AWS Machine Learning Engineer Nanodegree - Project Report

Definition

Project Overview

Student provides a high-level overview of the project in layman's terms. Background information such as the problem domain, the project origin, and related data sets or input data is given.

Refer to `proposal.md` or proposal.pdf in this repo.

Problem Statement

The problem which needs to be solved is clearly defined. A strategy for solving the problem, including discussion of the expected solution, has been made.

Refer to `proposal.md` or proposal.pdf in this repo.

Metrics

Metrics used to measure the performance of a model or result are clearly defined. Metrics are justified based on the characteristics of the problem.

Refer to `proposal.md` or `proposal.pdf` in this repo. Subsequent research into timeseries problems and based on the Amazon Forecast service, I will pursue different metrics for success. As explained in the developer documentation, the following evaluation metrics will be available:

```
Amazon Forecast produces accuracy metrics to evaluate predictors and help
you choose which to use to generate forecasts. Forecast evaluates
predictors using Root Mean Square Error (RMSE), Weighted Quantile Loss
(wQL), Mean Absolute Percentage Error (MAPE), Mean Absolute Scaled Error
(MASE), and Weighted Absolute Percentage Error (WAPE) metrics.

Amazon Forecast uses backtesting to tune parameters and produce accuracy
metrics. During backtesting, Forecast automatically splits your time-
series data into two sets: a training set and a testing set. The training
set is used to train a model and generate forecasts for data points within
the testing set. Forecast evaluates the model's accuracy by comparing
forecasted values with observed values in the testing set.

Forecast enables you to evaluate predictors using different forecast
types, which can be a set of quantile forecasts and the mean forecast. The
mean forecast provides a point estimate, whereas quantile forecasts
typically provide a range of possible outcomes.
```

I will examine all of the above, in particular the Weighted Quantile Loss (wQL). This is because this type of evaluation metrics allows us to incorporate different penalty (weights) to under and over-prediction of different quantiles. As discussed in the `proposal.md`, the cost of a false negative is expected to be greater than the cost of a false positive. Therefore we would rather the model predict a higher probability of inclusion into the exchange's watchlist than lower. Hence we will look at a higher percentile for each forecast, such as P90 or higher. In evaluation we will be focused on the respective wQL, e.g. wQL[90].

Analysis

Data Exploration

If a dataset is present, features and calculated statistics relevant to the problem have been reported and discussed, along with a sampling of the data. In lieu of a dataset, a thorough description of the input space or input data has been made. Abnormalities or characteristics of the data or input that need to be addressed have been identified.

The full dataset for each table has been provided in the directory `use_this_data`, as well as a few sample rows of data for each data table. Aggregate statistics and a description of the data is provided in `proposal.md`, but in summary the data covers related timeseries for the full universe (approximately 1000 stocks) listed on the Taiwan Stock Exchange, from 1/1/2022 to 10/31/2022.

Exploratory Visualization

A visualization has been provided that summarizes or extracts a relevant characteristic or feature about the dataset or input data with thorough discussion. Visual cues are clearly defined.

Null values were identified withing the notebook `01-EDA.ipynb`. Some are quite expected, in particular short sales volumes, and the watchlist (target) files, as clearly only a small subset of stocks are on the watchlist on any given day. Due to time constraints, further visual EDA has been forgone.

Algorithms and Techniques

Algorithms and techniques used in the project are thoroughly discussed and properly justified based on the characteristics of the problem.

Based on the documentation from Forecast, the algorithm will train the best predictor among several options. In particular for cases where many related timeseries (e.g. multliple SKUs for a retailer, or in our case multiple stocks on an exchange) whose behavior may have explanatory impact on the other timeseries, deep learning algorithms can be brought to bear to take advantage of this. Amazon's own DeepAR+ and CNN-QR algorithms are used for predicting product demand on Amazon.com, for example. Additionally, both static (non time-varying) item metadata as well as time-varying "related" data sets can be uploaded to Forecast. For example, weather data. In our case we will upload the watchlist data as the target timeseries and the closing price, short sales, p/b, p/e, and volumes data as related data frames.

According to AWS's description here https://aws.amazon.com/forecast/features/:

```
Amazon Forecast uses machine learning (ML) to generate more accurate
demand forecasts with just a few clicks, without requiring any prior ML
```

```
experience. Amazon Forecast includes algorithms that are based on over
twenty years of forecasting experience and developed expertise used by
Amazon.com bringing the same technology used at Amazon to developers as a
fully managed service, removing the need to manage resources. Amazon
Forecast uses ML to learn not only the best algorithm for each item, but
the best ensemble of algorithms for each item, automatically creating the
best model for your data.
```

Additionally, Forecast can be instructed to handle missing values with various strategies. We will discuss that later on.

Benchmark

Student clearly defines a benchmark result or threshold for comparing performances of solutions obtained.

There is no proper benchmark available. The baseline for the front office is to assume that a stock is not on the watchlist until the watchlist is received the following day.

Methodology

Data Preprocessing

All preprocessing steps have been clearly documented. Abnormalities or characteristics of the data or input that needed to be addressed have been corrected. If no data preprocessing is necessary, it has been clearly justified.

Data was first obtained by downloading from the website as discssed in `proposal.md`. Additional preprocessing was completed in the notebook `twse-scraper.ipynb`:

- The dataset `stockquotes` required parsing specific lines within a summary file downloaded on a daily basis.
- As can be seen in the `info` dictionary, for each dataset, the needed columns, data types, and lines to skip at the top or bottom were defined.
- I had issues with non utf-8 encoded characters which I dealt with by replacing them using the pandas function `read_csv`.
- I concatendated daily files for around 200 days or so into a single pandas dataframe, creating a new column called 'file_date' to indicate which file/date the data was from.
- The Security Code column was not clean so I cleaned it using a regular expression.
- The dataframes were saved as .parquet files.

This data was uploaded to the repository, and subsequently I took additional steps within `01-EDA.ipynb`:

- I ensured a common datetime index of the same length for all data, and exported 4 .parquet files for upload into Amazon Forecast.
- I will deal with missing values direclty in the Forecast api calls.

Implementation

The process for which metrics, algorithms, and techniques were implemented with the given datasets or input data has been thoroughly documented. Complications that occurred during the coding process are discussed.

For general guidance I am refering to the cheatsheet here: https://github.com/aws-samples/amazon-forecast-samples/blob/master/ForecastCheatSheet.md#tutorial :

Iterating Models and What-if Best Practices

```
Sequentially experiment. It may be tempting to run many experiments in
parallel at the same time. But this will prevent you from learning from
previous jobs, and in the process, you may miss an experiment that would
have worked.

As you experiment, it is best to keep the same Quantile choices. This is
why it is crucial to clarify the Business Requirements up front.
Recommended metrics to determine winning experiments are:

1. Lowest average over all wQLs.  If tie, then:
2. Lowest WAPE.  If tie, then:
3. Lowest RMSE.
As a developer or Business leader, here you need to think a little bit
like a Data Scientist. A good model, quite often, does not happen on the
first try. Machine learning models are only as good as the data put into
them, so the data itself very likely may need improvement.

As mentioned in Step 16, the best strategy is to:

start simple with just historical data (TTS) and AutoML. From there, you
will find out which is the best algorithm for your data.
For all future experiments, stick to this same algorithm, then use
HPO=True. AutoML mode did a light HPO, to verify which algorithm is best,
but the parameter optimization is not as deep as explicitly setting HPO
toggled on for a single algorithm.
Finally, when you have finished iterating, use the fixed algorithm and
fixed Training Parameters from the last HPO Predictor.
Iterating and scaling to value. Unlike Machine Learning Competitions, real
life POCs are not about "highest accuracy at any cost". In real life,
there is often a balance to think about: Accuracy, Scaleability, Effort.
Since human time is expensive, there might be other activities of more
value than trying to get the utmost extra amounts of accuracy out of
Forecast models.
```

Refinement

The process of improving upon the algorithms and techniques used is clearly documented. Both the initial and final solutions are reported, along with intermediate solutions, if necessary.

For all experiments, I will use a combination of the AWS console and Python SDK. I am choosing to use Auto Predictors, rather than the legacy predictors in Forecast. All code related to training predictors and other api calls to Amazon Forecast can be found in the notebook `02-Forecasting.ipynb`

Per AWS:

```
AutoPredictor is the default and preferred method to create a predictor
with Amazon Forecast. AutoPredictor creates predictors by applying the
optimal combination of algorithms for each time series in your dataset.

Predictors created with AutoPredictor are generally more accurate than
predictors created with AutoML or manual selection. The Forecast
Explainability and predictor retraining features are only available for
predictors created with AutoPredictor.
```

The process I am following is as follows:

- Experiment 01: Train a predictor on target (watchlist) data only. Review accuracy metrics and forecasts.
- Experiment 02: Update the target (watchlist) dataset so that each stock's timeseries reflects a value of zero for non-weekends if the stock is not on the watch list, value of 1 if it is on the watchlist, and missing values for weekends. Upload related datasets of closing prices, trade volumes, short sales volumes, p/e ratios, p/b ratios, and train new predictor. Evaluate accuracy.
- Experiment 03: If time allows, upload related dataset for Taiwan stock exchange holidays (need to obtain this data)
- Experiment 04: If time allows, upload shares outstanding item metadata (need to obtain from website), and train new predictor. Evaluate acuracy.

Experiment 01

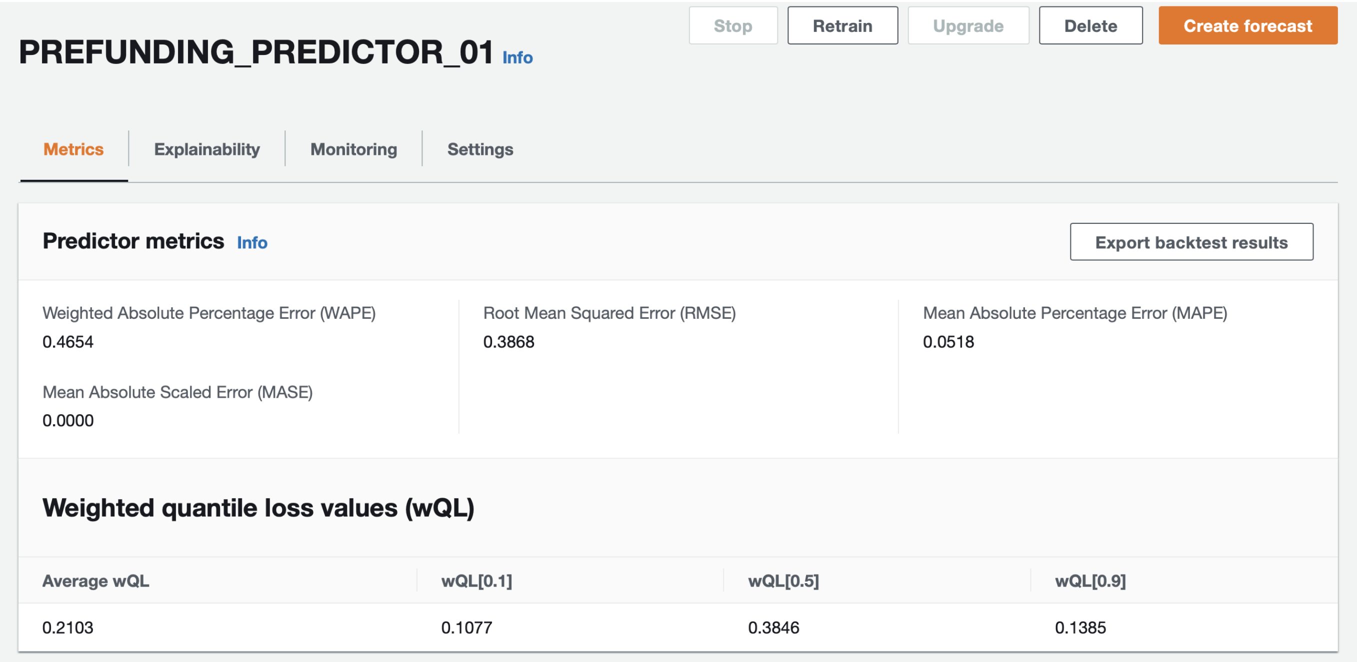
For my first experiment, per the best practices given above by AWS, I decided to start by creating a predictor on the target timeseries (watchlist) only. This will help determine the best algorithm to use in Forecast which I will likely stick with.

I had to go back and format the exported data within `forecast_import` directory, because Forecast expects only 3 columns and no index : `item_id`, `timestamp`, and `target_value`. After doing that I also tried to indicate Taiwan holiday calendar but this wasn't an available choice within the Forecast API, despite there being 66 countries. China wasn't available either. Per the exhange website, the holiday calendar includes unique holidays such as Chinese New Year, Children's day, and Mid-Autumn/Moon Festival, among others. In a future experiment, according to AWS documentation, we can account for custom holidays through a related timeseries data import in Forecast. Lack of this related data could affect accuracy because watch list data will reflect missing but this is only due to a holiday, rather than other features.

The featurizations used for Experiment-01 are listed below. Back and middle fill are appropriate for the target timeseries, as the null values for the watchlist are either due to weekends, holidays, or due to being not on the watchlist. Note that we will consider re-processing the watchlist dataset because it was constructed with nulls for all 3 instances (weekends, holidays, or not on watchlist), when weekend and holidays should be missing but business days should be the value of zero:

```
    {
        "AttributeName": "target_value",
        "Transformations": {
            "aggregation": "sum",
            "backfill": "zero",
            "frontfill": "none",
            "middlefill": "zero"
        }
    }
```

For aggregation, the default by Forecast is sum. This applies when forecast frequency does not align to the target timeseries frequency. In our case they do align, so summation is not needed. For additional details, refer to docs at https://docs.aws.amazon.com/forecast/latest/dg/how-aggregation-works.html. For in depth on handling missing values in Forecast, see https://docs.aws.amazon.com/forecast/latest/dg/howitworks-missing-values.html.




```
Weighted Quantile Loss (wQL): [
  {
    "Quantile": 0.9,
    "LossValue": 0.13846153846153844
  },
  {
    "Quantile": 0.5,
    "LossValue": 0.38461538461538464
  },
  {
    "Quantile": 0.1,
```

```
    "LossValue": 0.10769230769230768
  }
]
Root Mean Square Error (RMSE): 0.38682272190477407
Weighted Absolute Percentage Error (WAPE): 0.4653846153846153
Mean Absolute Percentage Error (MAPE): 0.051818181818181826
Mean Absolute Scaled Error (MASE): 1e-130`
```

I generated a forecast using the AWS console but noticed that the full universe of stocks wasn't generated by the forecast. See below:

	item_id	date	p50	p90	p95
3	1213	2022-11-01T00:00:00Z	1.0	1.0	1.0
2	1418	2022-11-01T00:00:00Z	0.0	1.0	1.0
1	1472	2022-11-01T00:00:00Z	1.0	1.0	1.0
5	1512	2022-11-01T00:00:00Z	1.0	1.0	1.0
0	1538	2022-11-01T00:00:00Z	1.0	1.0	1.0
1	2025	2022-11-01T00:00:00Z	1.0	1.0	1.0
2	2321	2022-11-01T00:00:00Z	1.0	1.0	1.0
0	2364	2022-11-01T00:00:00Z	0.0	1.0	1.0
2	2443	2022-11-01T00:00:00Z	1.0	1.0	1.0
5	2841	2022-11-01T00:00:00Z	0.0	1.0	1.0
4	3018	2022-11-01T00:00:00Z	1.0	1.0	1.0
0	3043	2022-11-01T00:00:00Z	1.0	1.0	1.0
3	3229	2022-11-01T00:00:00Z	1.0	1.0	1.0
4	3383	2022-11-01T00:00:00Z	1.0	1.0	1.0
0	3494	2022-11-01T00:00:00Z	0.0	1.0	1.0
3	3536	2022-11-01T00:00:00Z	1.0	1.0	1.0
1	4414	2022-11-01T00:00:00Z	0.0	1.0	1.0
4	6225	2022-11-01T00:00:00Z	1.0	1.0	1.0
2	6289	2022-11-01T00:00:00Z	1.0	1.0	1.0
4	8101	2022-11-01T00:00:00Z	1.0	1.0	1.0
1	9110	2022-11-01T00:00:00Z	1.0	1.0	1.0
3	9928	2022-11-01T00:00:00Z	1.0	1.0	1.0

2022/11/01 Full Delivery Securities

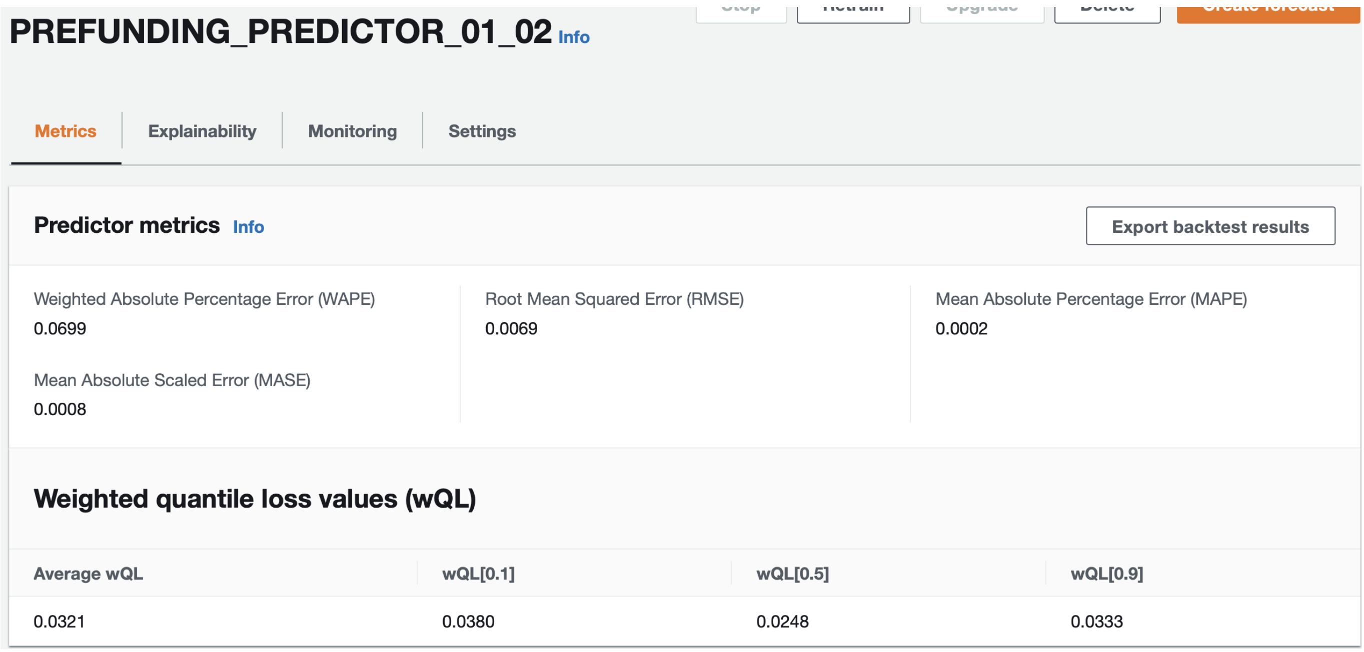
Security Code	Periodic Call Auction Trading
1213	
1472	
1512	**
1538	**
2025	
2321	**
2443	**
3018	
3043	**
3536	**
6225	**
8101	**
9110	

Calculating the recall based on this single forecast, using (TP / (TP + FN)), we get (13/(13+0)) = 100%. While this seems reassuring, we will proceed with further experimentation. For the front office, the P90 and P95 forecasts would be of highest interest.

Experiment 01.2

For this experiment I trained a new predictor on updated watchlist data, and used a forecast horizon of 5 days instead of 1. The updated data relects the need as mentioned above to correctly show 0 value for days that a stock had trading and was on the exchange, but was not on the watchlist. Null values would mean weekends, holidays, and/or the stock began/ended trading on the exchange.

After training the predictor I see a marked improvement in the accuracy metrics:




```
Weighted Quantile Loss (wQL): [
  {
    "Quantile": 0.9,
    "LossValue": 0.033315385946153776
  },
  {
    "Quantile": 0.5,
    "LossValue": 0.024813485476922994
  },
  {
    "Quantile": 0.1,
    "LossValue": 0.038043852469230935
  }
]
Root Mean Square Error (RMSE): 0.0069419847508758
Weighted Absolute Percentage Error (WAPE): 0.06988694954358965
Mean Absolute Percentage Error (MAPE): 0.00024693699124686194
Mean Absolute Scaled Error (MASE): 0.0008089736696903767
```

While this solved the issue of missing stocks due to the fact that there are 1195 unique item ids in the forecast export results, we still are seeing null predictions. For example 1213 shows forecasts but not 1472. Lastly, the predictions are now float values as opposed to integer values. This may not present a problem but is something to note.

item_id	date	p10	p50	p90
1213	2022-11-01T00:00:00Z	0.988473	1.001231	1.014586
1213	2022-11-02T00:00:00Z	0.986222	0.998600	1.009422
1213	2022-11-03T00:00:00Z	0.988338	0.997103	1.017501
1213	2022-11-04T00:00:00Z	0.922382	0.977046	1.015014

item_id	date	p10	p50	p90
1213	2022-11-05T00:00:00Z	-0.000159	0.005434	0.011387
2443	2022-11-01T00:00:00Z	0.989733	1.000846	1.016798
2443	2022-11-02T00:00:00Z	0.985751	0.999528	1.012005
2443	2022-11-03T00:00:00Z	0.987436	0.996902	1.007511
2443	2022-11-04T00:00:00Z	0.928538	0.980124	1.031793
2443	2022-11-05T00:00:00Z	-0.000949	0.006161	0.010979
3018	2022-11-01T00:00:00Z	0.992192	1.001669	1.016343
3018	2022-11-02T00:00:00Z	0.984520	0.997037	1.006006
3018	2022-11-03T00:00:00Z	0.985697	0.998131	1.012007
3018	2022-11-04T00:00:00Z	0.930763	0.975058	1.017591
3018	2022-11-05T00:00:00Z	-0.000420	0.005498	0.010892
6225	2022-11-01T00:00:00Z	0.993162	1.002569	1.012899
6225	2022-11-02T00:00:00Z	0.988835	0.999504	1.010648
6225	2022-11-03T00:00:00Z	0.988166	0.998975	1.009758
6225	2022-11-04T00:00:00Z	0.941486	0.973283	1.022647
6225	2022-11-05T00:00:00Z	0.000745	0.006251	0.011074

If we calculate the recall for 11/1 at the p90 level, assuming that we round to the nearest integer, we would see (TP / (TP + FN)) = (4 / (4 + 0)) = 100%. However, if we continue to treat nulls as a prediction of 0, then the recall for 11/1 becomes (4/(4+9)) = 30.7%.

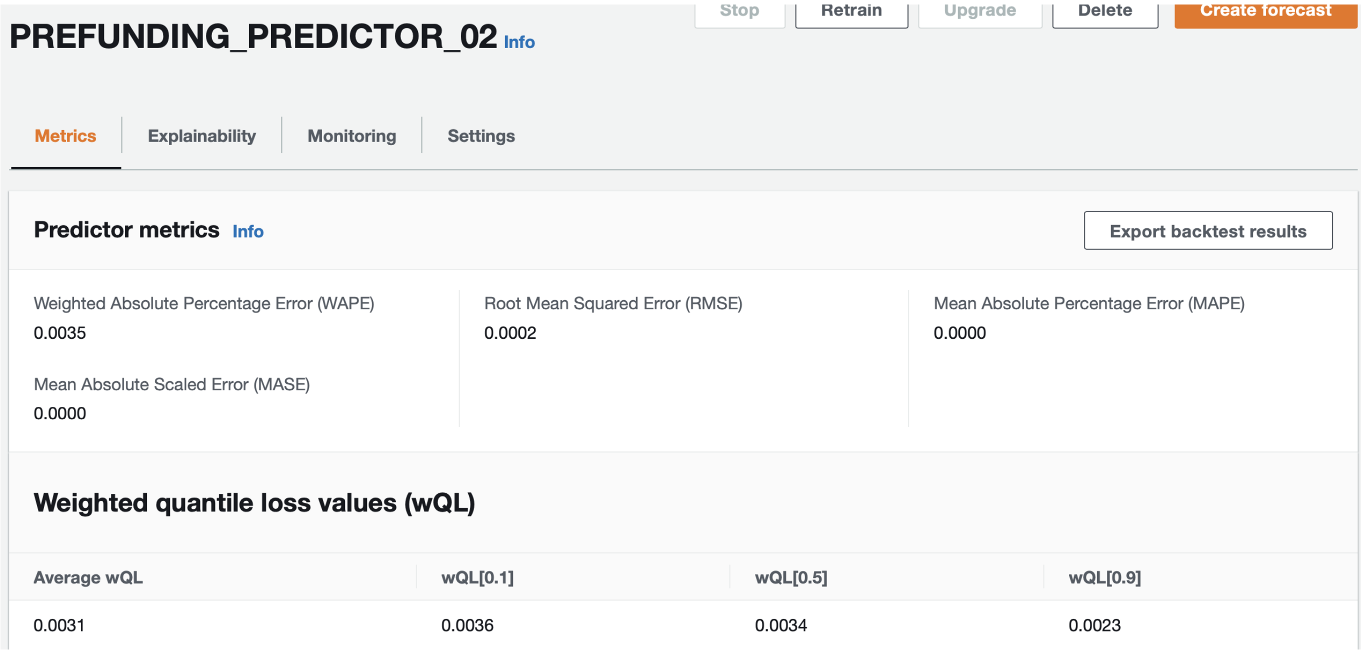
Experiment 02

For experiment 2, I will add a related dataset. This will include closing prices, trading volume, short trade volume, pe ratios, and pb ratios. In the terminology of Amazon Forecast, this will be a 'related timeseries' (RTS) that is "future-looking". See https://docs.aws.amazon.com/forecast/latest/dg/related-time-series-datasets.html for details. Additionally, there are requirements for these RTS datasets. One is that there can only be 1 RTS per dataset group, so I will include all columns mentioned in the same dataset. Second, RTS cannot have missing values. Forecast can handle missing values when creating a predictor through a 'FeaturizationPipeline' object (see https://docs.aws.amazon.com/forecast/latest/dg/howitworks-missing-values.html). Because there are missing values (notably the ratios features), we will either have to use pandas to fill these, or have them filled in Forecast. We have to specify the filling logic as there is no default in Forecast. Each column should be considered independently for the appropriate filling logic. In the case of trade volume and short sale volume, zero is an acceptable value and if the data was missing we will assume for the time being that the volume was zero. However for closing price and ratios, price would not be expected to be zero, so for missing ratios we will fill with 'mean' method, which takes the mean of the most recent 64 time periods before the missing value.

```
#count of nulls per column

item_id              0
timestamp            0
close_px          2961
pe_ratio         67127
pb_ratio         40955
trade_volume         0
ss_trading_vol   10356
```

After training the predictor I see further marked improvement in the accuracy metrics:




```
Weighted Quantile Loss (wQL): [
  {
    "Quantile": 0.9,
    "LossValue": 0.0023358869923076784
  },
  {
    "Quantile": 0.5,
    "LossValue": 0.003350276946153817
  },
  {
    "Quantile": 0.1,
    "LossValue": 0.0035952148061538505
  }
]
Root Mean Square Error (RMSE): 0.00019648022926739092
Weighted Absolute Percentage Error (WAPE): 0.00349125073846155
Mean Absolute Percentage Error (MAPE): 1.8640542092050313e-05
Mean Absolute Scaled Error (MASE): 1e-130
```

When I uploaded the target timseries I dropped the row of data for 10/31/2022, so that the related dataset would be "future-filled" with 10/31 data, simulating having the exchange's closing data on T for prices, volumes, etc. Since the prediction interval is 1 day, this would enable the algorithm to predict 10/31. Because 10/31 is a Monday, this left the latest timestamp in the watchlist timeseries to be Friday, 10/28. When running the prediction, Forecast provided a prediction for 10/29, which is Saturday. Saturday wouldn't be an actual trading day, and so we need to determine the best way to predict Monday's watchlist based on Friday's closing values. This will be a TODO item for future investigation. The forecasts were all very close to zero for the entire dataset, which is what we would expect on a weekend, but we just can't use that for trading purposes.

Results

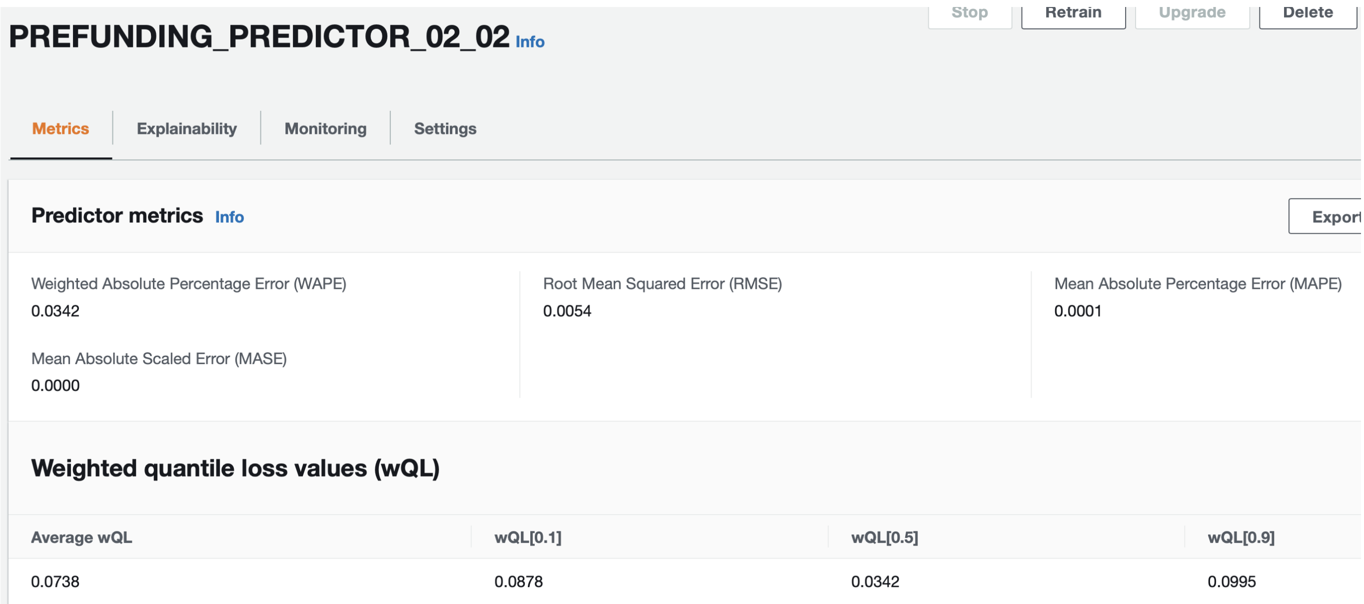
Model Evaluation and Validation

The final model's qualities—such as parameters—are evaluated in detail. Some type of analysis is used to validate the robustness of the model's solution.

Final Experiment 02-02

To remedy the above issues, I trained a predictor using watchlist data with 10/31/2022 and 10/28 dropped from the watchlist so that the latest target date will be Thursday 10/27. I will drop 10/31 from the rds dataset so that the latest rds data will be "future-filled" to 10/28.

After training the predictor I see a reduction in accuracy from experiment 01-02:




```
Weighted Quantile Loss (wQL): [
  {
    "Quantile": 0.9,
    "LossValue": 0.09947788085321617
  },
  {
    "Quantile": 0.5,
    "LossValue": 0.034191043409598214
```

```
    },
    {
      "Quantile": 0.1,
      "LossValue": 0.0878458818755974
    }
  ]
  Root Mean Square Error (RMSE): 0.005397236911839607
  Weighted Absolute Percentage Error (WAPE): 0.034191043409598214
  Mean Absolute Percentage Error (MAPE): 0.00014707609014489434
  Mean Absolute Scaled Error (MASE): 1e-130
```

Further investigation is needed to determine the cause. For example, using the explainability feature, we can see which factors may help explain the forecasts.

Actual list from 10/28:

	item_id	timestamp	target_value
233136	1213	2022-10-28 00:00:00	1.0
233220	1472	2022-10-28 00:00:00	1.0
233229	1512	2022-10-28 00:00:00	1.0
233252	1538	2022-10-28 00:00:00	1.0
233344	2025	2022-10-28 00:00:00	1.0
233395	2321	2022-10-28 00:00:00	1.0
233480	2443	2022-10-28 00:00:00	1.0
233659	3018	2022-10-28 00:00:00	1.0
233683	3043	2022-10-28 00:00:00	1.0
233746	3536	2022-10-28 00:00:00	1.0
233935	6225	2022-10-28 00:00:00	1.0
234031	8101	2022-10-28 00:00:00	1.0
234080	9110	2022-10-28 00:00:00	1.0

Showing the 1-day predictions for the 13 stocks that show up on the actual watchlist for 11/01/2022:

item_id	date	p10	p50	p90
1213	2022-10-28T00:00:00Z	0.647320	0.917718	1.188116
1472	2022-10-28T00:00:00Z	0.647320	0.917718	1.188116
1512	2022-10-28T00:00:00Z	0.647320	0.917718	1.188116
1538	2022-10-28T00:00:00Z	0.647320	0.917718	1.188116

item_id	date	p10	p50	p90
2025	2022-10-28T00:00:00Z	0.647320	0.917718	1.188116
2321	2022-10-28T00:00:00Z	0.647320	0.917718	1.188116
2443	2022-10-28T00:00:00Z	0.647320	0.917718	1.188116
3018	2022-10-28T00:00:00Z	0.754770	1.003360	1.251950
3043	2022-10-28T00:00:00Z	0.647320	0.917718	1.188116
3536	2022-10-28T00:00:00Z	0.647320	0.917718	1.188116
6225	2022-10-28T00:00:00Z	0.647320	0.917718	1.188116
8101	2022-10-28T00:00:00Z	0.602923	0.908494	1.214065
9110	2022-10-28T00:00:00Z	0.779972	1.012397	1.244822

Looking at the following distribution of p90 predictions for the stocks that were on the alert list, we get the following distribution:

```
count    13.000000
mean      1.199384
std       0.022937
min       1.188116
25%       1.188116
50%       1.188116
75%       1.188116
max       1.251950
Name: p90, dtype: float64
```

The distribution of p90 predictions for the stocks that were NOT on the watchlist is:

```
count    1182.000000
mean        0.002383
std         0.027927
min         0.000000
25%         0.000000
50%         0.000000
75%         0.000000
max         0.423319
Name: p90, dtype: float64
```

This suggests that if we were to take the rounded p90 value we would have matched the actual watch list for 10/28, which is would give a high recall.

The overall accuracy metrics have shown improvement since experiment 01, but they still lack a quality of communicability with business process owners. RMSE, or wQL can be explained but they do not convey the sense of classification accuracy that recall or sensitivity will.

Justificatiion

The final results are compared to the benchmark result or threshold with some type of statistical analysis. Justification is made as to whether the final model and solution is significant enough to have adequately solved the problem.

Despite limitations listed above, the results seem to be superior than a random guess or other naive benchmark.

As such, we would like to proprose possible future avenues of investigation:

- Train a standard binary classifier in sci-kit learn or other library, taking the approach of using features to encode lags, e.g. closing price 2,5,10 days ago, etc. Beginning with a logistic regression and proceeding from there, we can iteratively improve our understanding but from the beginning achieve better metrics which can be communicated to the business.
- Pursuing additional investigation within Amazon Forecast, we can upload item metadata such as float adjusted shares (to help differentiate large cap, small cap stocks, etc.), as well as generate additional related timeseries characteristics such as turnover. Lastly we could upload a custom RDS for Taiwan stock exchange holidays.

We aren't yet to the point of claiming a viable, operationalizable model to give to the business but are further along and have learned about available advanced machine learning services such as Amazon Forecast.