Periwinkle Trading

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Liaison: Scott Smallwood, CEO
Advisor: Professor Weiqing Gu

About Periwinkle Trading

- A remote, statistical arbitrage, systematic trading firm
- Use methods of analysis on commercial data
- Name comes from the Fibonacci-like spirals of a Periwinkle snail’s shell

How does Periwinkle Use Statistical Arbitrage

- Use market flow and data to make mathematically positive expected value trades
- Mostly short holding-period trades, but not high frequency
- Don’t hold opinions on major events nor carry long-term stock positions

Project Goals

Recreate Periwinkle Architecture

Implement Modularity and Automation for Experiments

Test New Ideas

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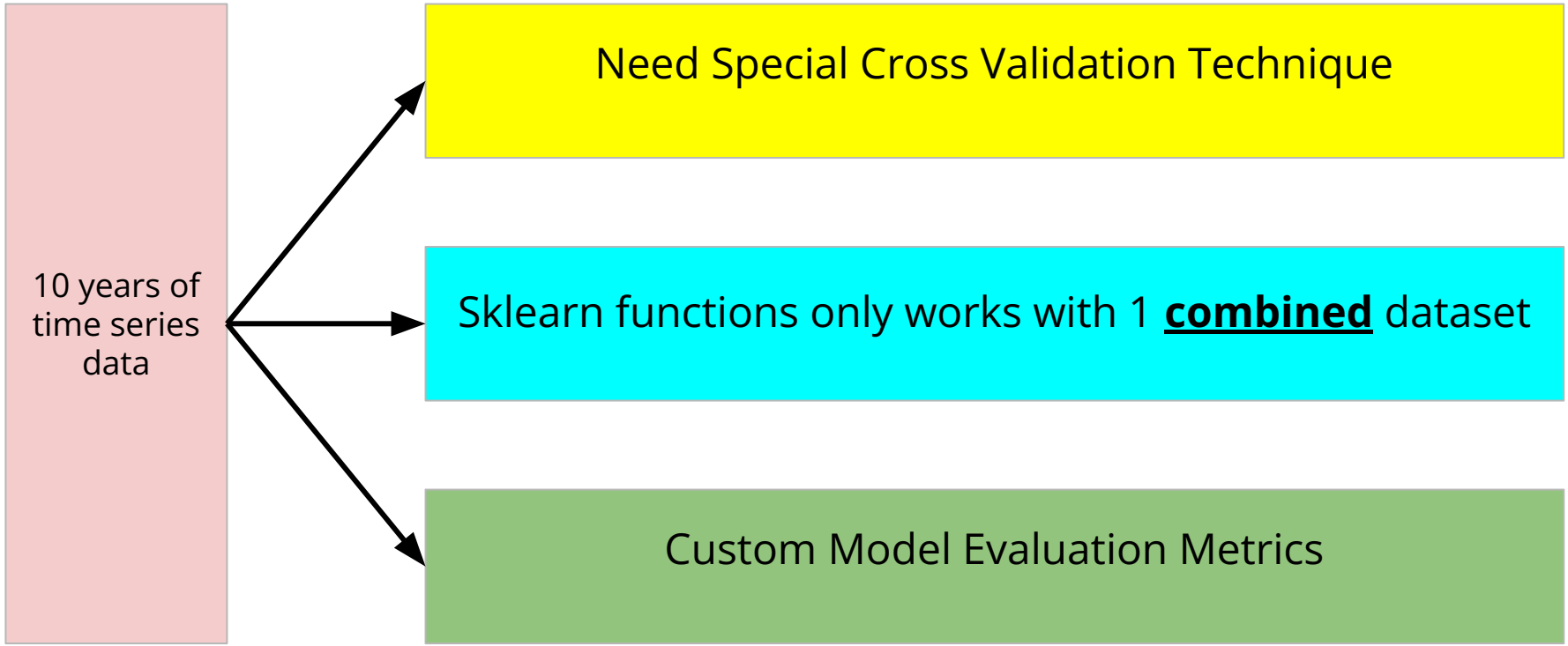
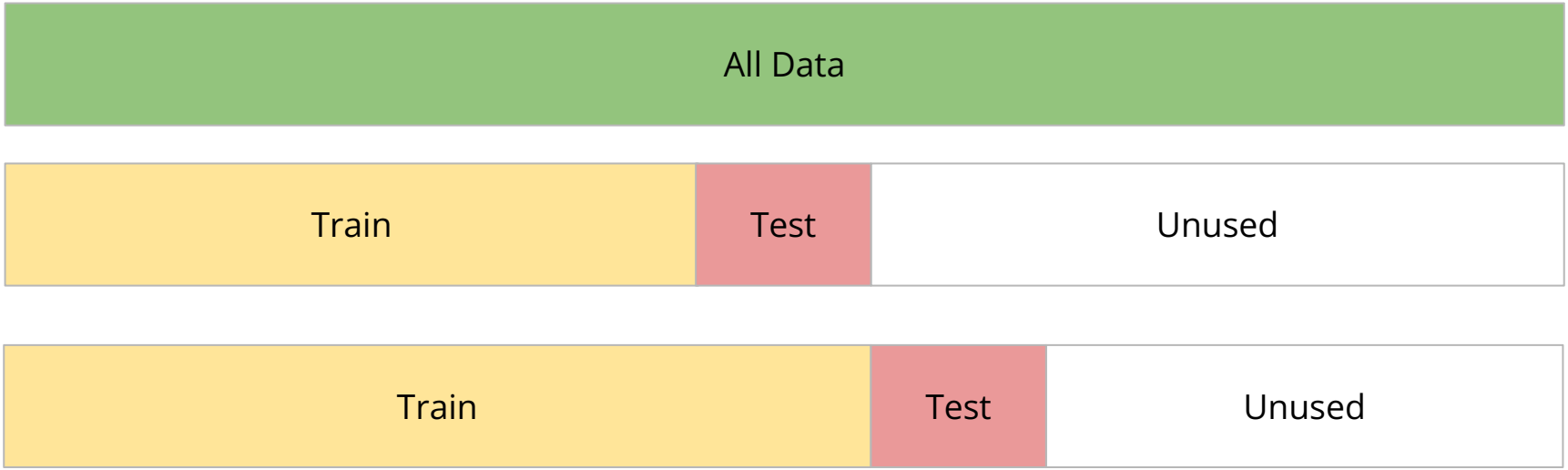
What makes our project special?

Project Specific Challenges - The Data



Time Series Cross Validation



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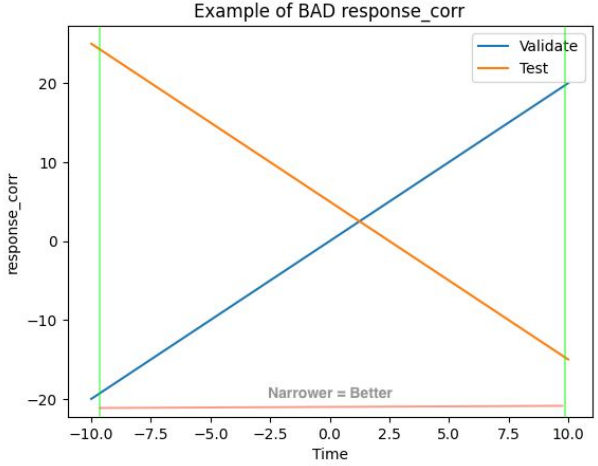
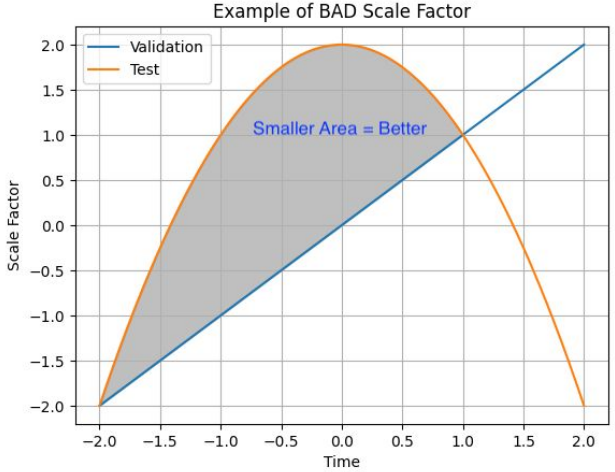
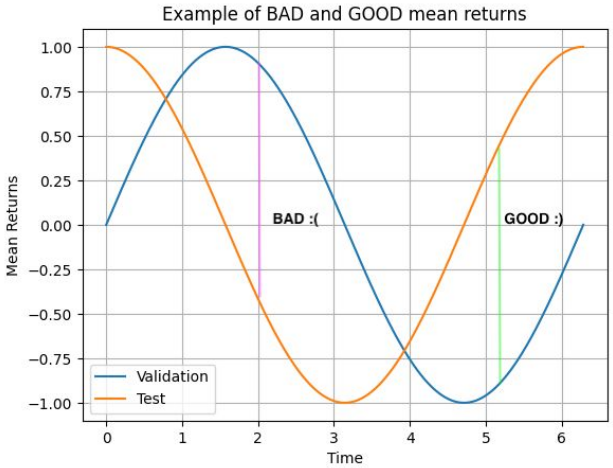
Evaluation Metrics

Customized Evaluation Metrics

- Response Correlation
  - Correlation between predicted and actual y
- Scale Factor
  - How much we need to multiple our prediction to match actual
- Mean Return: `np.mean(np.abs(actual_y) * (np.sign(actual_y) * np.sign(predicted_y)))`
  - How much money we gained







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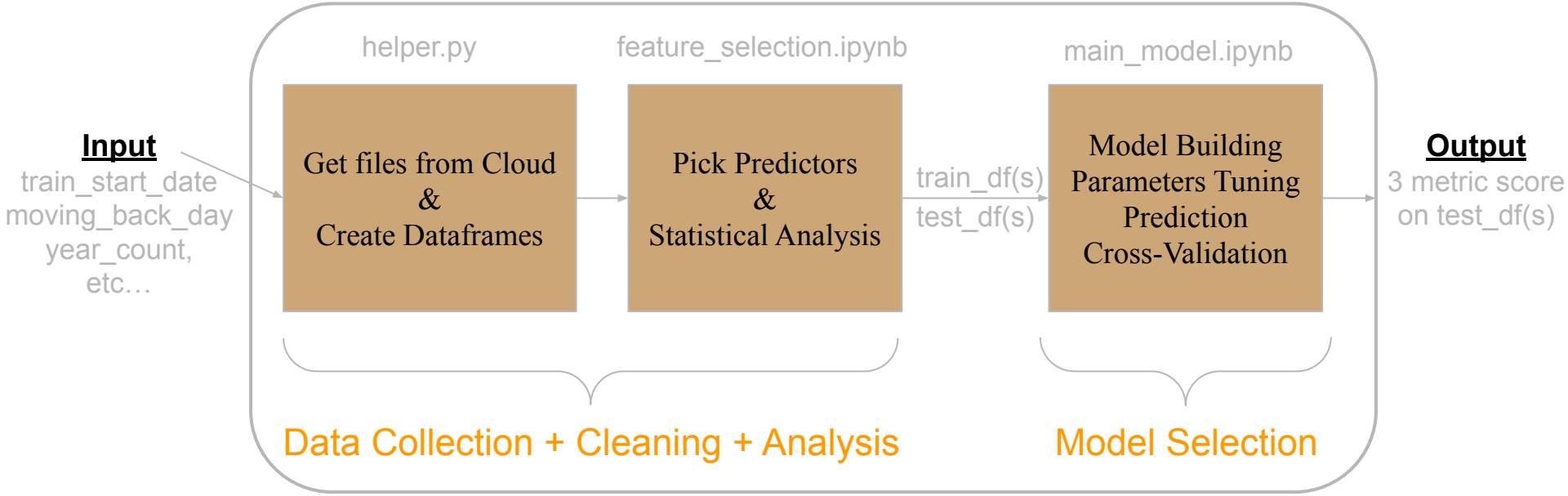
The Codebase

Automation

A pipeline for running experiments

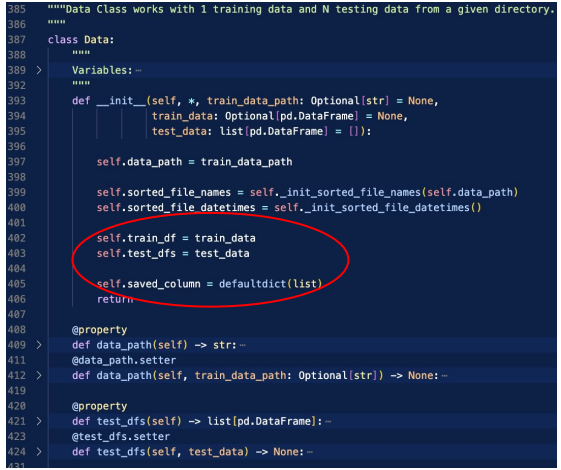


Black Box (require ideas)

Object-Oriented Design

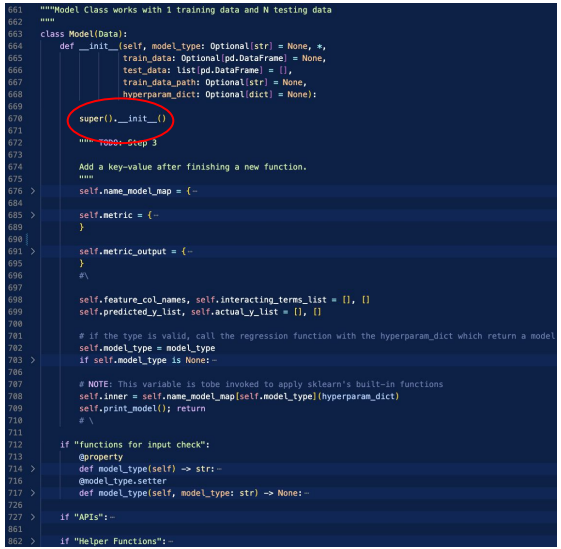
```
func extract_features_to_file
func stepwise_selection
func hypothesis_test_features
func scatter_lot
func histogram
func boxplot
func classification_validation_...
func validation_plot
class Data
class Model
```

Helper EcoSystem



```
"""Data Class works with 1 training data and N testing data from a given directory.
"""
class Data:
    """
    Variables:…
    """
    def __init__(self, *, train_data_path: Optional[str] = None,
                          train_data: Optional[pd.DataFrame] = None,
                          test_data: list[pd.DataFrame] = []):

        self.data_path = train_data_path

        self.sorted_file_names = self._init_sorted_file_names(self.data_path)
        self.sorted_file_datetimes = self._init_sorted_file_datetimes()

        self.train_df = train_data
        self.test_dfs = test_data

        self.saved_column = defaultdict(list)
        return

    @property
    def data_path(self) -> str:…
    @data_path.setter
    def data_path(self, train_data_path: Optional[str]) -> None:…

    @property
    def test_dfs(self) -> list[pd.DataFrame]:…
    @test_dfs.setter
    def test_dfs(self, test_data) -> None:…
```

Data Class
(272 lines)



```
"""Model Class works with 1 training data and N testing data
"""
class Model(Data):
    def __init__(self, model_type: Optional[str] = None, *,
                       train_data: Optional[pd.DataFrame] = None,
                       test_data: list[pd.DataFrame] = [],
                       train_data_path: Optional[str] = None,
                       hyperparam_dict: Optional[dict] = None):

        super().__init__()

        """ TODO: Step 3

        Add a key-value after finishing a new function.
        """
        self.name_model_map = {…

        self.metric = {…
        }

        self.metric_output = {…
        }
        #\

        self.feature_col_names, self.interacting_terms_list = [], []
        self.predicted_y_list, self.actual_y_list = [], []

        # if the type is valid, call the regression function with the hyperparam_dict which return a model
        self.model_type = model_type
        if self.model_type is None:…

        # NOTE: This variable is tobe invoked to apply sklearn's built-in functions
        self.inner = self.name_model_map[self.model_type](hyperparam_dict)
        self.print_model(); return
        # \

    if "functions for input check":
        @property
        def model_type(self) -> str:…
        @model_type.setter
        def model_type(self, model_type: str) -> None:…

    if "APIs":…

    if "Helper Functions":…
```

Model Class
(376 lines) - inherit Data

- Saves data in data objects:
  => Easy to test and build new models using saved data
  => Easy to add new data files to trained model

Example Experiment

```
if "Real-time, Continuous Development":
    importlib.reload(helper)

if "Init Model":
    model1 = helper.Model(f"{model_name}", hyperparam_dict = my_hyperparam_dict)

if "Train":
    model1.train(data_instance.train_df, feature_col_names=FEATURES)

if "Test":
    model1.test(data_instance.test_dfs)

if "Validate":
    helper.validation_plot(data_instance, model1, 10, TEST_DATE,
                           train_data_count= 30, data_path=FILE_PATH,
                           forward_dayCount = 15, features = FEATURES)
```

Pipeline: initialize custom model → predict (train) → test → validate

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Data and Strategies

Explore Data

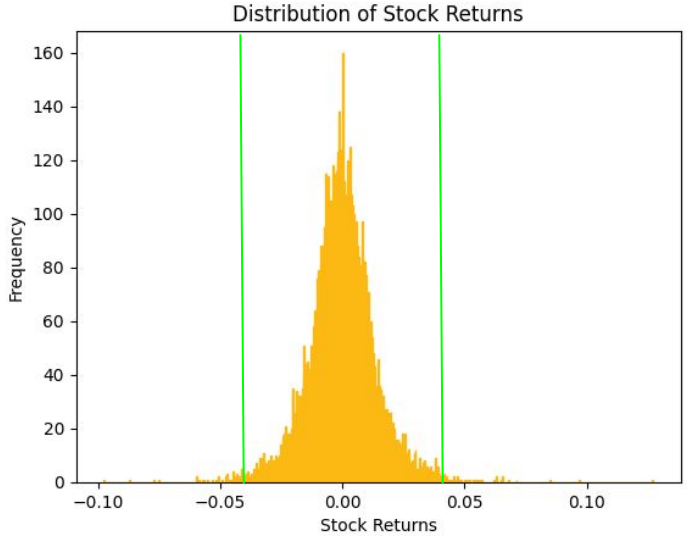
=> Target / Response Variable = 1-day stock returns (date randomly chosen).

1. **0** null values and all data is type **float**.
2. **Removed** duplicate observations and features = linear combination of others.

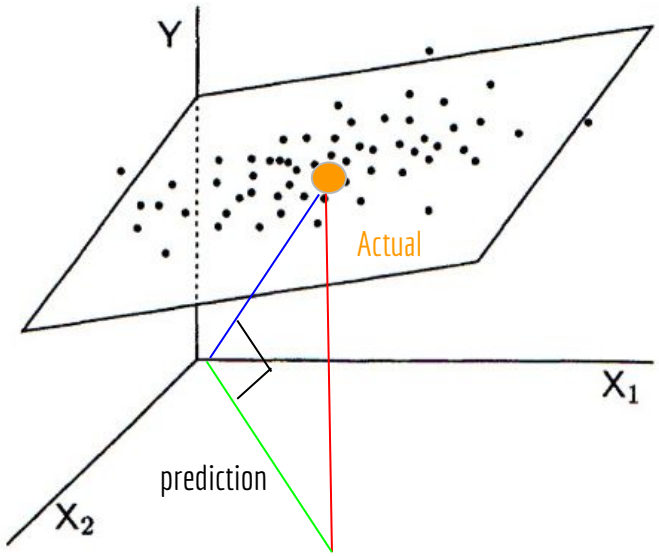
Interesting facts :)

a. -1 <= Stock Returns <= 1
b. Stock Returns ~ Normal(mean = 0)
c. Low Standard Deviation

```
Standard Deviation of Training Data: tonight    0.0138
dtype: float64
Standard Deviation of Testing Data: tonight     0.01479
dtype: float64
```



Strategy 1: With *all* features, Stock Returns follows the same path



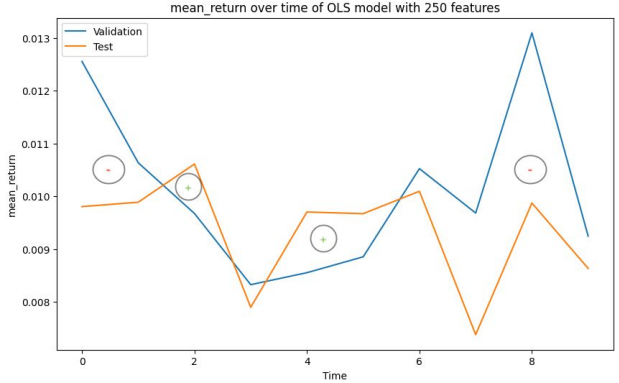
X_1	X_2
2	27

Linear Regression

Objective: Mean Squared Error

$$\text{Predicted Stock Return } = X(X^T X)^{-1} X^T \times (\text{Actual Stock Return})$$

Strategy 1 (continued): analysis for next steps



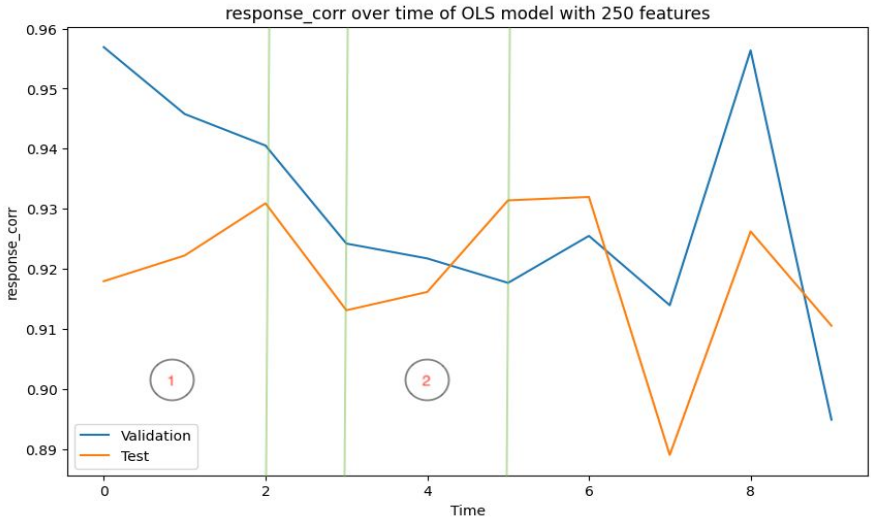
=> Overfit (response_corr, scale_factor)

Underfit (mean_returns)

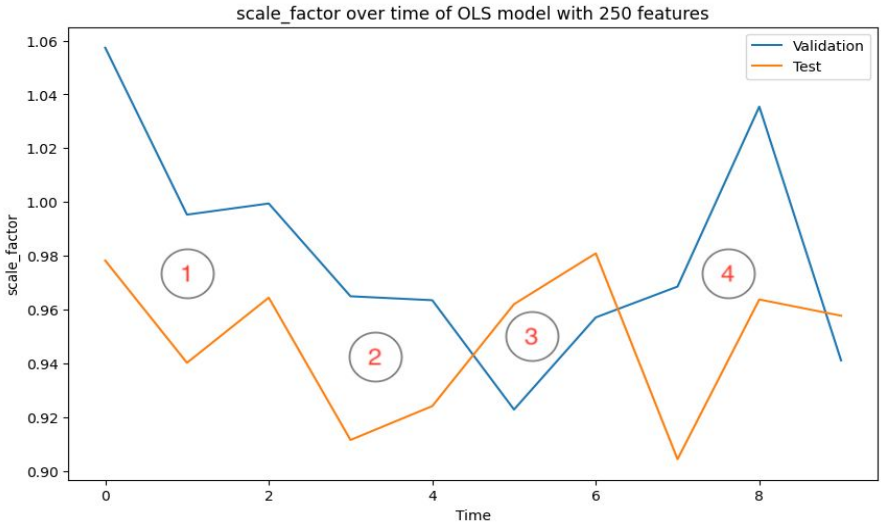
Strategy 2: Reduce features, then apply **Strategy 1**

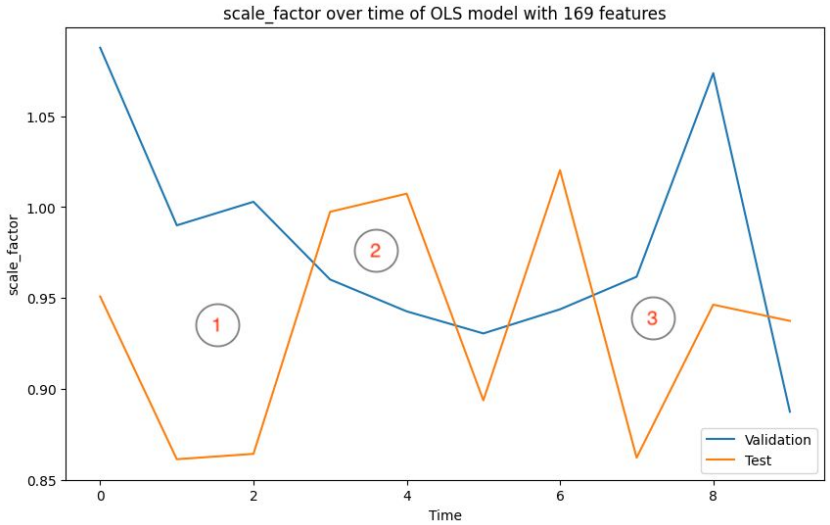
"Raise the bar": set higher objective => filter weaker features out.

- Objective: minimize **MSE** + $(0 \leq \alpha \leq 1) \times \sum_{\text{feature}} \|\beta_{i \in \{1,2,\ldots,n\}}\|$



Strategy 2 (continued): Output and Insights



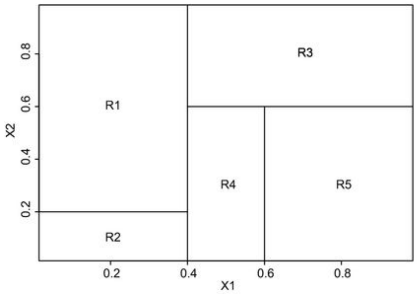


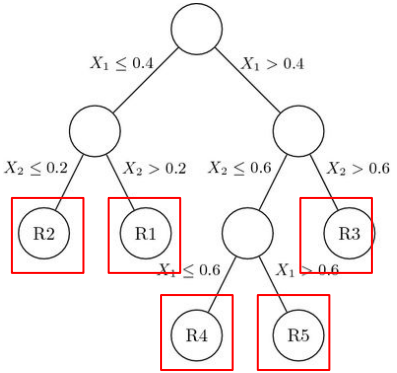
1. “Raise the bar” **reduces** accuracy when predicting **value**(stock return)
2. “Raise the bar” **improves** accuracy when predicting **sign**(stock return)
3. There exists observations that make the stock return **switch direction**.

Strategy 3: Divide and Conquer

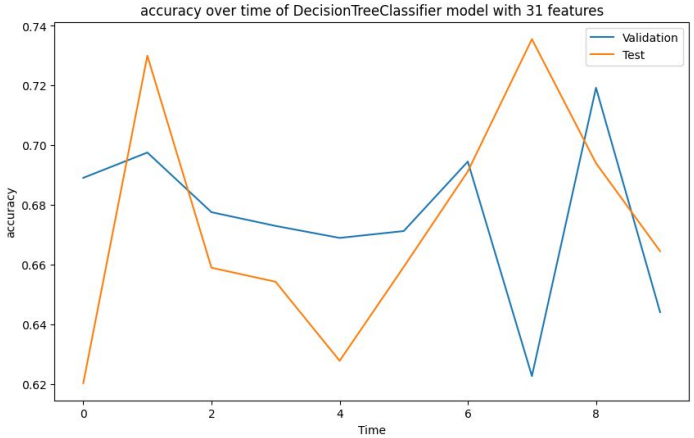
- (3) => **FORGET** features, **FOCUS ON** observations to find its **limit point**.
- Observation limit point = decision tree split point :
  => after this observation, the direction of Stock Returns changes.

- (2) => Predicting label accurately first => Objective: > 50% correct
  1. Transformed (temporarily) response to {-1, 0, 1}
  2. Find "limit observations" that the label changes
     3. For all observations:
        a. Assign it = "observation limit point",
        b. Build Classification Tree to the fullest based on *mean_allChild(Ratio(Correct, Total)^2) > 0.5*
        c. **"Raise The Bar"** with alpha from 0.01 to 1 => pruning
  4. Transfer hyperparameters to Prediction Tree, then apply **Strategy 1**
     => General Stepwise Additive Model. Or just Boosting Tree!






```
kwarg1 = {"random_state": 0,
          "booster": "gbtree",
          "reg_lambda": hyperparam_dict["ccp_alpha"],
          "max_depth": hyperparam_dict["max_depth"],
          "max_leaves": hyperparam_dict["max_leaf_nodes"],
          "random_state": hyperparam_dict["random_state"],
          "eval_metric": sklearn.metrics.mean_absolute_error,
          "learning_rate": 0.01, # cuz hyperparam_dict["ccp_alpha"] has 2 decimals
          }
model1 = helper.Model("XGBoost", hyperparam_dict = kwarg1)
model1.train(boost_data.train_df, feature_col_names = FEATURES)
model1.test(boost_data.test_dfs)
```



Strategy 3 (continued): Optimization

First Experiment:

```
helper.validation_plot(rf_regression_data, model3, 10, TEST_
                                    data_path=FILE_PATH, forward_dayCount
✓ 117m 4.7s
```

1. Function TreeBuilding(data, features, alpha)
   For all observations (*):
   - Pick that observation as the “observation limit”
   - **Build Classification Tree to the fullest**

   => Recursion to (*) => exponential runtime.
   => DFS with memoization:
   => Time Complexity = (MaxTree Size x No. observations)

2. During Cross Validation: Time Complexity = TreeBuilding x No. CV

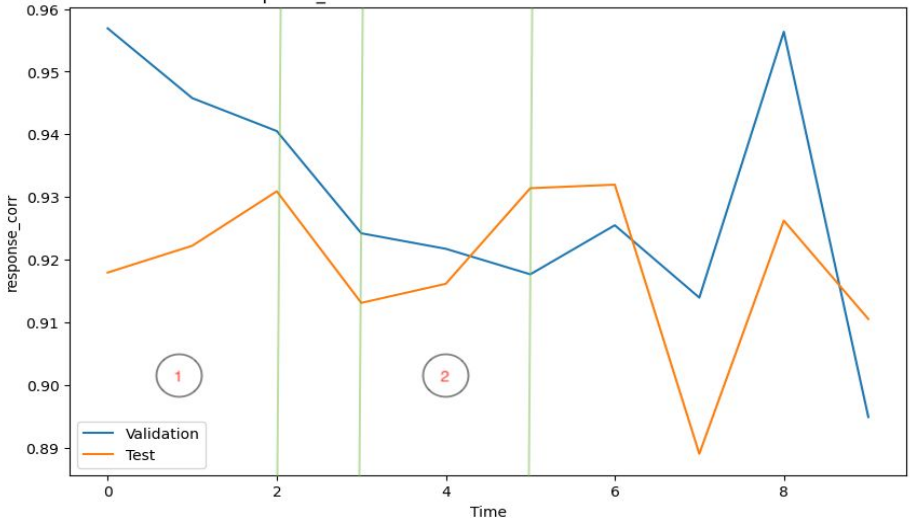
+ **OOP** + **Deque(**test_dfs**) =>** Amortized (TreeBuilding) runtime

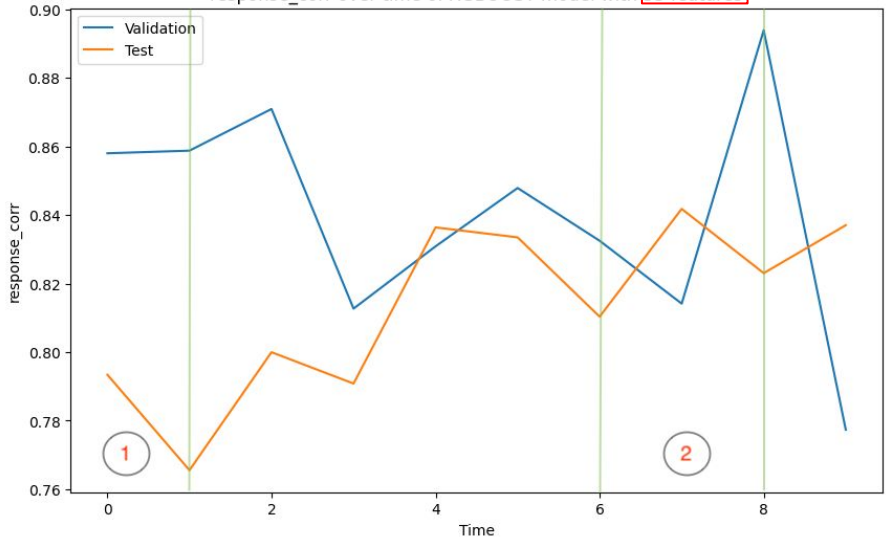
```
def optimized_tree_building(data, features, alpha):

    clf = Model('DecisionTreeClassifier')
    clf.train(data.train_df, feature_col_names=features)
    clf.test(data.test_dfs)

    costs = [0] * n_nodes; pruned = [False] * n_nodes

    if "Expand the Tree until New loss > Old loss":…

    if "The cost of the root is the total cost of the tree at index 0":

    if "Prune the tree by setting the children of pruned nodes to -1":…
```

```
filtered_features = filter_features(FEATURES, feature_important_scores)
helper.validation_plot(rf_data, transform_func, model2, 10, TEST_DATE, train_data_count= 30,
                       data_path=FILE_PATH, forward_dayCount = 15, features = filtered_features)
✓ 3m 44.0s
```

Strategy 3: Output

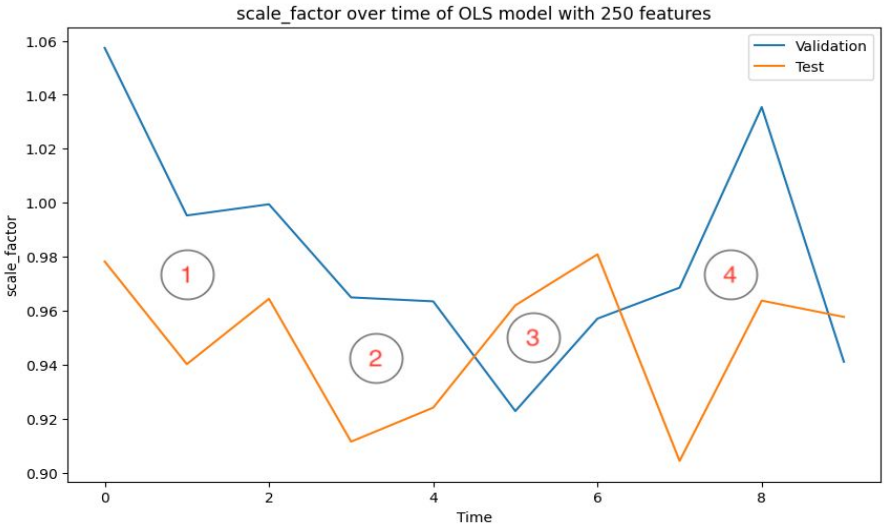
1. Response Correlation (how consistent is our price movement prediction)

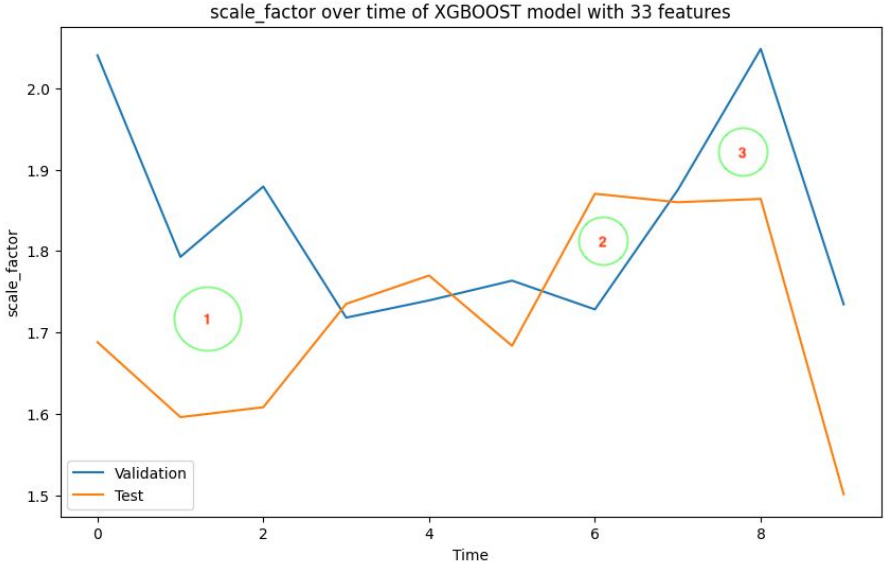




Strategy 3: Output

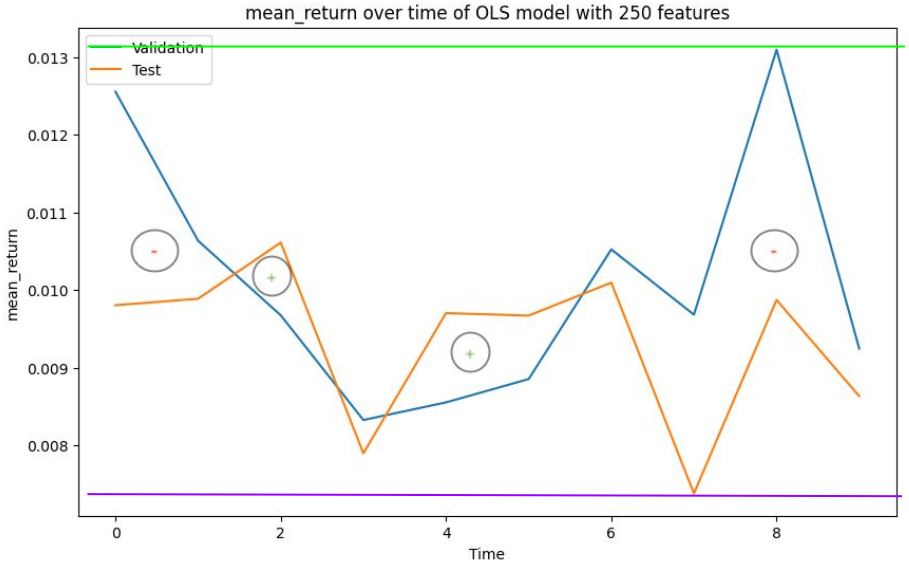
2. Scale Factor (how over-scaled / under-scaled is our predicted price)

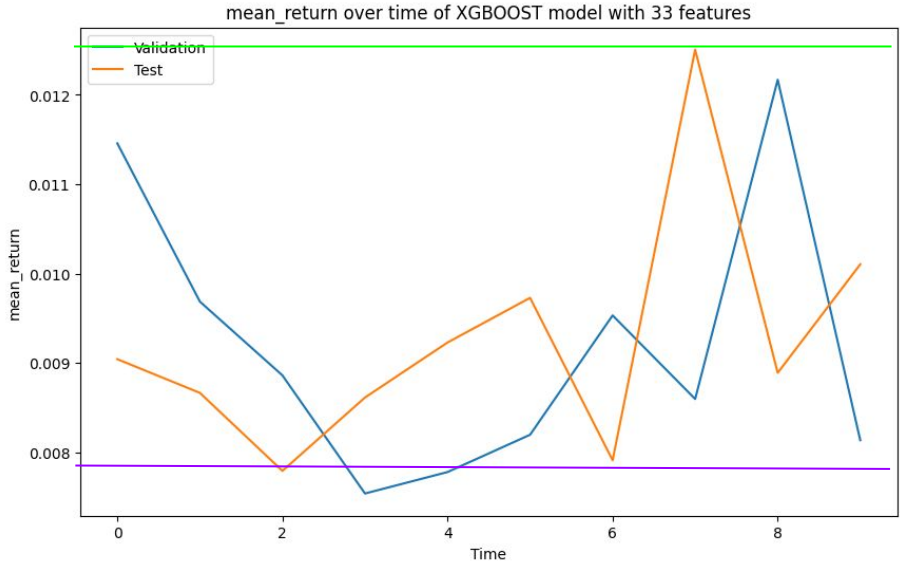




Strategy 3: Output

3. Mean Returns (what will be our relative percentage profit if we put money in?)

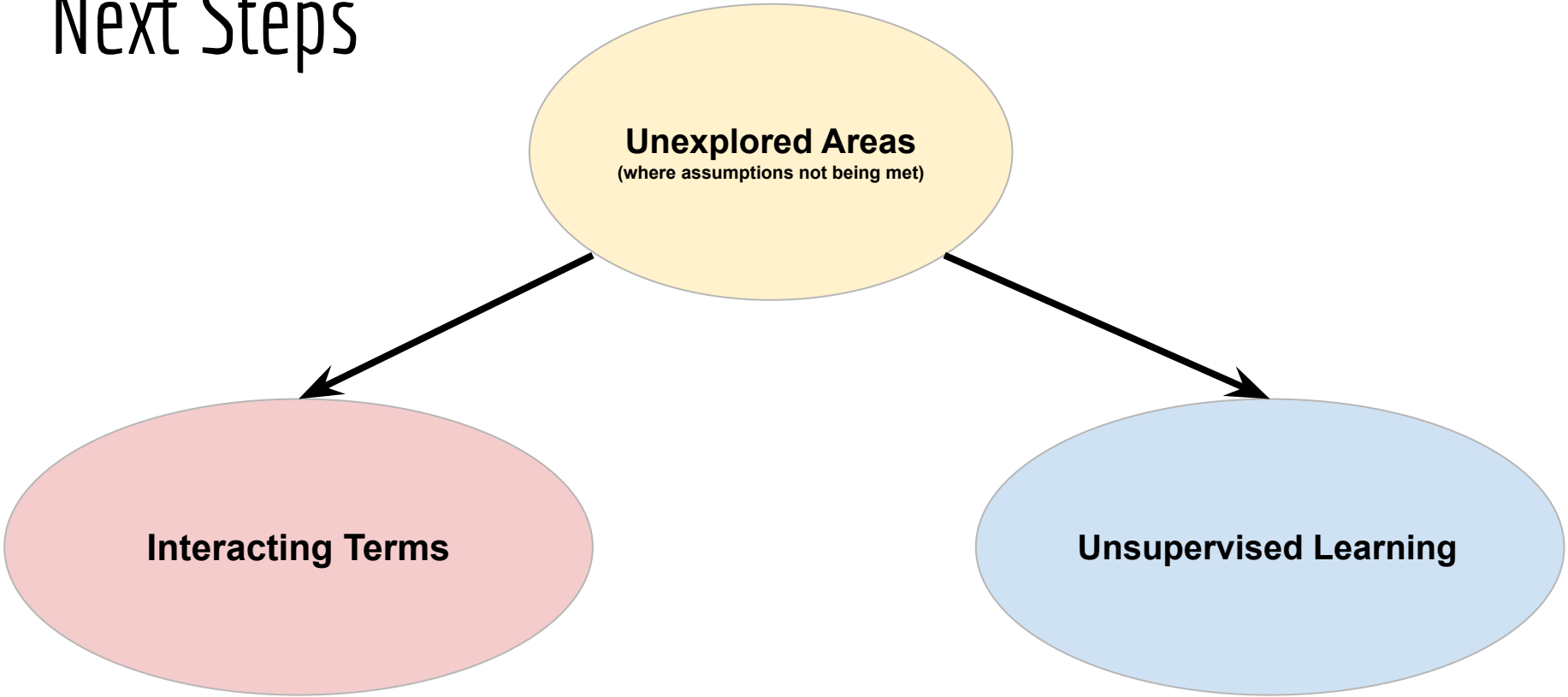




=> Solved Overfitting and Partially Solved Underfitting

Next Steps

Next Steps


Unexplored Areas
(where assumptions not being met)
Interacting Terms
Unsupervised Learning

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Thank you for listening!