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Commodities Time Series Prediction using Relevance Filtering and CEnet

NYU Capstone Project hosted by Bank of America

Andong Zhou (az1418), Anurag Rathore (ar6634), Jiayu Shi (js11603)

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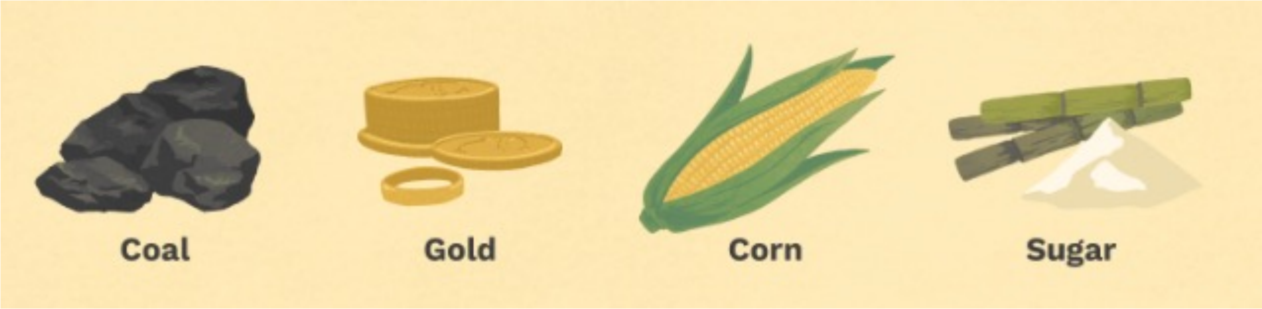
PART 01

Introduction & Motivation

Drawbacks of traditional time series analysis

Introduction - Commodity

- Commodities: grains, gold, beef, oil, and natural gas, etc.
    - producers and consumers: hedge price risk
    - Investors: diversify portfolios, hedge inflation and volatility



Motivation - Traditional Approach Drawbacks

1. **Observations Processing**

    - Not considering the relevance between historical observations and the most recent one.

    → relevance filtering (Czasonis et al., 2021)

2. **Feature Selection and Forecast Combination**

    - Multi-variate models in linear settings

    → C-Enet (Rapach and Zhou, 2020)

PART 02

Data

PART 02

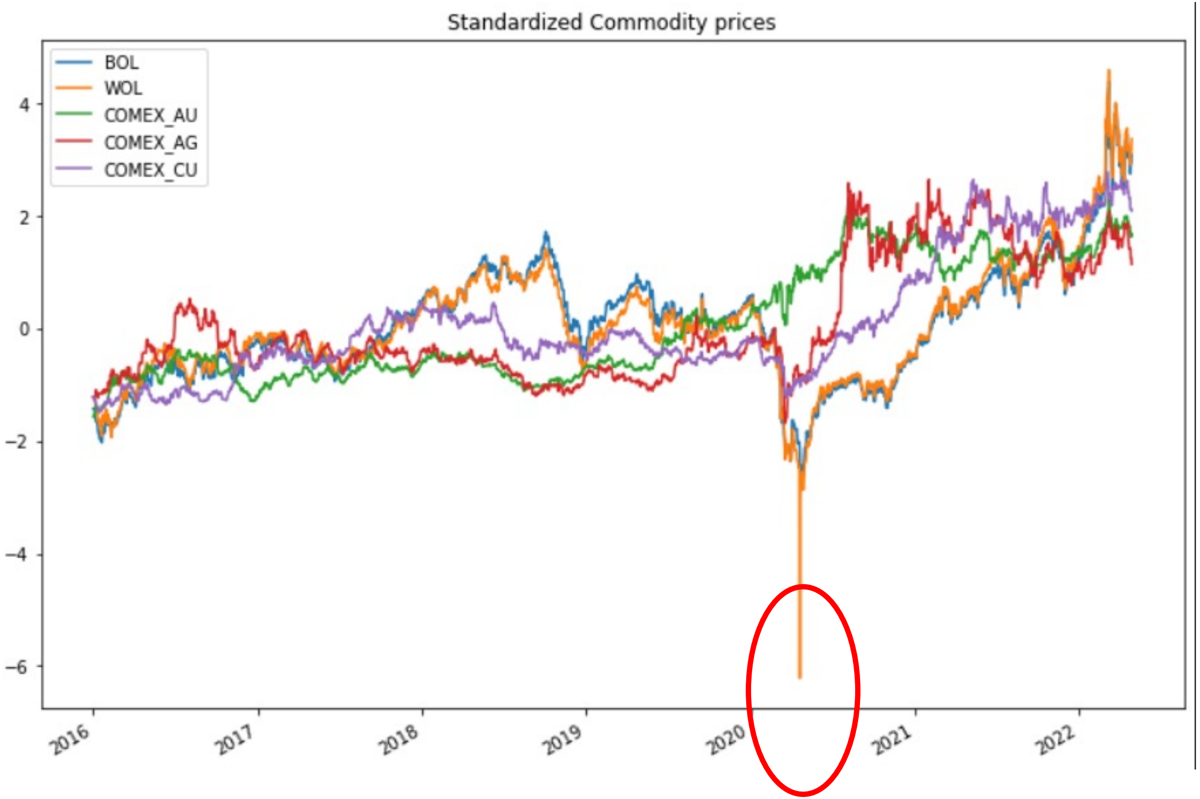
Data

- Source

Yahoo Finance API (yfinance)

- Time range

01/01/2016 ~ 04/30/2022



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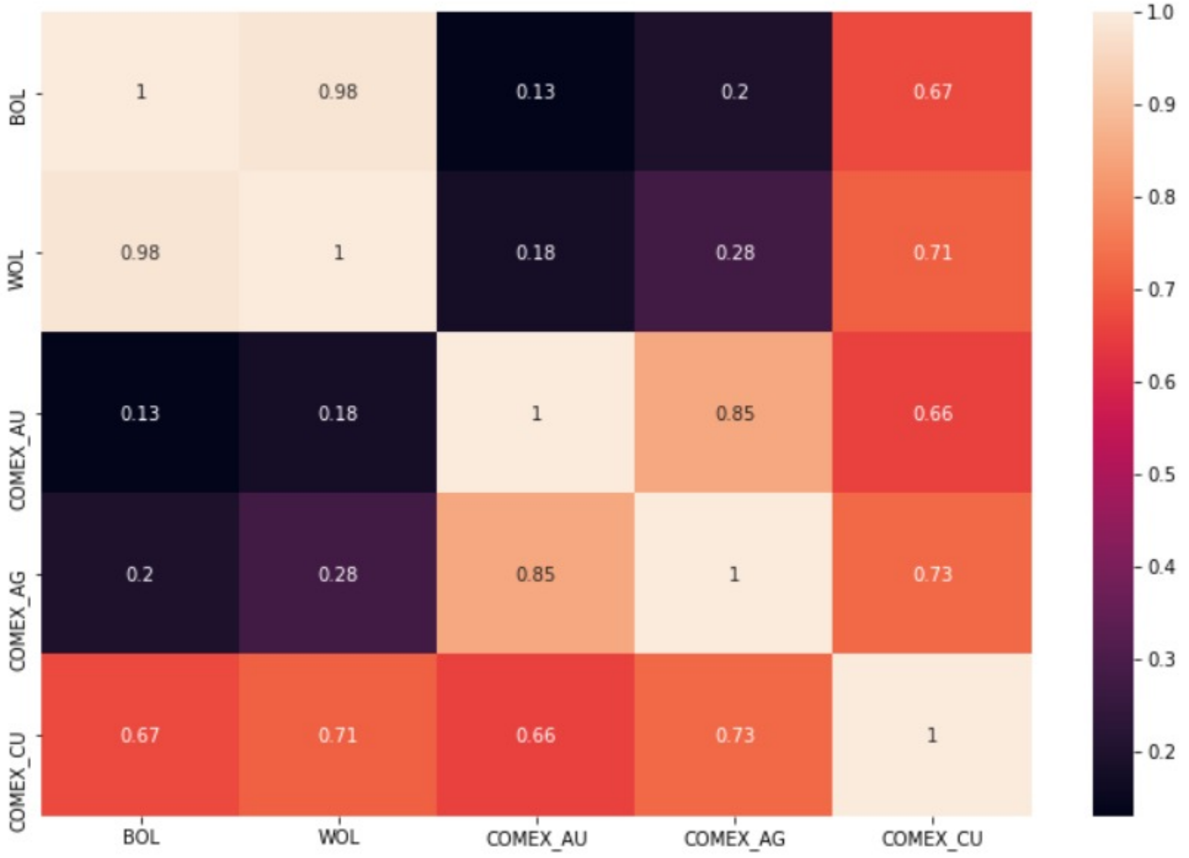
PART 02

Data



Commodity Correlation Matrix

PART 03

Methodologies

Relevance Filtering & CEnet

Methodology - Relevance Filtering

For any pair of observations x_i and x_j,

$$sim_{ij} = sim(x_i, x_j) = -\frac{1}{2}(x_i - x_j)\Omega^{-1}(x_i - x_j)'$$

$$info_i = info(x_i) = \frac{1}{2}(x_i - \overline{x})\Omega^{-1}(x_i - \overline{x})'$$

Relevance is defined as

$$r_{ij} = r(x_i, x_j) = sim_{ij} + info_i + info_j$$

Methodology - Relevance Filtering

The generalized equation for relevance can be given by:

$$r_{it} = (x_t - \overline{x})\Omega^{-1}(x_i - \overline{x})'$$

In our modelling, when predicting point $t + 1$, we consider only the observations that satisfy:

$$r_{it} > 0$$

for any i in the sample of interest.

Methodology - Combination Elastic Net

Conventional multiple predictive regression takes the form

$$r_t = \alpha + \sum_{j=1}^{J} \beta_j x_{j,t-1} + \varepsilon_t$$

$$\hat{r}_{t+1|t}^{OLS} = \hat{\alpha}_{1:t}^{OLS} + \sum_{j=1}^{J} \hat{\beta}_{j,1:t}^{OLS} x_{j,t}$$

Rapach and Zhou consider a combination forecast that takes the form of a simple average of the univariate predictive regression forecasts based on $x_{j,t}$ for $j = 1, \ldots, J$

$$r_t = \eta + \sum_{j=1}^{J} \theta_j \hat{r}_{t|t-1}^{(j)} + \varepsilon_t$$

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Methodology - Combination Elastic Net

Rapach and Zhou then consider the Granger and Ramanathan regression:

$$r_s = \eta + \sum_{j=1}^{J} \theta_j \hat{r}_{s|s-1}^{(j)} + \varepsilon_t$$

For $s = t_1 + 1, \dots, t$.

Let $\mathcal{J}_t \subseteq \{1, \dots, J\}$ denote the index set of individual univariate predictive regression forecasts selected by the ENet, i.e., $\theta_j > 0$.

$$\hat{r}_{t+1|t}^{CEnet} = \frac{1}{|\mathcal{J}_t|} \sum_{j \in \mathcal{J}_t} \hat{r}_{t+1|t}^{(j)}$$

Where $|\mathcal{J}_t|$ is the cardinality of $\mathcal{J}_t$

Methodology – Relevance Filtering + C-Enet

Step 1 For each predictor variable group, we compute rolling partial-sample multivariate predictive regression forecasts with relevance-filtered observations and L2 norm (Ridge) over the holdout out-of-sample period:

$$\hat{r}_{s|s-1}^{(c)} = \hat{\alpha}_{1:s-1}^{c} + \sum_{j=1}^{J_c} \hat{\beta}_{1:s-1}^{(c,j)} x_{c,j,s-1}$$

For $c = 1, \dots, C$, $s = t_1 + 1, \dots, t$ and $j = 1, \dots, J_c$.

Step 2 We estimate the Granger and Ramanathan regression via the ENet over the holdout out-of-sample period:

$$r_s = \eta + \sum_{c=1}^{C} \theta_c \hat{r}_{s|s-1}^{(c)} + \varepsilon_s$$

For $s = t_1 + 1, \dots, t$. Let $\mathcal{C}_t \subseteq \{1, \dots, C\}$ denote the index set of categorical multivariate predictive regression forecasts selected by the ENet.

Step 3 We compute the C-ENet forecast as

$$\hat{r}_{t+1|t}^{CEnet} = \frac{1}{|\mathcal{C}_t|} \sum_{c \in \mathcal{C}_t} \hat{r}_{t+1|t}^{(c)}$$

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PART 04

Model

Model - Variables

- Dependent variable (Y)
  - Oil group: Brent Crude Oil Price, WTI Oil price
  - Metal group: COMEX Gold, Silver, and Copper price

- Independent variable (X), total 79
  - Stock market indices (10)
  - CBOE volatility index (VIX) (7)
  - Treasuries (5)
  - Transport fees (6)
  - Commodity prices and indices (7)
  - Fundamentals of commodity (33)
  - Simple combination of features (11)

Model

1. derive respective relevance filtered daily predictions (Observations Selection)
   - 126-day (half-a-year) rolling basis
2. train C-Enet on predictions of all groups (Feature Selection and Forecast Combination)
   - rotational 3-year in-sample
   - 3-month holdout period

Model - Benchmarks

1. Relevance-filtered regression
2. Ridge regression
    - 126-day (half-a-year) rolling basis

Model - Metrics

1. R^2_{OS} statistic

$$R^2_{OS} = 100 * \left(1 - \frac{MSFE_{PREP}}{MSFE_{HM}}\right) = 100 * \left[1 - \frac{\sum_{t=t_0}^{T-1} (r_{t+1} - \widehat{r_{t+1}})^2}{\sum_{t=t_0}^{T-1} (r_{t+1} - \overline{r_t})^2}\right]$$

2. cumulative sum of squared error differences (CSSED)

$$CSSED_{it} = \sum_{\tau=1}^{\tau=t} (e^2_{Bmk,i\tau} - e^2_{Pbrk,i\tau})$$

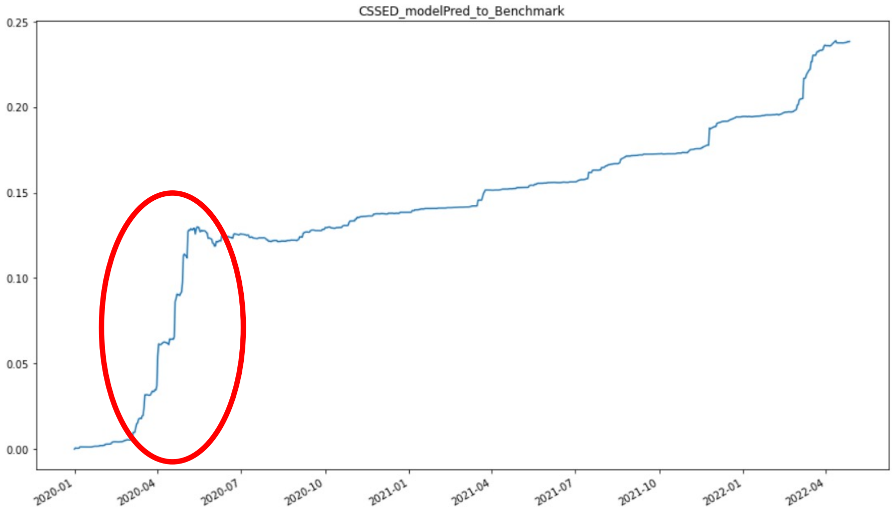
PART 05

Experiment Result

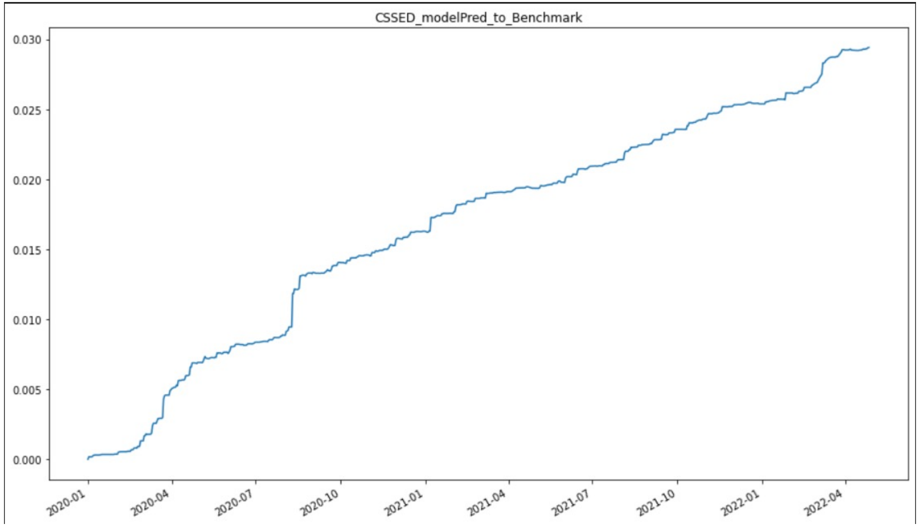
Result - Proportional Reduction

Proportional reduction	Oil group	Metal group
in model prediction error	0.6672	0.7015
in relevance filtered prediction error	0.5103	0.4835
in benchmark prediction error	0.3140	0.2950

Result - Cumulative Sum of Squared Error Differences compared to Benchmark



Oil group



Metal group

PART 06

Reference

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Thank you!