Milestone #:6

Implementing MLRATE

Estee Lauder 1B

01

Code Implementation

Implementing MLRATE

Code Implementation

```
# Step 0. Rename treatment column for consistency
df.rename(columns={'Group': 'treatment'}, inplace=True)

# Convert treatment to numeric (0 = Control, 1 = Treatment)
df['treatment'] = df['treatment'].map({'Control': 0, 'Treatment': 1})

#  Step 1. Define function for out-of-fold predictions
def out_of_fold_predict_baseline(X, y, model=None, n_splits=5):
    if model is None:
        model = RandomForestRegressor(n_estimators=200, random_state=42)

    oof_preds = np.zeros(len(X))
    kf = KFold(n_splits=n_splits, shuffle=True, random_state=42)

    for train_idx, val_idx in kf.split(X):
        X_train, X_val = X.iloc[train_idx], X.iloc[val_idx]
        y_train = y.iloc[train_idx]

        model.fit(X_train, y_train)
        oof_preds[val_idx] = model.predict(X_val)

    return oof_preds
```

Code Implementation

```
#  Step 2. Predict baseline (G(x))
T = df['treatment']  # treatment assignment (0 or 1)
y = df['revenue (t)']  # observed post-treatment outcome
X = df[['aov (t-1)', 'days_since_last_purchase (t-1)', 'tenure_in_days(t-1)', 'loyalty_membership']]  # pre-treatment features

g_hat = out_of_fold_predict_baseline(X, y)

#  Step 3. Center G(x)
g_bar = g_hat.mean()
g_centered = g_hat - g_bar

#  Step 4. Build regression design
X_reg_df = pd.DataFrame({
    'T': T,
    'g_hat': g_hat,
    'T * (g_hat - g_bar)': T * g_centered
})
X_reg_df = sm.add_constant(X_reg_df)
```

Code Implementation

```
#  Step 5. Fit MLRATE model
ols = sm.OLS(y, X_reg_df).fit(cov_type="HC0")

#  Step 6. Extract ATE results
ate = ols.params['T']
ci_lower, ci_upper = ols.conf_int().loc['T']

print(f"MLRATE ATE: {ate:.4f}")
print(f"95% CI: [{ci_lower:.4f}, {ci_upper:.4f}]")
print(f"p-value: {ols.pvalues[1]:.8f}")

print("\nFeature matrix shape:", X.shape)
print("\nFirst few outcomes:\n", y.head())
print("\nTreatment group counts:\n", T.value_counts())

print("\nModel Summary:\n", ols.summary())
```

Code Results

```
MLRATE ATE: 5.3194
95% CI: [4.5915, 6.0474]
p-value: 0.00000000

Feature matrix shape: (5556, 4)

First few outcomes:
 9841    140.9200
412     155.2110
8337    129.8745
5118    133.7800
9479    101.6000
Name: revenue (t), dtype: float64

Treatment group counts:
 treatment
1    2783
0    2773
Name: count, dtype: int64
```

Code Results

```
Model Summary:
                            OLS Regression Results
==============================================================================
Dep. Variable:            revenue (t)   R-squared:                       0.671
Model:                            OLS   Adj. R-squared:                  0.671
Method:                 Least Squares   F-statistic:                     3644.
Date:                Thu, 13 Nov 2025   Prob (F-statistic):               0.00
Time:                        19:18:37   Log-Likelihood:                -22484.
No. Observations:                5556   AIC:                         4.498e+04
Df Residuals:                    5552   BIC:                         4.500e+04
Df Model:                           3
Covariance Type:                  HC0
=======================================================================================
                          coef    std err          z      P>|z|      [0.025      0.975]
---------------------------------------------------------------------------------------
const                   3.6446      1.562      2.333      0.020       0.583       6.706
T                       5.3194      0.371     14.322      0.000       4.591       6.047
g_hat                   0.9470      0.013     73.987      0.000       0.922       0.972
T * (g_hat - g_bar)    -0.0030      0.018     -0.163      0.871      -0.039       0.033
==============================================================================
Omnibus:                        5.447   Durbin-Watson:                   1.986
Prob(Omnibus):                  0.066   Jarque-Bera (JB):                6.046
Skew:                           0.008   Prob(JB):                       0.0486
Kurtosis:                       3.161   Cond. No.                     1.02e+03
==============================================================================
```

02 Reflections

Implementing MLRATE

Comparing Unadjusted ATE vs. MLRATE ATE

Unadjusted ATE vs. MLRATE ATE:

- Unadjusted ATE: 5.10
- MLRATE ATE: 5.3194

95% Confidence Interval:

- Unadjusted: [3.838, 6.365]
  - Unadjusted CI Width: $6.365 - 3.838 = **2.527**
- MLRATE: [4.5915, 6.0474]
  - MLRATE CI Width: $6.0474 - 4.5915 = **1.4559**
- MLRATE → slightly narrower

Interpretation:

- Adding the predictive baseline $G(x)$ improved precision (narrowed CI).
- The treatment effect remains statistically significant ($p \approx 0$).
- Higher precision increases confidence in the decision to implement the gift strategy.

Baseline Model G(x) Predictiveness & Model Fit

Predictiveness of G(x):

- Coefficient for g_hat: 0.9470, $p < 0.001$ → very predictive
- $R^2 = 0.671$ → G(x) explains ~67% of revenue variance

Interaction term T * (g_hat - g_bar):

- Coefficient ≈ -0.003, $p = 0.871$ → no significant treatment heterogeneity

Implications:

- Baseline is strong → MLRATE gives meaningful improvement in CI
- If G(x) were weak, MLRATE would offer little precision gain

Reflection & Business Takeaways

Precision & decision-making:

- Narrower CI increases confidence that treatment effect is positive
- Supports “launch gift strategy” decision

Coefficient interpretation:

- const = 3.6446 → baseline revenue for average customer without treatment
- T = 5.3194 → estimated lift from treatment
- g_hat = 0.9470 → strong predictor of revenue
- T * (g_hat - g_bar) ≈ 0 → treatment effect consistent across predicted revenue

Model reliability:

- No signs of leakage → out-of-fold predictions used
- Condition number = 1.02e3 → slight multicollinearity, but not critical

Thank you!

Notebook Link