BECOME A KAGGLE MASTER - HW2

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Sommaire

1. Exploratory data analysis

2. Feature augmentation and selection

3. Models
   a. Transformers?
   b. Base models
   c. Ridge model

4. Hyperparameter tuning

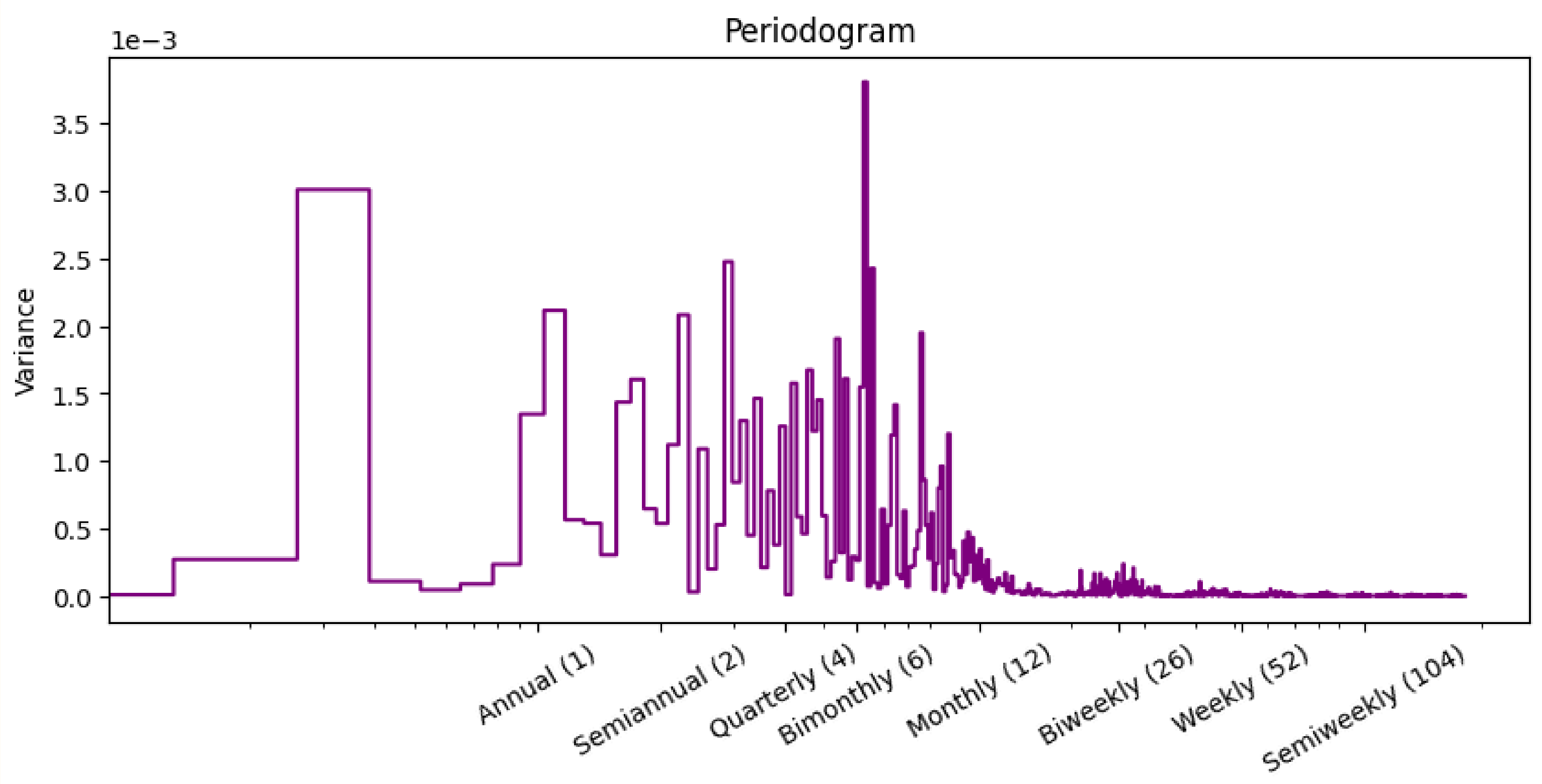
5. Results

1. Exploratory data analysis - 1

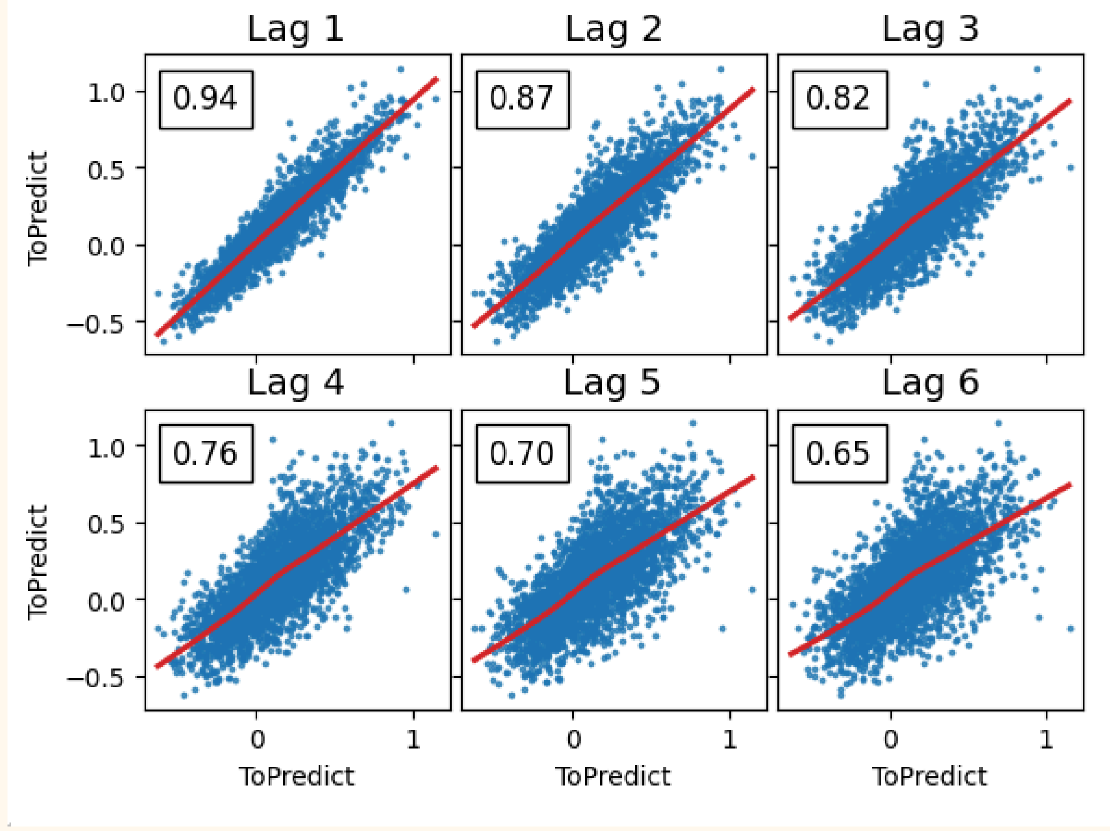
Dataset:

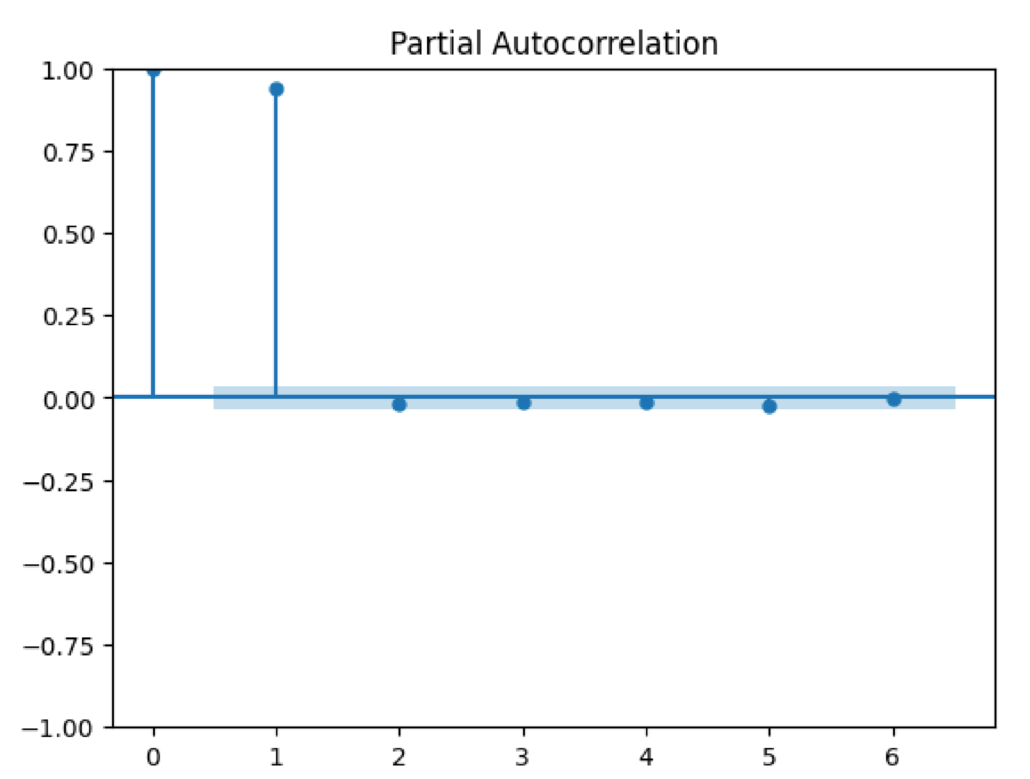
- 133 features
- ToPredict is a float
- Train: 2811 lines
- Test: 1206 lines
- 5 days per week - 260 days per year

1. Exploratory data analysis - 2



Periodogram: strong bimonthly seasonality

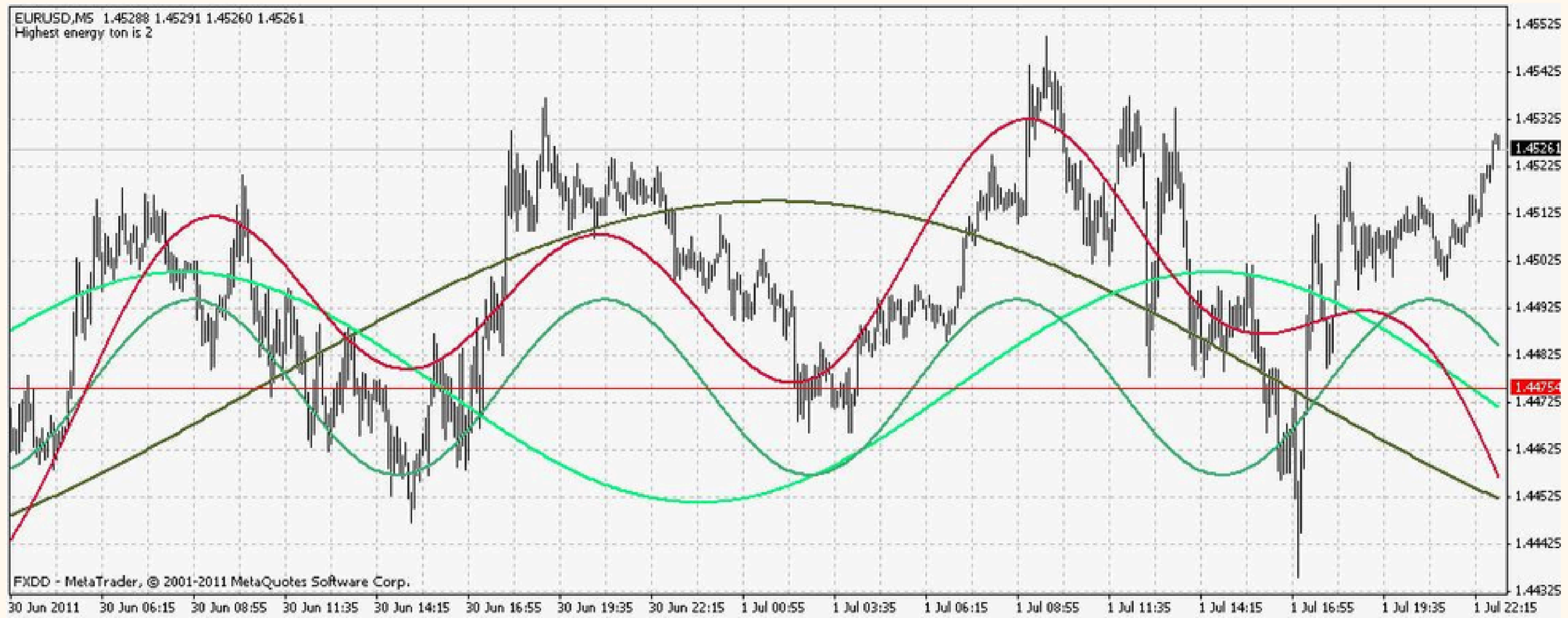


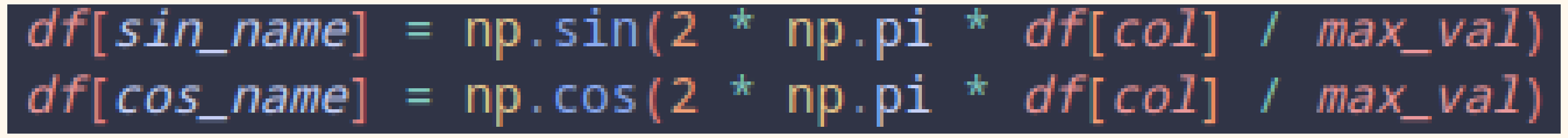


Lag 1 with strong autocorrelation

2. Feature augmentation and selection

- **sinusoidal encoding**
  - weekly: 5 days
  - monthly : 21 days
  - quarterly: 65 days
  - annual: 260 days
  - week of year: 52 weeks
  - month of year: 12 weeks
- **Feature transformations**
  - Log
  - Lag (shift: 1, 3, 7)
  - rolling mean/std (shift: 3, 7)





```
df[sin_name] = np.sin(2 * np.pi * df[col] / max_val)
df[cos_name] = np.cos(2 * np.pi * df[col] / max_val)
```

2. Feature augmentation and selection

Temporal Categorical Encoding

- Day of week effects
  - Monday/ Friday
- Start and End of the month/ year/ Quarter
- Month:
  - January/ December

Technical indicators

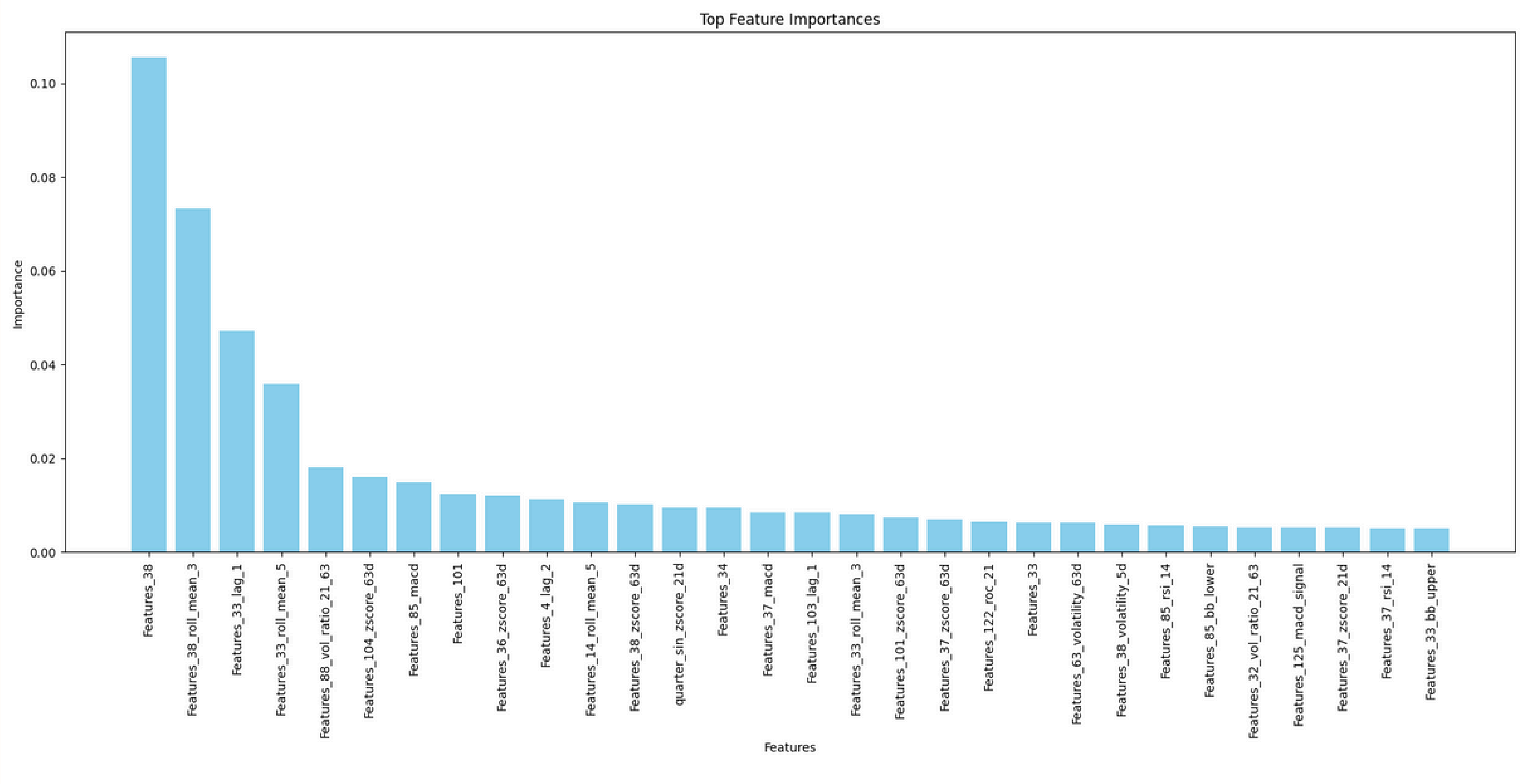
- RSI (Relative Strength Index)
- MACD (Moving Average Convergence Divergence)
- Bollinger Band
- ROC (Rate of change)
- Volatility
- Mean reversion and Momentum indicators

$$RS = \frac{\text{moyenne des gains sur N jours}}{\text{moyenne des pertes sur N jours}}$$

$$\mathrm{ROC}_n = \left(\frac{P_{\text{aujourd'hui}} - P_{t-n}}{P_{t-n}} \right) \times 100$$

2. Feature augmentation and selection

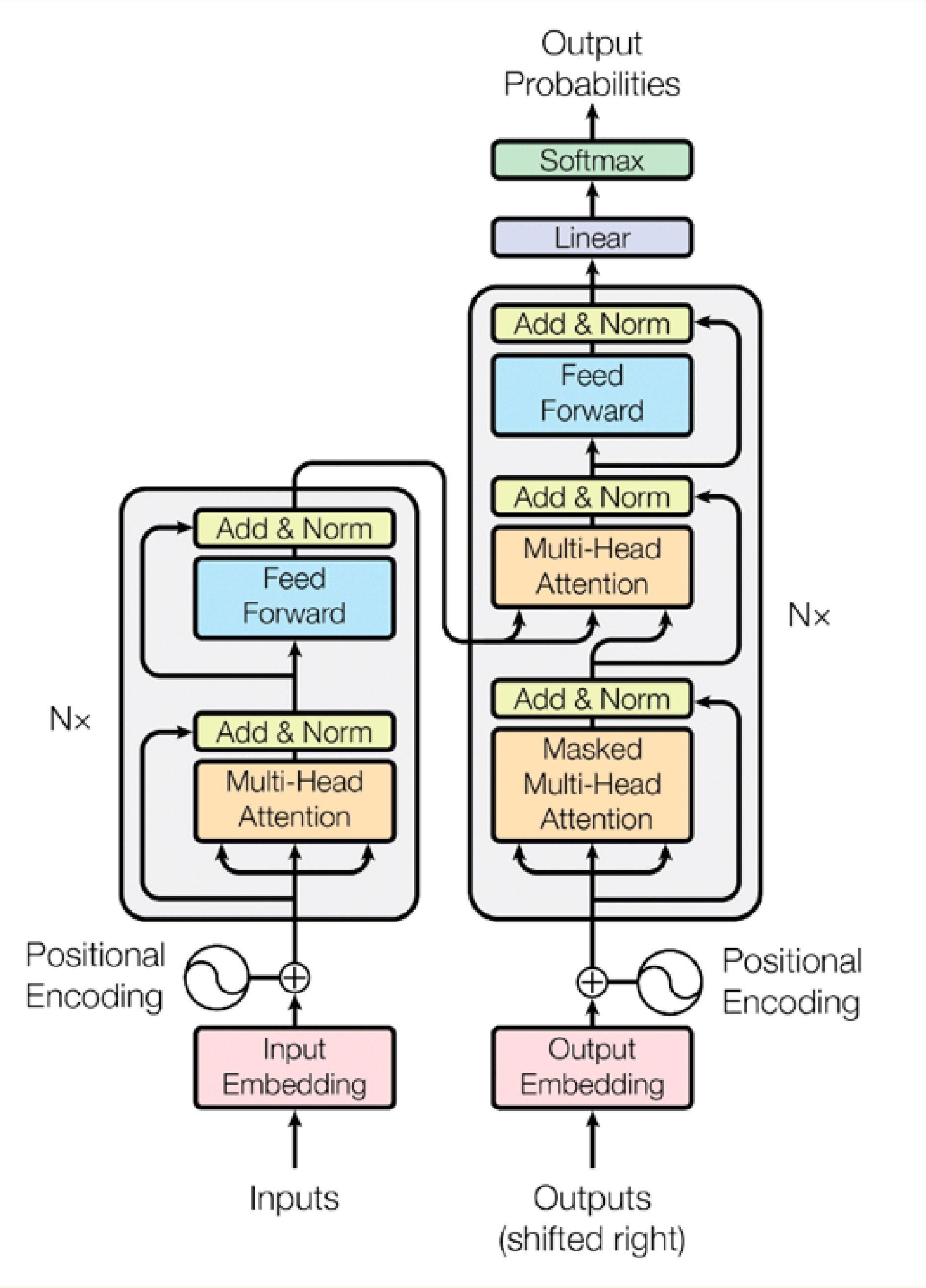
- Feature selection
  - **XGBRegressor** with threshold
  - 4698 columns → 166 columns (Threshold at 0.001)



3. Models

a. Transformers?

- **Differential Former**
  - ○ Noise Cancellation
- Insufficient Data



3. Models
b. Base models

1) CatBoost Regressor:

- Less overfitting
- Performs well with limited training samples

2) XGBoost Regressor:

- Handles high-dimensional data efficiently
- Captures complex non-linear relationships

3) RandomForest Regressor:

- Diversity through ensemble of uncorrelated trees
- Robust to outliers

Objective:

- Balanced Complexity
- Less prone to overfitting
- Diversity

3. Models
c. Ridge model

1) **Regularization**: prevents overfitting when combining the base models

2) **Simplicity**: linear meta-models fast to train

3) **Stability**: less sensitive to correlation between base model predictions

→ **Make the most of our different models**

- Training with **5-fold validation** with **TimeSeriesSplit**
- **One model** at the time, then Ridge model

4. Hyperparameter tuning

Use of **Optuna** library

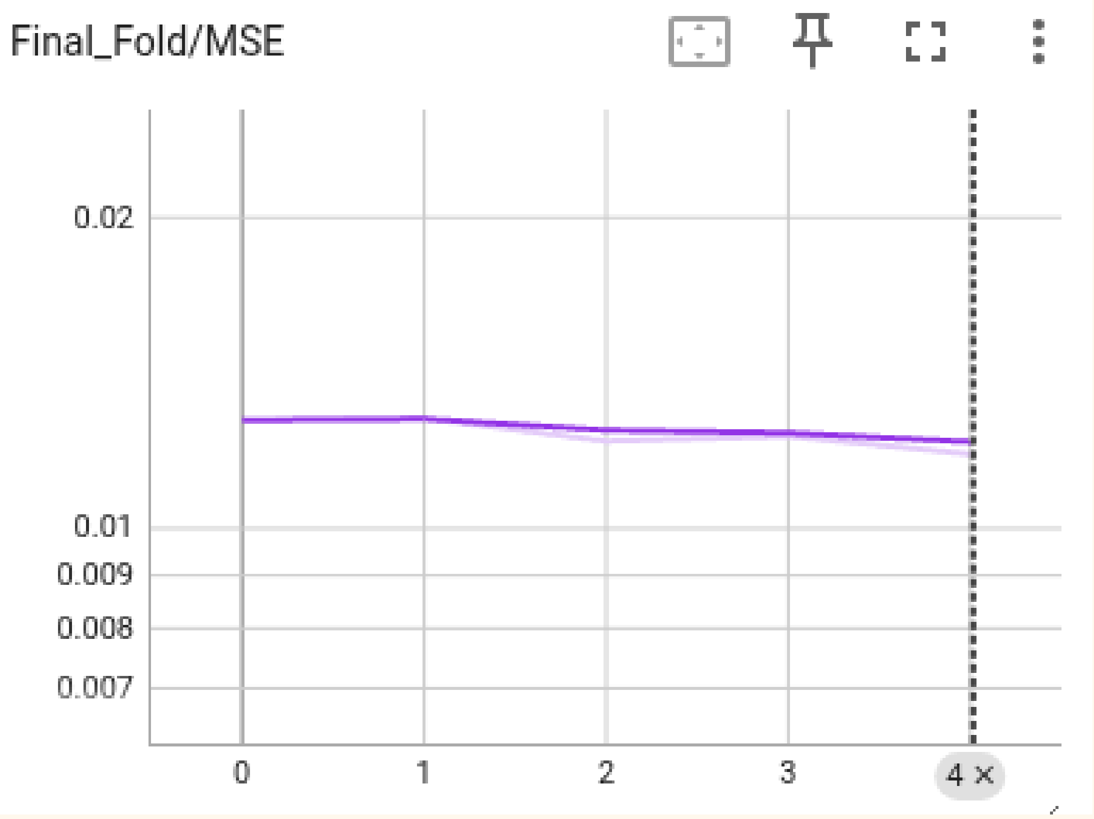
Multi-model approach: separately optimized XGBoost, CatBoost, and RandomForest

→ Optimize Ridge model on the trained models

Optimization method: TimeSeriesSplit (5 folds), 50 jobs, monitored with TensorBoard

Results: combined approach reduced prediction error and maintained computational efficiency

5. Results



- **Stable MSE on train**: from 0.01273 to 0.01213

- MSE on **public** leaderboard: 0.01114
- MSE on **private** leaderboard: 0.01104