3_BinaryClassification

November 5, 2024

0.1 Libraries & Loading

[86]:
```
!pip install lightgbm
!pip install xgboost
!pip install imbalanced-learn
```

```
Requirement already satisfied: lightgbm in /opt/conda/lib/python3.11/site-
packages (4.5.0)
Requirement already satisfied: numpy>=1.17.0 in /opt/conda/lib/python3.11/site-
packages (from lightgbm) (1.26.4)
Requirement already satisfied: scipy in /opt/conda/lib/python3.11/site-packages
(from lightgbm) (1.14.0)
Requirement already satisfied: xgboost in /opt/conda/lib/python3.11/site-
packages (2.1.2)
Requirement already satisfied: numpy in /opt/conda/lib/python3.11/site-packages
(from xgboost) (1.26.4)
Requirement already satisfied: nvidia-nccl-cu12 in
/opt/conda/lib/python3.11/site-packages (from xgboost) (2.23.4)
Requirement already satisfied: scipy in /opt/conda/lib/python3.11/site-packages
(from xgboost) (1.14.0)
Requirement already satisfied: imbalanced-learn in
/opt/conda/lib/python3.11/site-packages (0.12.4)
Requirement already satisfied: numpy>=1.17.3 in /opt/conda/lib/python3.11/site-
packages (from imbalanced-learn) (1.26.4)
Requirement already satisfied: scipy>=1.5.0 in /opt/conda/lib/python3.11/site-
packages (from imbalanced-learn) (1.14.0)
Requirement already satisfied: scikit-learn>=1.0.2 in
/opt/conda/lib/python3.11/site-packages (from imbalanced-learn) (1.5.1)
Requirement already satisfied: joblib>=1.1.1 in /opt/conda/lib/python3.11/site-
packages (from imbalanced-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/opt/conda/lib/python3.11/site-packages (from imbalanced-learn) (3.5.0)
```

[118]:
```
# Loading libraries
import os
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib import pyplot
```

```
import numpy as np
import seaborn as sns
import calendar
from sklearn.model_selection import train_test_split, ParameterGrid,␣
 ↪GridSearchCV, TimeSeriesSplit
from sklearn.preprocessing import StandardScaler
from lightgbm import LGBMClassifier
import lightgbm as lgb
from xgboost import plot_importance
from sklearn.metrics import f1_score, classification_report, confusion_matrix,␣
 ↪roc_auc_score, roc_curve, auc
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.arima.model import ARIMA
from matplotlib.offsetbox import AnchoredText
import math
from sklearn.linear_model import LogisticRegression
from imblearn.over_sampling import RandomOverSampler
import statsmodels.api as sm
import scipy.stats as stats
```

[119]:
```
# Defining file paths & reading CSVs - separate file for DF containing ic data
csv_path = '/home/n8309116/swan/IFN704 Project/Saved_DFs/'
hourly_df = pd.read_csv(csv_path + 'preprocessed_hourly_data2.csv')
hourly_ic_df = pd.read_csv(csv_path + 'preprocessed_hourly_ic_data2.csv')
```

[120]:
```
print(hourly_df.dtypes)
```

```
time               object
dem_poe10         float64
dem_poe50         float64
dem_poe90         float64
dem_act           float64
rrp               float64
power_qld         float64
bris_temp         float64
bris_wind         float64
bris_dp           float64
public_holiday      int64
dow                 int64
doy                 int64
month               int64
hour                int64
dtype: object
```

[121]:
```
print(hourly_ic_df.dtypes)
```

```
time                  object
net_ic_flow          float64
dem_poe10            float64
dem_poe50            float64
dem_poe90            float64
dem_act              float64
rrp                  float64
power_qld            float64
bris_temp            float64
bris_wind            float64
bris_dp              float64
public_holiday         int64
dow                    int64
doy                    int64
month                  int64
hour                   int64
dtype: object
```

[122]:
```python
# Reusing function for lag features
def create_lag_features(df, lags=2):
  y = hourly_df.loc[:, "dem_act"]
  for lag in range(lags):
    df[f"lag{lag + 1}"] = y.shift(lag + 1)
  return df
```

Classifying demand exceedances of POE10, I propose a logit model:

$$\log\left(\frac{P}{1-P}\right) = \text{bris\_temp} + \text{net\_ic\_flow} + \text{demand}_{t-1} + \text{hour} + \text{month} + \epsilon_t, \quad \epsilon_t \sim N(0, \sigma^2)$$

[123]:
```python
# Checking exceedance distribution
print((hourly_ic_df['dem_act'] > hourly_ic_df['dem_poe10']).sum())
print((hourly_ic_df['dem_act'] <= hourly_ic_df['dem_poe10']).sum())
```

```
406
11191
```

[124]:
```python
hourly_ic_df = create_lag_features(hourly_ic_df, lags=1)
```

[125]:
```python
# DF for GLM
logit_df = hourly_ic_df[['net_ic_flow', 'hour', 'month', 'bris_temp', 'lag1']].
↪copy()
logit_df['target'] = (hourly_ic_df['dem_act'] > hourly_ic_df['dem_poe10']).
↪astype(int)
logit_df.head()
```

[125]:

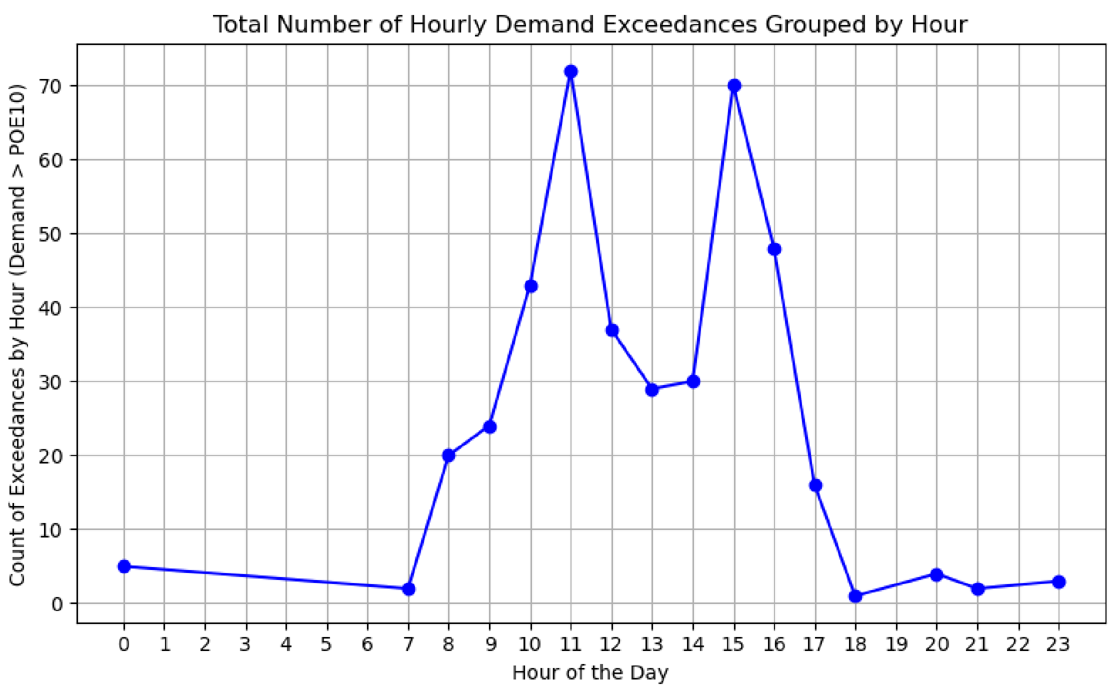
	net_ic_flow	hour	month	bris_temp	lag1	target
0	-5688.50113	10	3	27.90	NaN	0

```
1  -5653.10117    11      3      28.45   5837.5        0
2  -5967.20118    12      3      29.30   5659.5        0
3 -10919.30117    13      3      29.70   5561.5        0
4 -13638.00108    14      3      29.20   5501.0        0
```

[126]:
```python
print(logit_df['target'].value_counts())
```

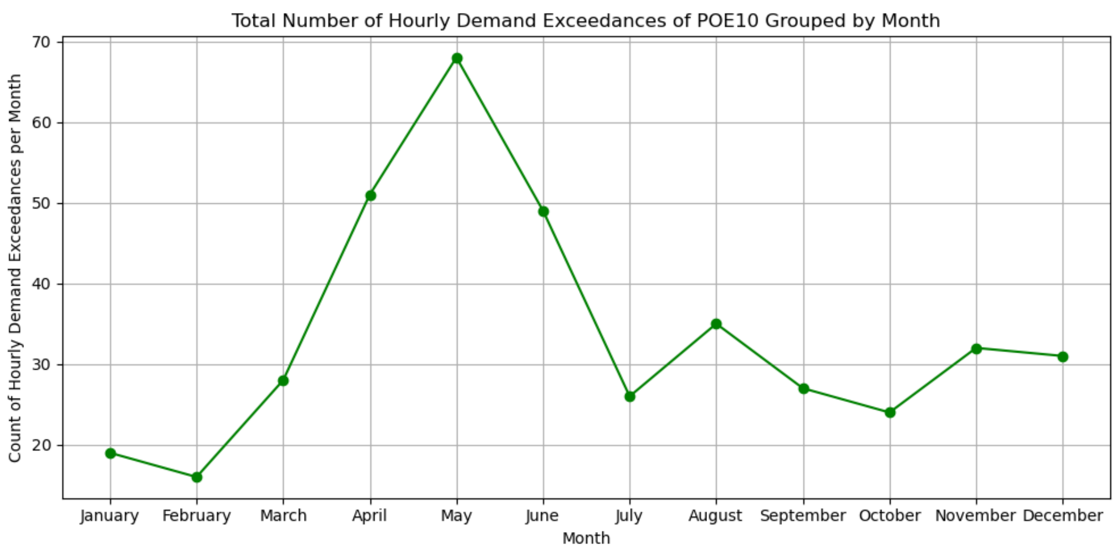
```
target
0    11191
1      406
Name: count, dtype: int64
```

[127]:
```python
# Checking distribution by hour
exceedances_by_hour = logit_df[logit_df['target'] == 1].groupby('hour').size()

# Plotting
plt.figure(figsize=(8, 5))
plt.plot(exceedances_by_hour.index, exceedances_by_hour.values, marker='o',
 ↪linestyle='-', color='blue')
plt.xlabel('Hour of the Day')
plt.ylabel('Count of Exceedances by Hour (Demand > POE10)')
plt.title('Total Number of Hourly Demand Exceedances Grouped by Hour')
plt.grid(True)
plt.xticks(range(24))  # Ensure x-axis has labels for every hour (0-23)
plt.tight_layout()
plt.show()
```



[128]:

```
# Checking distribution by month
exceedances_by_month = logit_df[logit_df['target'] == 1].groupby('month').size()

# Creating list
month_names = [calendar.month_name[i] for i in exceedances_by_month.index]

# Plotting
plt.figure(figsize=(10, 5))
plt.plot(month_names, exceedances_by_month.values, marker='o', linestyle='-',␣
↪color='green')
plt.xlabel('Month')
plt.ylabel('Count of Hourly Demand Exceedances per Month')
plt.title('Total Number of Hourly Demand Exceedances of POE10 Grouped by Month')
plt.grid(True)
plt.tight_layout()
plt.show()
```



[129]:

```
# Removing NAN row (1st row)
logit_df = logit_df.iloc[1:].reset_index(drop=True)
logit_df.head(5)
```

[129]:

	net_ic_flow	hour	month	bris_temp	lag1	target
0	-5653.10117	11	3	28.45	5837.5	0
1	-5967.20118	12	3	29.30	5659.5	0
2	-10919.30117	13	3	29.70	5561.5	0
3	-13638.00108	14	3	29.20	5501.0	0
4	-15231.30146	15	3	28.60	5490.0	0

[130]:
```
print(logit_df.dtypes)
```

```
net_ic_flow    float64
hour             int64
month            int64
bris_temp      float64
lag1           float64
target           int64
dtype: object
```

0.2 Pre-processing for Logit

- Standardising numeric variables
- One-hot encoding categorical variables (hour & month)
- Oversampling training set to achieve 50/50 class balance

[131]:
```
# Copying DF for cleanliness & one hot encoding (OHE)
logit_df_encoded = logit_df.copy()
logit_df_encoded['hour'] = logit_df_encoded['hour'].astype('category')
logit_df_encoded['month'] = logit_df_encoded['month'].astype('category')
logit_df_encoded = pd.get_dummies(logit_df, columns=['hour', 'month'],␣
↪drop_first=True)

# Splitting data
X = logit_df_encoded.drop(columns=['target'])
y = logit_df_encoded['target']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,␣
↪stratify=y, random_state=42) # will use same random_state for LGB model

# Oversampling
oversampler = RandomOverSampler(sampling_strategy=0.5, random_state=42)
X_train_resampled, y_train_resampled = oversampler.fit_resample(X_train,␣
↪y_train)

# Standardising numeric vars
numeric_columns = ['net_ic_flow', 'bris_temp', 'lag1']
scaler = StandardScaler()
X_train_resampled_standardized = X_train_resampled.copy()
X_test_standardized = X_test.copy()
X_train_resampled_standardized[numeric_columns] = scaler.
↪fit_transform(X_train_resampled[numeric_columns])
X_test_standardized[numeric_columns] = scaler.transform(X_test[numeric_columns])

# Constant term added
X_train_resampled_with_const = sm.add_constant(X_train_resampled_standardized)
X_test_with_const = sm.add_constant(X_test_standardized)

# Convert boolean columns to integers
```

```
X_train_resampled_with_const = X_train_resampled_with_const.astype(int)
X_test_with_const = X_test_with_const.astype(int)
```

[132]:

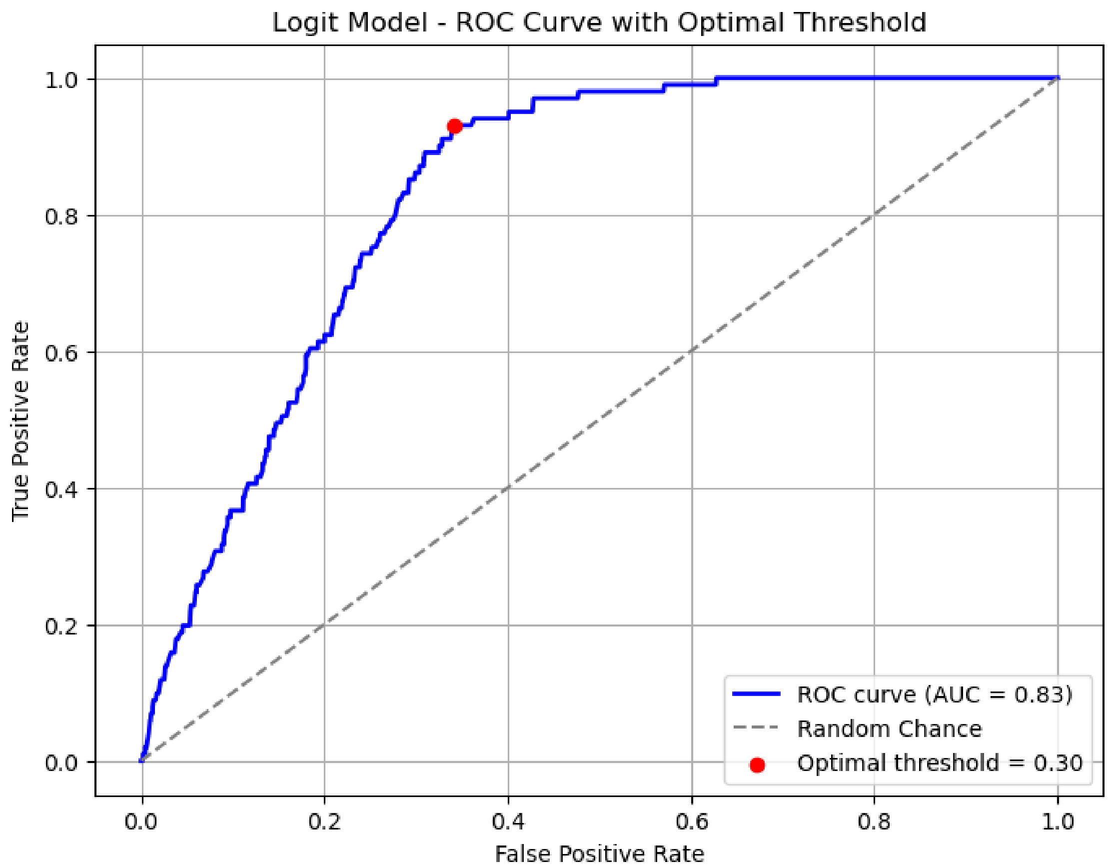
```
# Fitting model
logit_model = sm.Logit(y_train_resampled, X_train_resampled_with_const)
result = logit_model.fit(maxiter=250)

# Printing summary and predicting for 0.5 threshold
print(result.summary())
y_pred = result.predict(X_test_with_const)
y_pred_binary = [1 if x >= 0.5 else 0 for x in y_pred]

# Evaluating
print("\nConfusion Matrix:")
print(confusion_matrix(y_test, y_pred_binary))
print("\nClassification Report:")
print(classification_report(y_test, y_pred_binary))
```

```
Warning: Maximum number of iterations has been exceeded.
         Current function value: 0.414887
         Iterations: 250
                           Logit Regression Results
==============================================================================
Dep. Variable:                 target   No. Observations:                12588
Model:                          Logit   Df Residuals:                    12550
Method:                           MLE   Df Model:                           37
Date:                Tue, 05 Nov 2024   Pseudo R-squ.:                  0.3482
Time:                        12:28:37   Log-Likelihood:                -5222.6
converged:                      False   LL-Null:                       -8012.4
Covariance Type:            nonrobust   LLR p-value:                     0.000
===============================================================================
                  coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------
const          -2.3634      0.175    -13.497      0.000      -2.707      -2.020
net_ic_flow     0.3897      0.042      9.371      0.000       0.308       0.471
bris_temp       0.0986      0.063      1.557      0.120      -0.026       0.223
lag1           -0.0164      0.073     -0.225      0.822      -0.159       0.126
hour_1       -115.2179   1.29e+24  -8.92e-23      1.000   -2.53e+24    2.53e+24
hour_2        -22.7540   1.09e+04     -0.002      0.998   -2.14e+04    2.14e+04
hour_3        -22.9704    1.2e+04     -0.002      0.998   -2.36e+04    2.36e+04
hour_4        -30.0318    4.2e+05  -7.16e-05      1.000   -8.22e+05    8.22e+05
hour_5        -25.6955   4.66e+04     -0.001      1.000   -9.14e+04    9.14e+04
hour_6         -7.0271      4.237     -1.659      0.097     -15.331       1.276
hour_7         -1.5854      0.329     -4.812      0.000      -2.231      -0.940
hour_8          1.2657      0.169      7.503      0.000       0.935       1.596
hour_9          1.5239      0.166      9.198      0.000       1.199       1.849
hour_10         2.0558      0.163     12.579      0.000       1.735       2.376
hour_11         2.6460      0.161     16.477      0.000       2.331       2.961
```

```
hour_12          2.0064      0.165     12.151      0.000       1.683       2.330
hour_13          1.6280      0.168      9.670      0.000       1.298       1.958
hour_14          1.6161      0.167      9.682      0.000       1.289       1.943
hour_15          2.6642      0.160     16.630      0.000       2.350       2.978
hour_16          2.2579      0.160     14.081      0.000       1.944       2.572
hour_17          0.7086      0.176      4.021      0.000       0.363       1.054
hour_18         -1.5897      0.306     -5.190      0.000      -2.190      -0.989
hour_19        -22.6196   1.01e+04     -0.002      0.998   -1.99e+04    1.99e+04
hour_20         -0.3819      0.209     -1.824      0.068      -0.792       0.028
hour_21         -1.6802      0.325     -5.177      0.000      -2.316      -1.044
hour_22        -26.0115    5.4e+04     -0.000      1.000   -1.06e+05    1.06e+05
hour_23         -1.1594      0.263     -4.408      0.000      -1.675      -0.644
month_2         -0.2653      0.152     -1.747      0.081      -0.563       0.032
month_3         -0.2130      0.135     -1.577      0.115      -0.478       0.052
month_4          0.7136      0.133      5.371      0.000       0.453       0.974
month_5          0.9845      0.140      7.015      0.000       0.709       1.260
month_6          0.6996      0.145      4.809      0.000       0.414       0.985
month_7          0.9044      0.156      5.798      0.000       0.599       1.210
month_8          0.9726      0.150      6.473      0.000       0.678       1.267
month_9          0.7827      0.147      5.323      0.000       0.495       1.071
month_10         0.6127      0.145      4.231      0.000       0.329       0.897
month_11         0.7655      0.142      5.387      0.000       0.487       1.044
month_12         0.3309      0.139      2.385      0.017       0.059       0.603
==============================================================================

Possibly complete quasi-separation: A fraction 0.21 of observations can be
perfectly predicted. This might indicate that there is complete
quasi-separation. In this case some parameters will not be identified.

Confusion Matrix:
[[2274  524]
 [  40   61]]

Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.81      0.89      2798
           1       0.10      0.60      0.18       101

    accuracy                           0.81      2899
   macro avg       0.54      0.71      0.53      2899
weighted avg       0.95      0.81      0.86      2899

/opt/conda/lib/python3.11/site-packages/statsmodels/base/model.py:607:
ConvergenceWarning: Maximum Likelihood optimization failed to converge. Check
mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
```

- As expected, model heavily overpredicts the minority class due to oversampling (precision for positive class is 0.1)
- Net IC flow significant coefficient - OR is 1.477 (exp(coeff)) meaning 48% increased odds of an hour exceeding POE10 demand for 1 std inc in net_ic_flow
- This reflects perhaps there is unpredictable volatility/factors influencing flows that cannot be modelled with this data (e.g., intrastate effects in NSW)
- This justifies using the actual hour flow not the lag one, i.e. wouldn't be available if building a predictive model, goal is explaining factors

[133]:
```
# Plotting ROC curve with inflection point (furthest from diagonal 0.5 line)
y_pred_proba = result.predict(X_test_with_const)

# Obtaining necessary values
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)
roc_auc = auc(fpr, tpr)

# Calculating Youden's J statistic - seeks to balance TPR + TNR, maximise␣
↪recall for positive class
j_scores = tpr - fpr
optimal_idx = np.argmax(j_scores)
optimal_threshold = thresholds[optimal_idx]

# Plotting
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label=f'ROC curve (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='gray', linestyle='--', label='Random Chance')
plt.scatter(fpr[optimal_idx], tpr[optimal_idx], color='red', label=f'Optimal␣
↪threshold = {optimal_threshold:.2f}', zorder=5)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Logit Model - ROC Curve with Optimal Threshold')
plt.legend(loc="lower right")
plt.grid(True)
plt.show()
print(f"Optimal threshold: {optimal_threshold:.2f}")
```




```
Optimal threshold: 0.30
```

[134]:

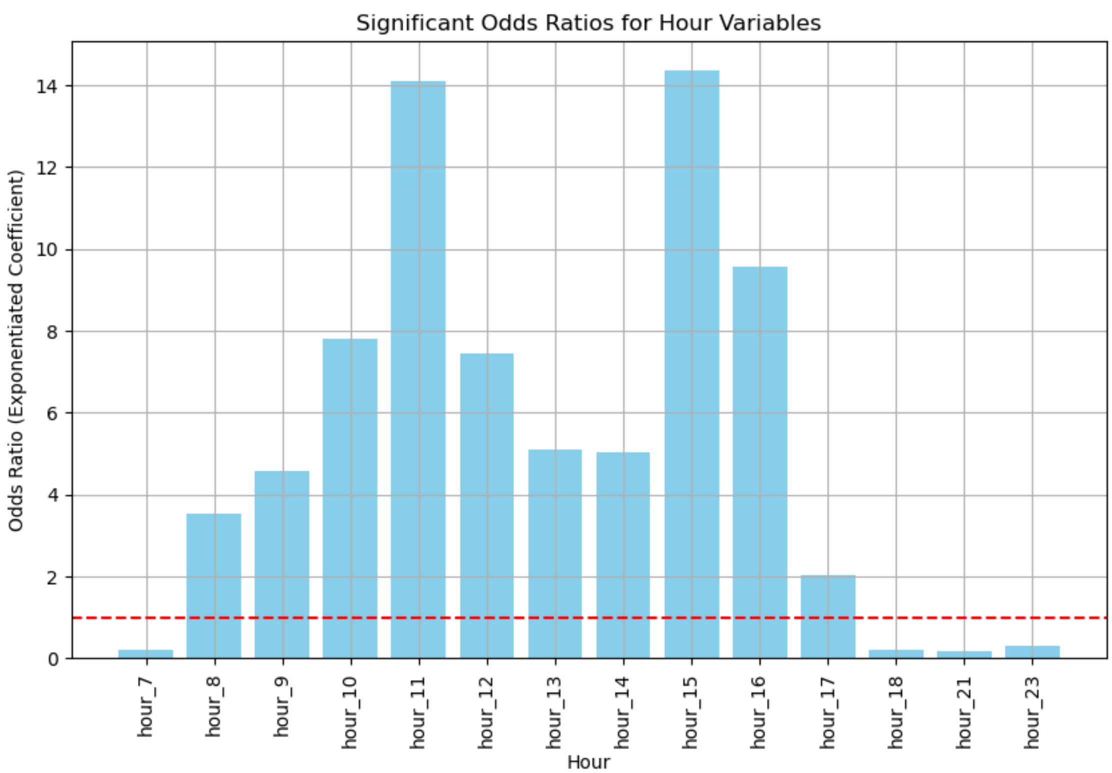
```
# Convert predictions to binary with desired threshold of 0.3
y_pred_binary = [1 if x >= 0.3 else 0 for x in y_pred]

# Evaluating
print("\nConfusion Matrix:")
print(confusion_matrix(y_test, y_pred_binary))
print("\nClassification Report:")
print(classification_report(y_test, y_pred_binary))
```

```
Confusion Matrix:
[[1848  950]
 [   8   93]]

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.66      0.79      2798
```

```
           1       0.09      0.92      0.16       101

    accuracy                           0.67      2899
   macro avg       0.54      0.79      0.48      2899
weighted avg       0.96      0.67      0.77      2899
```

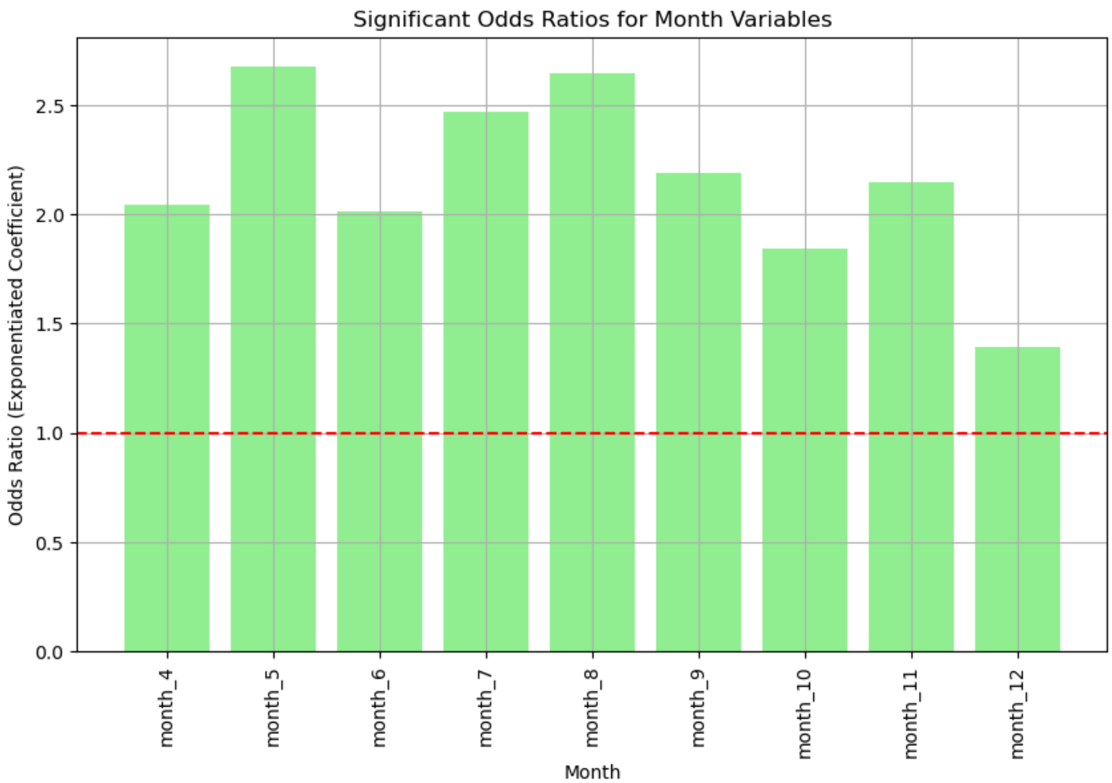
[135]:

```python
# Plotting significant hour ORs
hour_coeffs = result.params.filter(like='hour')
hour_pvals = result.pvalues.filter(like='hour')
significant_hours = hour_pvals[hour_pvals < 0.05].index
odds_ratios_hours = np.exp(hour_coeffs[significant_hours])

# Plotting
plt.figure(figsize=(10, 6))
plt.bar(significant_hours, odds_ratios_hours, color='skyblue')
plt.axhline(y=1, color='red', linestyle='--')  # Dashed line at 1
plt.xlabel('Hour')
plt.ylabel('Odds Ratio (Exponentiated Coefficient)')
plt.title('Significant Odds Ratios for Hour Variables')
plt.xticks(rotation=90)
plt.grid(True)
plt.show()
```



[136]:

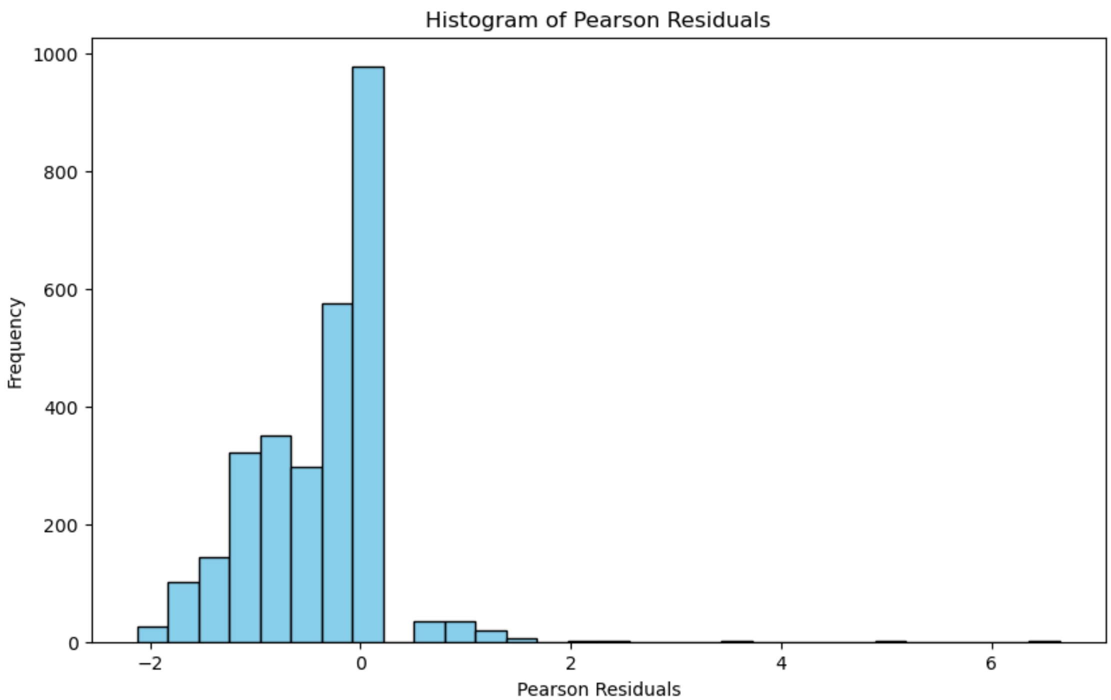
```python
# Plotting significant month ORs
month_coeffs = result.params.filter(like='month')
month_pvals = result.pvalues.filter(like='month')
significant_months = month_pvals[month_pvals < 0.05].index
odds_ratios_months = np.exp(month_coeffs[significant_months])

# Plotting
plt.figure(figsize=(10, 6))
plt.bar(significant_months, odds_ratios_months, color='lightgreen')
plt.axhline(y=1, color='red', linestyle='--')  # Dashed line at 1
plt.xlabel('Month')
plt.ylabel('Odds Ratio (Exponentiated Coefficient)')
plt.title('Significant Odds Ratios for Month Variables')
plt.xticks(rotation=90)
plt.grid(True)
plt.show()
```



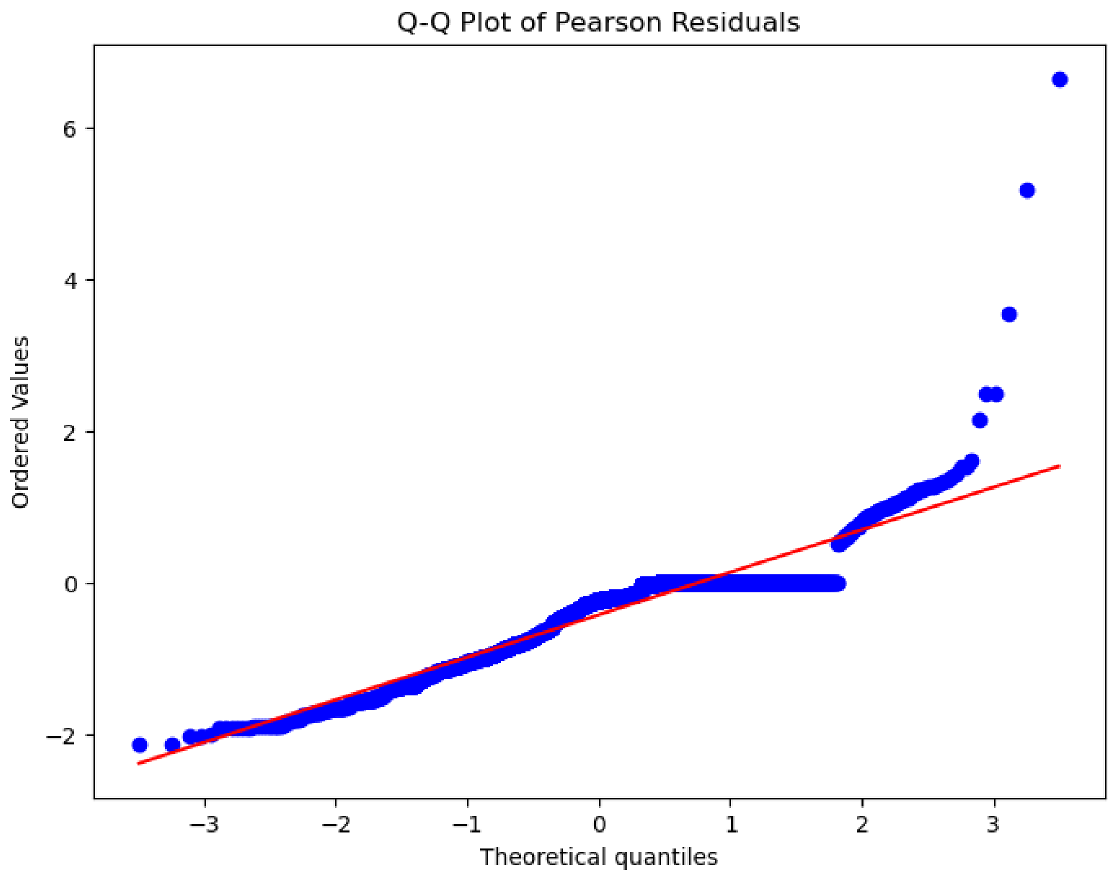
0.2.1 Checking Normality of Errors

[137]:
```
# Predicted probabilities
predicted_probs = result.predict(X_test_with_const)
# Residuals: observed - predicted
pearson_residuals = (y_test - predicted_probs) / np.sqrt(predicted_probs * (1 -␣
↪predicted_probs))
```

[138]:
```
# Histogram
plt.figure(figsize=(10, 6))
plt.hist(pearson_residuals, bins=30, color='skyblue', edgecolor='black')
plt.title("Histogram of Pearson Residuals")
plt.xlabel("Pearson Residuals")
plt.ylabel("Frequency")
plt.show()
```



[139]:
```
# QQ Plot
plt.figure(figsize=(8, 6))
stats.probplot(pearson_residuals, dist="norm", plot=plt)
plt.title("Q-Q Plot of Pearson Residuals")
plt.show()
```



[140]:
```
# Shapiro-Wilk test for normality
shapiro_test = stats.shapiro(pearson_residuals)
print(f"Shapiro-Wilk Test: W={shapiro_test.statistic}, p-value={shapiro_test.
 ↪pvalue}")
```

```
Shapiro-Wilk Test: W=0.8761164535462728, p-value=3.381476558860939e-43
```

0.3 Observations

- Clear deviation from normality confirmed by histogram, QQ plot and Shapiro-Wilk test
- Many hour and month coefficients are highly significant, consistent with the plots earlier
- Net IC flow is significant and positive, while the other numeric variables are non-significant

0.4 LightGBM Classifier

[141]:
```
# Splitting X & y
X, y = logit_df.drop(columns=['target']), logit_df['target']
```

[142]:
```
# Splitting data into 1) train/test, and 2) splitting training into train/val␣
 ↪for tuning
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,␣
↪stratify=y, random_state=42)
X_train, X_valid, y_train, y_valid = train_test_split(X_train, y_train,␣
↪test_size=0.2, stratify=y_train, random_state=42)
```

[143]:
```
# from sklearn.metrics import roc_auc_score
# import lightgbm as lgbm
# from lightgbm import early_stopping, log_evaluation

# # Small grid search
# param_grid = {
#     'num_leaves': [15, 30, 50],
#     'max_depth': [5, 10],
#     'min_child_samples': [20, 50],
#     'colsample_bytree': [0.6, 0.8],
#     'n_estimators': [50, 100]  # Reduced values for faster training
# }

# # Generating HP combinations
# param_list = list(ParameterGrid(param_grid))

# # Initialising variables
# best_score = -np.inf
# best_params = None

# # Loop through
# for params in param_list:
#     # LightGBM model with current hyperparameters
#     model = lgbm.LGBMClassifier(
#         learning_rate=0.01,
#         **params,
#         is_unbalance=True
#     )

#     # Training model
#     model.fit(
#         X_train, y_train,
#         eval_set=[(X_valid, y_valid)],
#         eval_metric='auc',
#         callbacks=[log_evaluation(0)]  # Disable training output for faster␣
↪execution
#     )

#     # Predicting
#     y_pred = model.predict_proba(X_valid)[:, 1]

#     # Calculate AUC
```

```
#     auc = roc_auc_score(y_valid, y_pred)

#     # Update best score and parameters if current model is better
#     if auc > best_score:
#         best_score = auc
#         best_params = params.copy()
#         best_model = model

# # Printing optimal results
# print("Best hyperparameters:", best_params)
# print(f"Best validation AUC: {best_score:.4f}")
```

Note the above code block is commented out to suppress the output and tidy the notebook. The values defined below are those found by the grid search.

[144]:
```
best_params = {'colsample_bytree': 0.8, 'max_depth': 5, 'min_child_samples':␣
↪50, 'n_estimators': 100, 'num_leaves': 30}
```

[145]:
```
# Re-combining training and validation sets for re-training
X_train_final = np.concatenate((X_train, X_valid), axis=0)
y_train_final = np.concatenate((y_train, y_valid), axis=0)

# Oversampling
oversampler = RandomOverSampler(sampling_strategy=0.5, random_state=42)
X_train_final_resampled, y_train_final_resampled = oversampler.
↪fit_resample(X_train_final, y_train_final)

# Initialising LGBM model
model = lgb.LGBMClassifier(
    learning_rate=0.01,
    **best_params,
    is_unbalance=True,
    verbose=-1 # Suppress extensive output
)
```

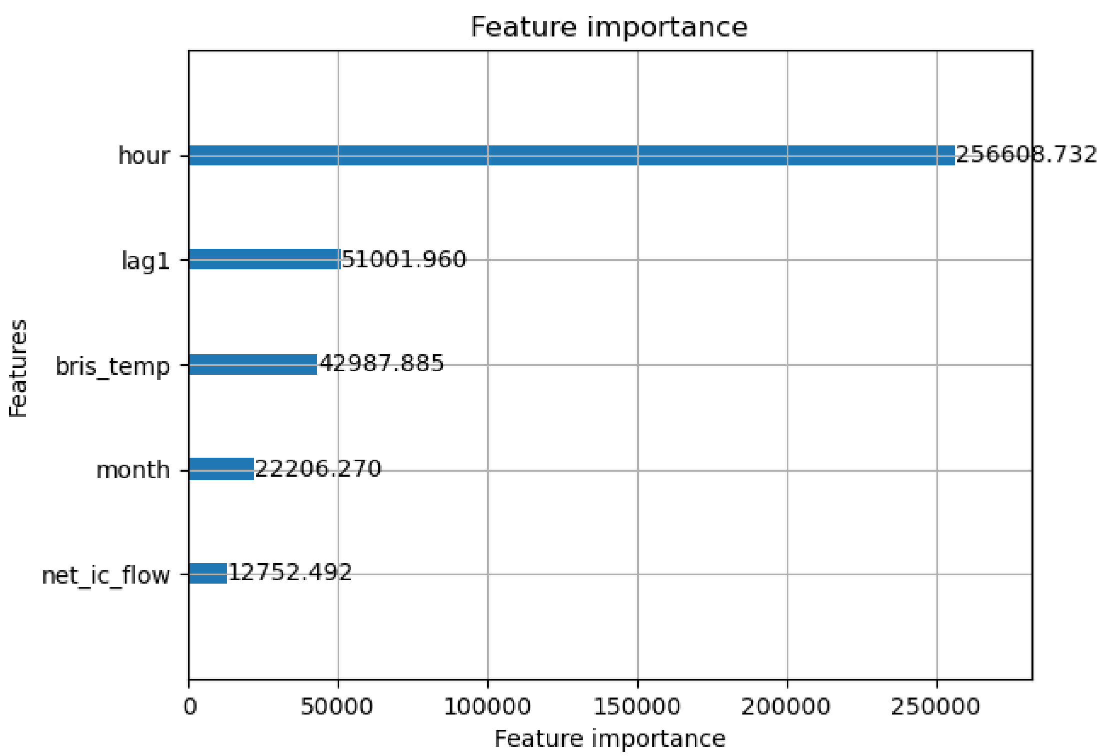
[146]:
```
# Training model on resampled set
lgb_model = model.fit(X_train_final_resampled, y_train_final_resampled,␣
↪feature_name=list(X.columns))

# Evaluating
y_pred = model.predict(X_test)
print("\nConfusion Matrix:")
print(confusion_matrix(y_test, y_pred))
print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

```
Confusion Matrix:
```

```
[[2062  736]
 [  20   81]]

Classification Report:
              precision    recall  f1-score   support

           0       0.99      0.74      0.85      2798
           1       0.10      0.80      0.18       101

    accuracy                           0.74      2899
   macro avg       0.54      0.77      0.51      2899
weighted avg       0.96      0.74      0.82      2899
```

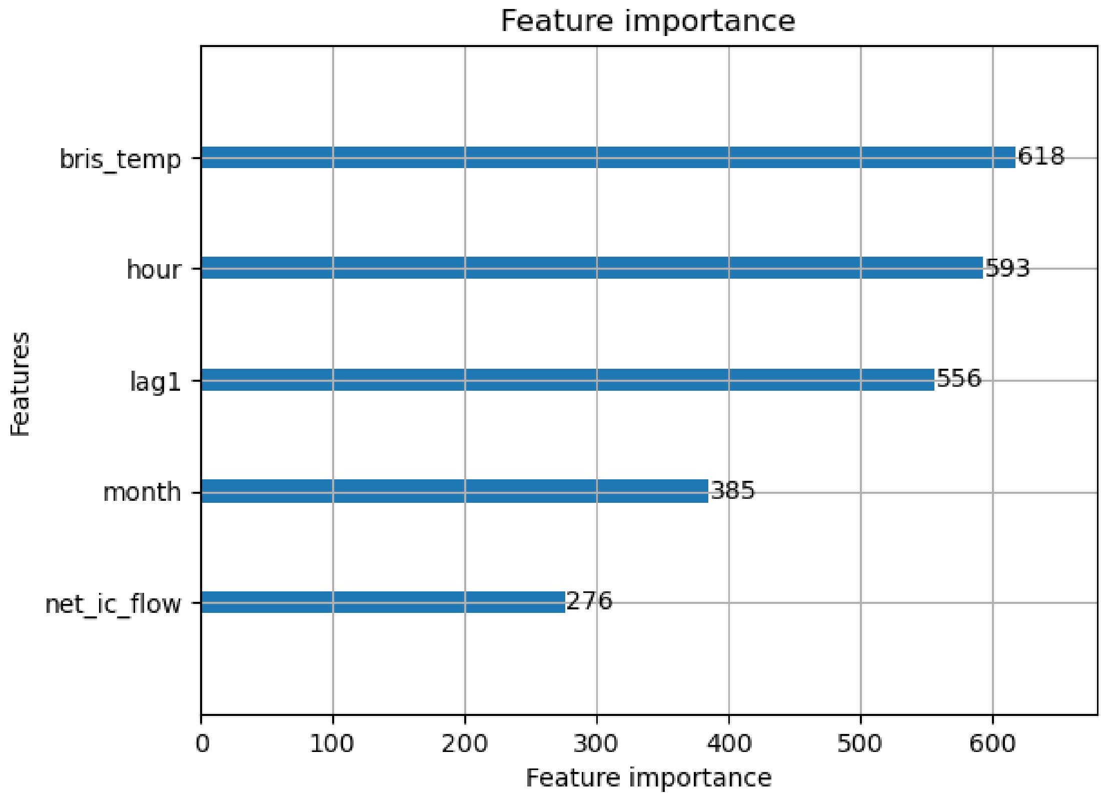
Observe biggest difference in LGBM v Logit is in recall for each class - LGBM much better at minority class, despite both being oversampled 50/50 split in training.

[147]:
```
# LGB importance - accuracy improvement = 'gain'
lgb.plot_importance(lgb_model, importance_type='gain')
plt.show()
```



[148]:
```
# LGB importance - split counts
lgb.plot_importance(lgb_model)
```

```
plt.show()
```


Feature importance
bris_temp
hour
lag1
month
net_ic_flow
Features
618
593
556
385
276
0
100
200
300
400
500
600
Feature importance

[ ]:

```

```

[ ]:

```

```