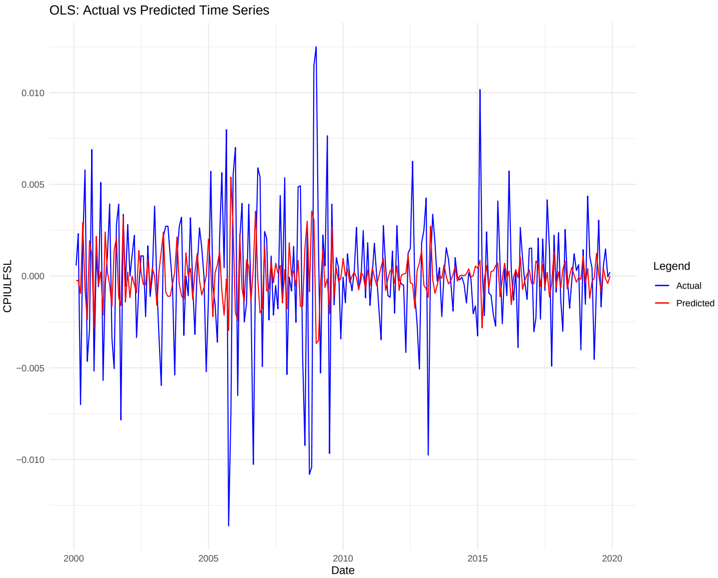


Also known as time series cross-validation; I adopt the expanding window version

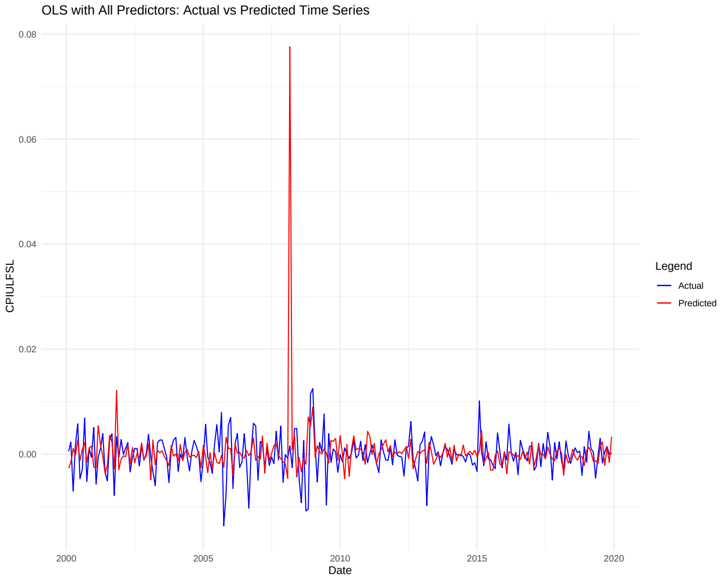
Setting a Baseline with AR(1)

- AR(1) is the simplest model and surprisingly hard to beat
- It requires little to no computational power
- MSFE and a plot of actual vs. forecasted values are used to compare models
- This provides a baseline to analyze trade-offs and results (approximatory, as this is an exploratory study)
- E.g., while an advanced neural network may outperform AR(1), it is not always guaranteed
- Neural networks also require significantly more time, data and computational power

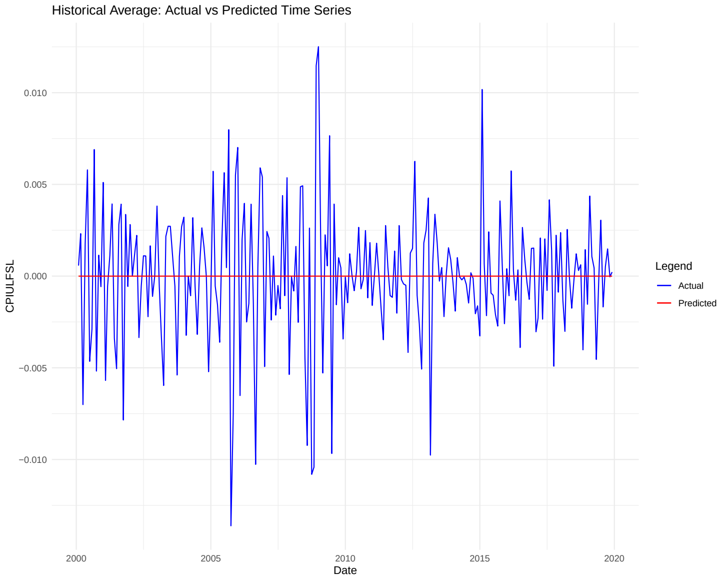
AR(1) Results (MSFE: 1.351304e-05)



Overfitting? (OLS with All Predictors)



Underfitting? (Historical Average)



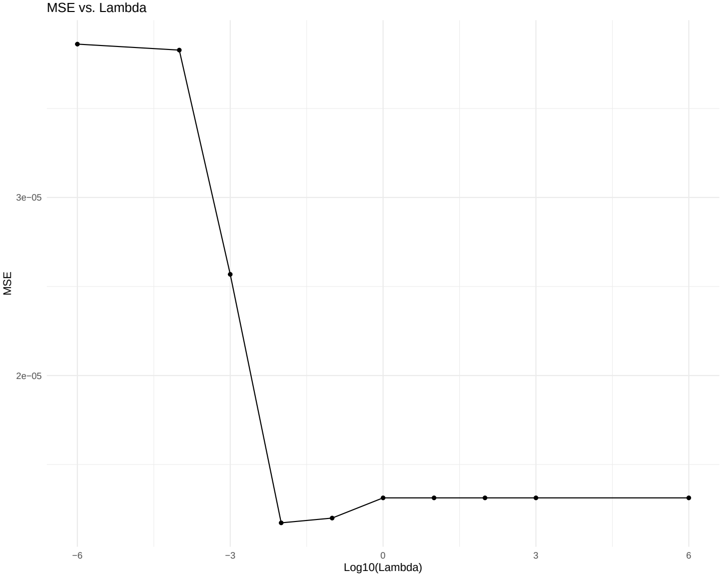
Regularisation Methods (Lasso)

- Lasso estimates the coefficients as:

$$\hat{\beta} = \arg\min_{\beta} \left(\underbrace{\|y - X\beta\|_2^2}_{\text{RSS}} + \lambda \underbrace{\|\beta\|_1}_{\text{L1 Penalty}} \right)$$

- Can set some coefficients exactly to zero, effectively performing variable selection
- Requires an appropriate penalty parameter λ
- I perform a "grid search" to find the optimal λ (similar to the approach used in the paper)
- Some of its properties (similar to Ridge) will be explored next

Lasso Results (Best MSFE = 1.172451e-05)



Regularisation Methods (Ridge)

- Ridge estimates the coefficients as:

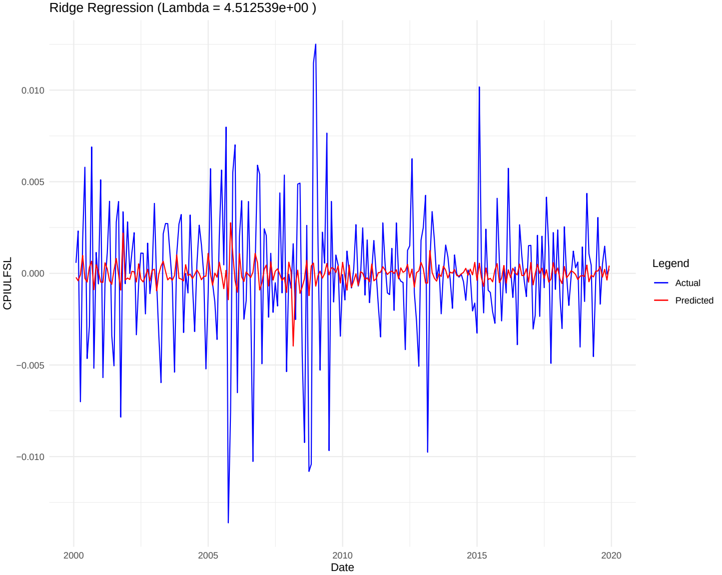
$$\hat{\beta} = \arg\min_{\beta} \left(\underbrace{\|y - X\beta\|_2^2}_{\text{RSS}} + \lambda \underbrace{\|\beta\|_2^2}_{\text{L2 Penalty}} \right)$$

- Similar to Lasso but shrinks coefficients towards zero instead of setting them exactly to zero
- The optimal λ is (roughly) suggested by the paper as:

$$\lambda \approx \frac{P}{\sqrt{T}}$$

- As $\lambda \to \infty$, heavy penalization shrinks $\hat{\beta}$ to zero
- As $\lambda \to 0$, it resembles OLS with all predictors

Ridge Results (Optimal λ MSFE = 1.257817e-05)



Ridge Results (Rounded Values)

Lambda Value	MSFE
1e-06	3.861e-05
1e-04	3.847e-05
1e-03	3.538e-05
1e-02	2.819e-05
1e-01	1.596e-05
1e+00	1.186e-05
1e+01	1.280e-05
1e+02	1.308e-05
1e+03	1.312e-05
1e+06	1.313e-05
Optimal Guess 1	1.264e-05
Optimal Guess 2	1.258e-05

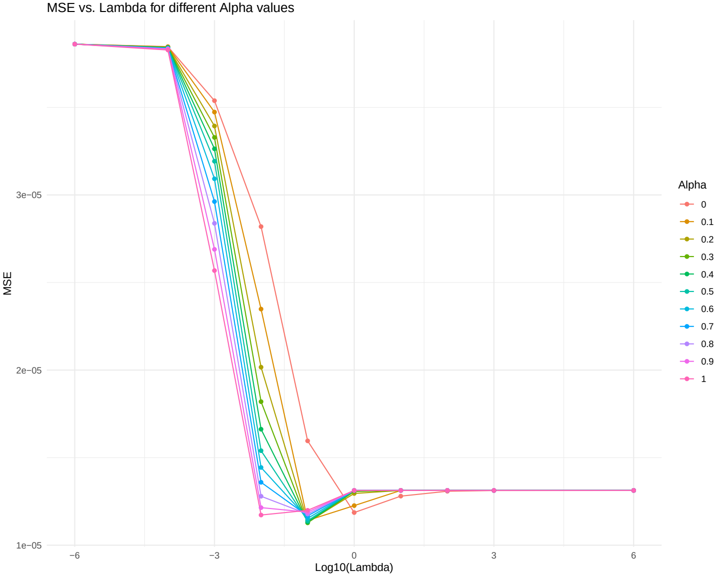
Regularisation Methods (Elastic Net)

- Elastic Net combines Lasso and Ridge to balance sparsity and shrinkage
- Useful when predictors are highly correlated (Lasso drops variables arbitrarily)
- The estimated coefficients are now given by:

$$\hat{\beta} = \arg\min_{\beta} \left(\|y - X\beta\|_2^2 + \lambda \left(\alpha \|\beta\|_1 + (1-\alpha)\|\beta\|_2^2 \right) \right)$$

- α controls the balance between L1 and L2 penalties
- The "grid search" is now extended over λ and α

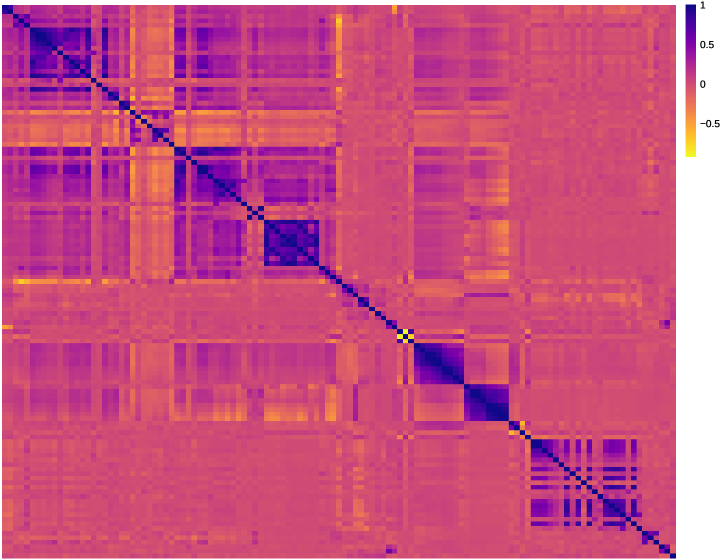
Elastic Net Results (Best MSFE = 1.127735e-05)



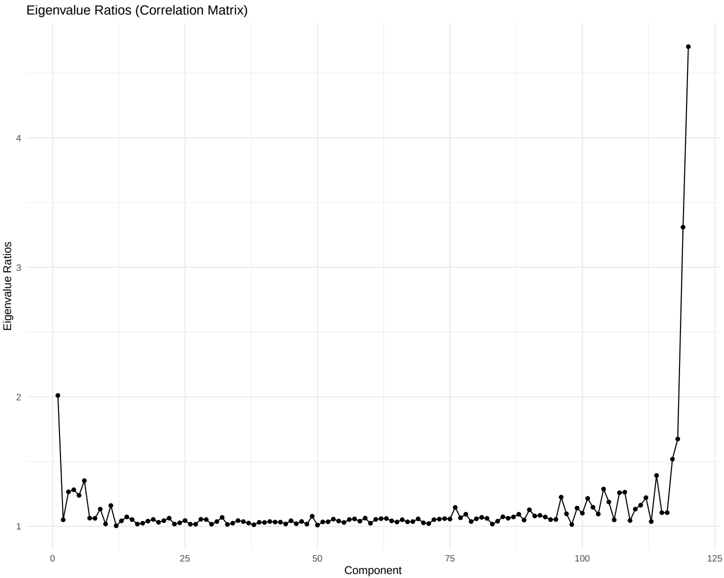
Principal Component Regression

- PCA identifies orthogonal directions (principal components) that capture the most variance in the data
- A classic technique for dimensionality reduction, heavily simplifying calculations
- Principal components are often difficult to interpret
- PCR is simply linear regression with the principal components (PCs) as regressors
- I start with eigenvalue-based selection from the correlation matrix, then empirically try different PCs

Correlation Matrix Heatmap of FRED-MD



Eigenvalue Ratios for Component Selection



PCR Results (Rounded Values)

Number of Components	MSFE
1	1.323e-05
2	1.311e-05
3	1.340e-05
5	1.351e-05
10	1.307e-05
25	2.002e-05
50	1.219e-05
75	5.756e-05
121 (all regressors)	3.704e-05

The sweet spot for dimensionality reduction lies around 10 or 50 PC's

VAR and its Challenges with "Big Data"

- VAR(p) is "simply" the multivariate extension of AR(p):

$$Y_t = A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + \epsilon_t$$

- This application focuses on forecasting accuracy, though VAR is versatile
- VAR struggles with many variables due to overparameterization
- E.g., Bayesian VAR is popular as it introduces shrinkage to address this issue
- I experiment with a VAR using PCA on X to forecast Y, which is effective (but not interpretable)

VAR Results (Rounded Values)

Number of Components	MSFE
2	1.380e-05
3	1.334e-05
5	1.332e-05
10	1.299e-05
25	1.253e-05
50	1.193e-05
75	1.245e-05
No PCA (all variables)	3.528e-05

Like PCR, more components help until “overfitting” occurs, as in OLS

Random Forest (1/2)

- Random Forest (RF) averages predictions from multiple decision trees to reduce variance:

$$\hat{y} = \frac{1}{M} \sum_{m=1}^{M} \hat{y}_m$$

- Non-linear (can capture complex patterns) and scale-invariant
- Uses bootstrapped samples of training data
- Each tree considers a random subset of features at each split
- More trees reduce variance, improve stability, but increase computation
- Deeper trees capture more details but risk overfitting

Random Forest (2/2)

- I only tune the number of trees (M) and maximum nodes per tree (indirectly controls depth and complexity)
- RF hyperparameter tuning is more complex due to multiple interacting parameters; here are a few more
- Min samples per split (minimum observations needed to split)
- Max features (random subset per split)
- Max depth (prevents trees from growing too deep and overfitting)
- Min samples per leaf (ensures enough data per leaf for stability)

Random Forest Results (Rounded Values)

Number of Trees	Max Nodes	MSFE
10	5	1.304e-05
25	8	1.293e-05
50	10	1.285e-05
75	12	1.256e-05
100	15	1.267e-05
150	18	1.266e-05
200	20	1.245e-05
500	25	1.262e-05

Noticeable improvement with 75 trees, gains stall around 200 trees

Conclusions (1/2)

- It may be tempting to conclude that each ML method outperformed AR(1) with proper tuning
- However, assessing forecasting accuracy is more complex!
- A rigorous setup requires a clear separation between train, validation, and test sets
- In this exercise, the test set effectively acted as a validation set
- To properly assess performance, a final unseen test set is essential to confirm that the chosen model generalizes well

Conclusions (2/2)

- As mentioned earlier, this exercise is intentionally stylized (similar to the approach in the referenced paper)
- This approach is useful for exploring the mechanics of different methods
- However, other important limitations remain
- Regime changes are not considered: Are pre- and post-Fed periods comparable?
- The expanding window assumes old patterns persist: Are 1960s trends still relevant? A rolling window may suit better

References

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