In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, GridSearchCV, RandomizedSearchCV,KFold
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import OneHotEncoder, StandardScaler, FunctionTransformer
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer
from sklearn.linear_model import LinearRegression, Lasso, LogisticRegression
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import cross_val_score
from sklearn.preprocessing import PolynomialFeatures
from sklearn.metrics import classification_report, accuracy_score
import pickle
import warnings
```

In [2]:
```
warnings.filterwarnings('ignore')
```

Import data and visualize the distribution

In [3]:
```
#load the data
data = pd.read_csv('supermarket_sales.csv')
data.head()
```

Out[3]:

	Invoice ID	Branch	City	Customer type	Gender	Product line	Unit price	Quantity	Total	Date	Time	Payment	cogs	gross margin percentage	gross income	Rating
0	750-67-8428	A	Yangon	Member	Female	Health and beauty	74.69	7	548.9715	1/5/2019	13:08	Ewallet	522.83	4.761905	26.1415	9.1
1	226-31-3081	C	Naypyitaw	Normal	Female	Electronic accessories	15.28	5	80.2200	3/8/2019	10:29	Cash	76.40	4.761905	3.8200	9.6
2	631-41-3108	A	Yangon	Normal	Male	Home and lifestyle	46.33	7	340.5255	3/3/2019	13:23	Credit card	324.31	4.761905	16.2155	7.4
3	123-19-1176	A	Yangon	Member	Male	Health and beauty	58.22	8	489.0480	1/27/2019	20:33	Ewallet	465.76	4.761905	23.2880	8.4
4	373-73-7910	A	Yangon	Normal	Male	Sports and travel	86.31	7	634.3785	2/8/2019	10:37	Ewallet	604.17	4.761905	30.2085	5.3

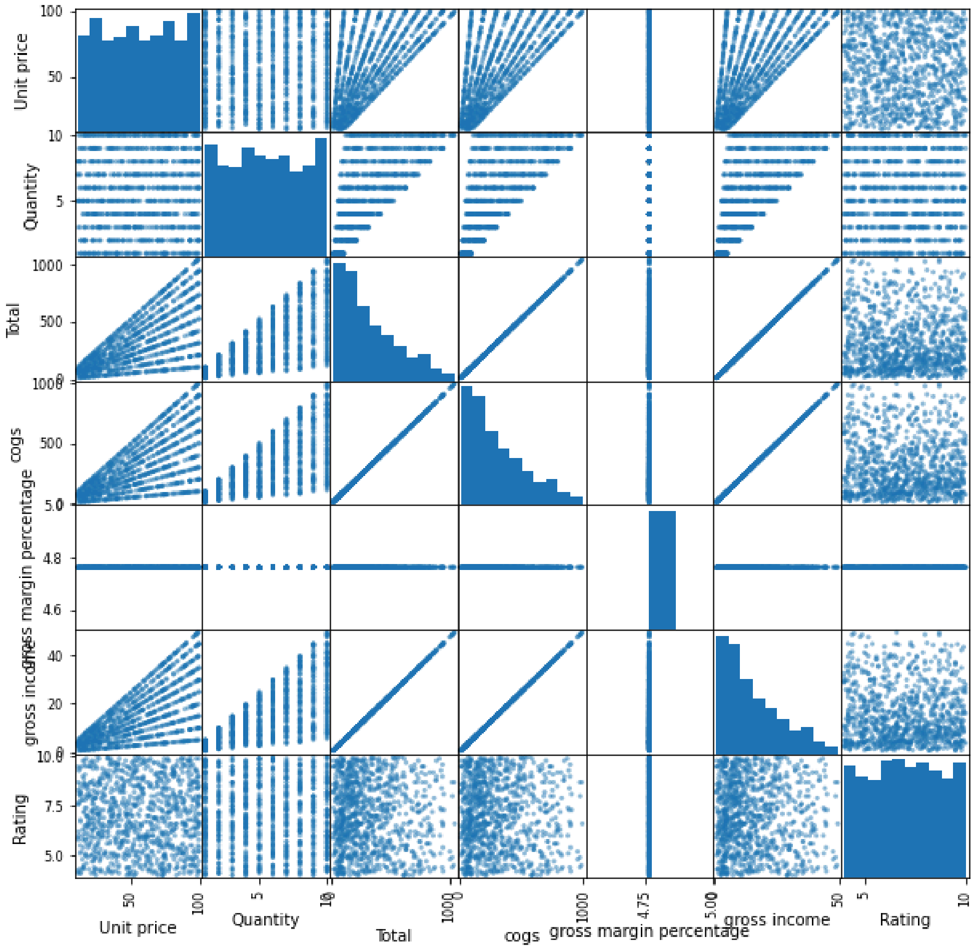
In [4]:
```
# check if the data is missing any values and datatypes in dataframe
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 16 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Invoice ID               1000 non-null   object 
 1   Branch                   1000 non-null   object 
 2   City                     1000 non-null   object 
 3   Customer type            1000 non-null   object 
 4   Gender                   1000 non-null   object 
 5   Product line             1000 non-null   object 
 6   Unit price               1000 non-null   float64
 7   Quantity                 1000 non-null   int64  
 8   Total                    1000 non-null   float64
 9   Date                     1000 non-null   object 
 10  Time                     1000 non-null   object 
 11  Payment                  1000 non-null   object 
 12  cogs                     1000 non-null   float64
 13  gross margin percentage  1000 non-null   float64
 14  gross income             1000 non-null   float64
 15  Rating                   1000 non-null   float64
dtypes: float64(6), int64(1), object(9)
memory usage: 125.1+ KB
```

Infer: Since there are no empty values we do not have to fill any null values.

In [5]:

```python
from pandas.plotting import scatter_matrix

scatter_matrix(data,figsize=(10,10));
```



In [6]:
```
unique_values = {col: data[col].unique() for col in data.columns}

# Print the unique values for each column
for col, values in unique_values.items():
    print(f"Column: {col}")
    print(f"Number of Unique values: {values.size}\n")
```

```
Column: Invoice ID
Number of Unique values: 1000

Column: Branch
Number of Unique values: 3

Column: City
Number of Unique values: 3

Column: Customer type
Number of Unique values: 2

Column: Gender
Number of Unique values: 2

Column: Product line
Number of Unique values: 6

Column: Unit price
Number of Unique values: 943

Column: Quantity
Number of Unique values: 10

Column: Total
Number of Unique values: 990

Column: Date
Number of Unique values: 89

Column: Time
Number of Unique values: 506

Column: Payment
Number of Unique values: 3

Column: cogs
Number of Unique values: 990

Column: gross margin percentage
Number of Unique values: 1

Column: gross income
Number of Unique values: 990

Column: Rating
Number of Unique values: 61
```

- From unique values of each columns,

- Since 'Gross margin percentage' column has same values for all entries, we can remove the column.
- We can remove the 'Invoice ID' column as well, as it is containes different values for different entries and it will not be helpful for model selection and training with too many distinct values.
- Remove 'City' or 'Branch' column as well as they both represent same value in different notation.

In [7]:
```
data.drop(columns=['City', 'Invoice ID','gross margin percentage'], inplace=True)
```

1. Date and Time Encoding:

```
- Extracting useful features like day of week and time slot helps to uncover patterns in sales related to specific times or days pattern.
```

In [8]:
```
def Day_of_week(X):
    return pd.to_datetime(X['Date']).dt.day_name().values.reshape(-1,1)

def Timeslot(X):
    def time_slot(time_str):
        hour = int(time_str.split(':')[0])
        if 10 <= hour < 12:
            return 'Morning'
        elif 12 <= hour < 17:
            return 'Afternoon'
        elif 17 <= hour < 19:
            return 'Evening'
        else:
            return 'Night'

    return pd.Series(X['Time']).apply(time_slot).values.reshape(-1,1)
```

2a. Multiple linear regression without Lasso regularization to predict 'gross income'

In [9]:
```
# Split the data into train_set and test_set based on stratification.
# Used {Branch,Product line,Payment} as stratification columns to represent the same ratio of distribution as original dataset.
X1 = data.drop(columns=['gross income'], axis=1)
t1 = data['gross income']
```

In [10]:
```
corr_matrix = data.corr(method='pearson', numeric_only=True)
corr_matrix
```

Out[10]:

	Unit price	Quantity	Total	cogs	gross income	Rating
Unit price	1.000000	0.010778	0.633962	0.633962	0.633962	-0.008778
Quantity	0.010778	1.000000	0.705510	0.705510	0.705510	-0.015815
Total	0.633962	0.705510	1.000000	1.000000	1.000000	-0.036442
cogs	0.633962	0.705510	1.000000	1.000000	1.000000	-0.036442
gross income	0.633962	0.705510	1.000000	1.000000	1.000000	-0.036442
Rating	-0.008778	-0.015815	-0.036442	-0.036442	-0.036442	1.000000

1. While predicting gross income, we have to exclude 'Total' and 'cogs' columns as well as these columns are highly correlated (correlation=1) which undermines the importance of other features. To find out the impact of other features on prediction we have to exclude 'Total' and 'cogs' columns.

In [11]:
```
X1.drop(columns=['Total','cogs'],inplace=True)
```

1. Train test split based on stratification of columns 'Gender', 'Branch', 'Product line' and 'Payment' to ensure the split is the same proportion as the original dataset.

2. Excluded 'Customer type' for stratification as this leads to very low cases in y.

In [12]:
```
data['stratify_column'] = data['Gender'] +  '_' + data['Branch'] + '_' + data['Product line'] + '_' + data['Payment']
X1_train, X1_test,t1_train,t1_test= train_test_split(X1, t1, test_size=0.2, random_state=1, shuffle=True, stratify=data['stratify_column'])
data.drop(columns=['stratify_column'],inplace=True)
X1_train.shape,X1_test.shape
```

Out[12]:
```
((800, 10), (200, 10))
```

In [13]:
```
date_feature = ['Date']
time_feature = ['Time']
num_cat_data = X1_train.drop(columns=['Date','Time']) #to exclude date and time features of other features
num_features = [col for col in num_cat_data.columns if num_cat_data[col].dtype != "object"]
cat_features = [col for col in num_cat_data.columns if num_cat_data[col].dtype == "object"]
print("Categorical features:",cat_features)
print("Numerical features:",num_features)
```

```
Categorical features: ['Branch', 'Customer type', 'Gender', 'Product line', 'Payment']
Numerical features: ['Unit price', 'Quantity', 'Rating']
```

In [14]:
```
num_pipeline = Pipeline([
    ('scaler', StandardScaler())
])

cat_pipeline = Pipeline([
    ('encoder', OneHotEncoder(handle_unknown='ignore'))
])
```

```python
date_pipeline = Pipeline([
    ('DayofWeek', FunctionTransformer(Day_of_week)),
    ('encoder', OneHotEncoder(handle_unknown='ignore'))
])


time_pipeline = Pipeline([
    ('Timeslot', FunctionTransformer(Timeslot)),
    ('encoder', OneHotEncoder(handle_unknown='ignore'))
])
```

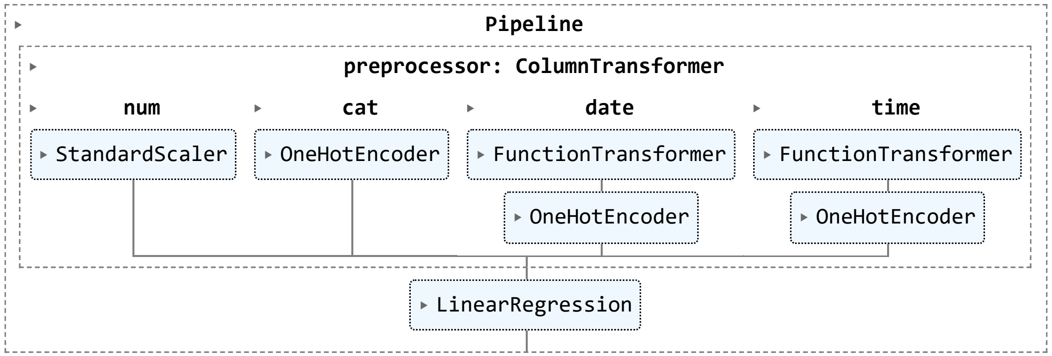
In [15]:

```python
full_pipeline = ColumnTransformer([
    ('num', num_pipeline, num_features),  # Process numeric features
    ('cat', cat_pipeline, cat_features),  # Process categorical features
    ('date', date_pipeline, date_feature),  # Process the 'Date' column
    ('time', time_pipeline, time_feature)  # Process the 'Time' column
])
```

In [16]:

```python
lr_pipeline = Pipeline([
     ('preprocessor',full_pipeline),
     ('lin_reg', LinearRegression())
])

model1_lr=lr_pipeline.fit(X1_train,t1_train)
model1_lr
```

Out[16]:



2b.Multiple linear regression with Lasso regularization to predict 'gross income'

In [17]:

```python
lasso_pipeline = Pipeline([
    ('preprocessor',full_pipeline),
    ('regressor',Lasso())
])

param_grid_lasso = {
```

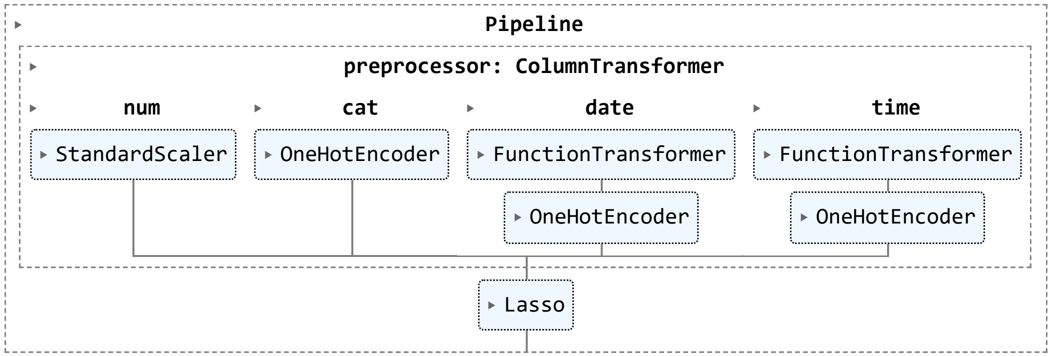
```
    'regressor__alpha':np.linspace(0.001,0.2,1000)
}
kf = KFold(n_splits=10, shuffle=True, random_state=42)#Use best kfold cross validation
lasso_grid = GridSearchCV(lasso_pipeline,param_grid=param_grid_lasso,cv=kf,scoring='r2')
lasso_grid.fit(X1_train,t1_train)
best_params_grid_search_poly_lasso = lasso_grid.best_params_
print("Best hyperparamaters for GridsearchCV for Linear Regression with lasso:", best_params_grid_search_poly_lasso)
```

```
Best hyperparamaters for GridsearchCV for Linear Regression with lasso: {'regressor__alpha': 0.15776976976976978}
```

In [18]:

```
model1_lasso = Pipeline([
    ('preprocessor',full_pipeline),
    ('regressor',Lasso(alpha= best_params_grid_search_poly_lasso['regressor__alpha']))
]).fit(X1_train,t1_train)
model1_lasso
```

Out[18]:



Impact of features on models ability to predict 'Gross income'

In [19]:

```
#To check how gross income is affected by unit price, quantity, and other variables like day, time slot, and product line.
date_feature_names = list(full_pipeline.transformers_[2][1].named_steps['encoder'].get_feature_names_out(date_feature))
time_feature_names = list(full_pipeline.transformers_[3][1].named_steps['encoder'].get_feature_names_out(time_feature))
num_feature_names = num_features  # Since num_features is predefined
cat_feature_names = full_pipeline.transformers_[1][1].named_steps['encoder'].get_feature_names_out(cat_features)
```

In [20]:

```
coefficients = lr_pipeline.named_steps['lin_reg'].coef_
feature_names = np.concatenate([
    num_feature_names,
    cat_feature_names,
    date_feature_names,
    time_feature_names
])
coef_df = pd.DataFrame({'Feature name': feature_names, 'Coefficient value': coefficients})
coef_df['AbsCoefficient'] = coef_df['Coefficient value'].abs()
coef_df = coef_df.sort_values(by='AbsCoefficient', ascending=False)
print("Coefiiceints of linear regression")
```

```python
# Display sorted coefficients by absolute value
coef_df
```

Coefiiceints of linear regression

Out[20]:

	Feature name	Coefficient value	AbsCoefficient
1	Quantity	8.126293	8.126293
0	Unit price	7.269379	7.269379
24	Date_Tuesday	0.574926	0.574926
25	Date_Wednesday	-0.566977	0.566977
17	Payment_Credit card	0.432963	0.432963
21	Date_Saturday	0.351029	0.351029
20	Date_Monday	-0.286998	0.286998
14	Product line_Home and lifestyle	0.283939	0.283939
28	Time_Morning	-0.268838	0.268838
5	Branch_C	0.242520	0.242520
26	Time_Afternoon	0.241552	0.241552
18	Payment_Ewallet	-0.229281	0.229281
10	Product line_Electronic accessories	-0.227760	0.227760
19	Date_Friday	-0.211671	0.211671
13	Product line_Health and beauty	-0.205458	0.205458
16	Payment_Cash	-0.203681	0.203681
27	Time_Evening	0.175458	0.175458
7	Customer type_Normal	0.169899	0.169899
6	Customer type_Member	-0.169899	0.169899
2	Rating	-0.152776	0.152776
22	Date_Sunday	0.152599	0.152599
15	Product line_Sports and travel	0.152347	0.152347
3	Branch_A	-0.149806	0.149806
29	Time_Night	-0.148172	0.148172
11	Product line_Fashion accessories	-0.098961	0.098961
12	Product line_Food and beverages	0.095892	0.095892
4	Branch_B	-0.092713	0.092713
8	Gender_Female	0.088908	0.088908

	Feature name	Coefficient value	AbsCoefficient
9	Gender_Male	-0.088908	0.088908
23	Date_Thursday	-0.012908	0.012908

In [21]:
```
coefficients = model1_lasso.named_steps['regressor'].coef_
feature_names = np.concatenate([
    num_feature_names,
    cat_feature_names,
    date_feature_names,
    time_feature_names
])
coef_df = pd.DataFrame({'Feature name': feature_names, 'Coefficient value': coefficients})
coef_df['AbsCoefficient'] = coef_df['Coefficient value'].abs()
coef_df = coef_df.sort_values(by='AbsCoefficient', ascending=False)
print("Coefiiceints of linear regression with lasso")
# Display sorted coefficients by absolute value
coef_df
```

```
Coefiiceints of linear regression with lasso
```

Out[21]:

	Feature name	Coefficient value	AbsCoefficient
1	Quantity	7.981798	7.981798
0	Unit price	7.093737	7.093737
28	Time_Morning	-0.000000	0.000000
27	Time_Evening	0.000000	0.000000
26	Time_Afternoon	0.000000	0.000000
25	Date_Wednesday	-0.000000	0.000000
24	Date_Tuesday	0.000000	0.000000
23	Date_Thursday	-0.000000	0.000000
22	Date_Sunday	0.000000	0.000000
21	Date_Saturday	0.000000	0.000000
20	Date_Monday	-0.000000	0.000000
19	Date_Friday	-0.000000	0.000000
18	Payment_Ewallet	-0.000000	0.000000
17	Payment_Credit card	0.000000	0.000000
16	Payment_Cash	-0.000000	0.000000
15	Product line_Sports and travel	0.000000	0.000000
14	Product line_Home and lifestyle	0.000000	0.000000
13	Product line_Health and beauty	-0.000000	0.000000
12	Product line_Food and beverages	0.000000	0.000000
11	Product line_Fashion accessories	-0.000000	0.000000
10	Product line_Electronic accessories	-0.000000	0.000000
9	Gender_Male	-0.000000	0.000000
8	Gender_Female	0.000000	0.000000
7	Customer type_Normal	0.000000	0.000000
6	Customer type_Member	-0.000000	0.000000
5	Branch_C	0.000000	0.000000
4	Branch_B	-0.000000	0.000000
3	Branch_A	-0.000000	0.000000

	Feature name	Coefficient value	AbsCoefficient
2	Rating	-0.000000	0.000000
29	Time_Night	-0.000000	0.000000

In [22]:
```
with open('model1_lr.pkl','wb') as f:
    pickle.dump(model1_lr,f)
with open('model1_lasso.pkl','wb') as f:
    pickle.dump(model1_lasso,f)
with open('X1_test.pkl', 'wb') as f:
    pickle.dump(X1_test, f)
with open('t1_test.pkl', 'wb') as f:
    pickle.dump(t1_test, f)
```

1. How is the gross income affected by unit price, quantity, and other variables like day, time slot, and product line in general?

- In the model linear regression without lasso, it is observed from the coefficients of features that, gross income is most affected by Quantity followed closely by Unit price. As long as quantity or unit price increases, gross income also increases. Related to day,time slot and product line, gross income is highly affetced by 'Tuesday', 'Product line_Home and lifestyle' and 'Time_Morning' slots the highest in these respective categories.
- In the model linear regression with lasso, lasso regularization parameter removes the influence of all the factors except Quantity and Unit price. These two features only affect the gross income.

3a. Multiple linear regression to predict unit price without lasso regularization

In [23]:
```
X2 = data.drop(columns=['Unit price'], axis=1)
t2 = data['Unit price']
X2.head()
```

Out[23]:

	Branch	Customer type	Gender	Product line	Quantity	Total	Date	Time	Payment	cogs	gross income	Rating
0	A	Member	Female	Health and beauty	7	548.9715	1/5/2019	13:08	Ewallet	522.83	26.1415	9.1
1	C	Normal	Female	Electronic accessories	5	80.2200	3/8/2019	10:29	Cash	76.40	3.8200	9.6
2	A	Normal	Male	Home and lifestyle	7	340.5255	3/3/2019	13:23	Credit card	324.31	16.2155	7.4
3	A	Member	Male	Health and beauty	8	489.0480	1/27/2019	20:33	Ewallet	465.76	23.2880	8.4
4	A	Normal	Male	Sports and travel	7	634.3785	2/8/2019	10:37	Ewallet	604.17	30.2085	5.3

In [24]:
```
corr2= data.corr(method='pearson',numeric_only=True)
corr2
```

Out[24]:

	Unit price	Quantity	Total	cogs	gross income	Rating
Unit price	1.000000	0.010778	0.633962	0.633962	0.633962	-0.008778
Quantity	0.010778	1.000000	0.705510	0.705510	0.705510	-0.015815
Total	0.633962	0.705510	1.000000	1.000000	1.000000	-0.036442
cogs	0.633962	0.705510	1.000000	1.000000	1.000000	-0.036442
gross income	0.633962	0.705510	1.000000	1.000000	1.000000	-0.036442
Rating	-0.008778	-0.015815	-0.036442	-0.036442	-0.036442	1.000000

No need to exclude any extra column as their presence doesnot overshadow the other features impact on models performance.

In [25]:
```
data['stratify_column'] = data['Gender'] +  '_' + data['Branch'] + '_' + data['Product line'] + '_' + data['Payment']
X2_train, X2_test,t2_train,t2_test= train_test_split(X2, t2, test_size=0.2, random_state=1, shuffle=True, stratify=data['stratify_column'])
data.drop(columns=['stratify_column'],inplace=True)
X2_train.shape,X2_test.shape
```

Out[25]:
```
((800, 12), (200, 12))
```

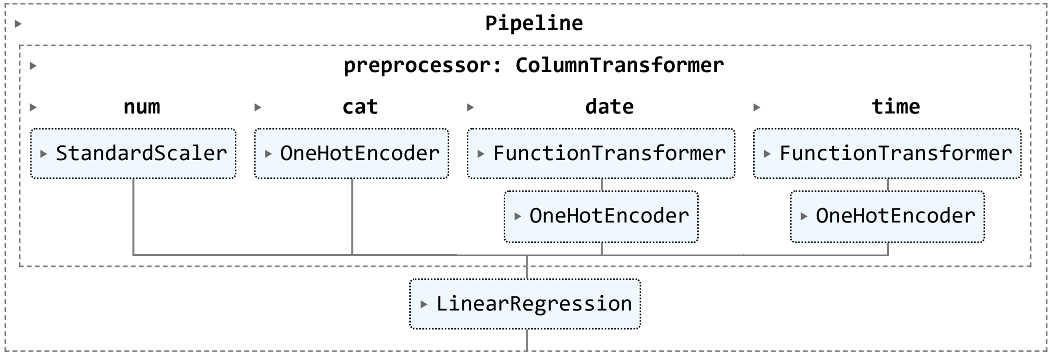
In [26]:
```
date_feature2 = ['Date']
time_feature2 = ['Time']
num_cat_data2 = X2_train.drop(columns=['Date','Time']) #to exclude date and time features of other features
num_features2 = [col for col in num_cat_data2.columns if num_cat_data2[col].dtype != "object"]
cat_features2 = [col for col in num_cat_data2.columns if num_cat_data2[col].dtype == "object"]
print("Categorical features:",cat_features2)
print("Numerical features:",num_features2)
```

```
Categorical features: ['Branch', 'Customer type', 'Gender', 'Product line', 'Payment']
Numerical features: ['Quantity', 'Total', 'cogs', 'gross income', 'Rating']
```

In [27]:
```
full_pipeline2 = ColumnTransformer([
    ('num', num_pipeline, num_features2),
    ('cat', cat_pipeline, cat_features2),
    ('date', date_pipeline, date_feature2),
    ('time', time_pipeline, time_feature2)
])
```

In [28]:
```
lr_pipeline2 = Pipeline([
     ('preprocessor',full_pipeline2),
     ('lin_reg', LinearRegression())
])

model2_lr=lr_pipeline2.fit(X2_train,t2_train)
model2_lr
```

Out[28]:



3b. Multiple linear regression to predict unit price with lasso regularization

In [29]:

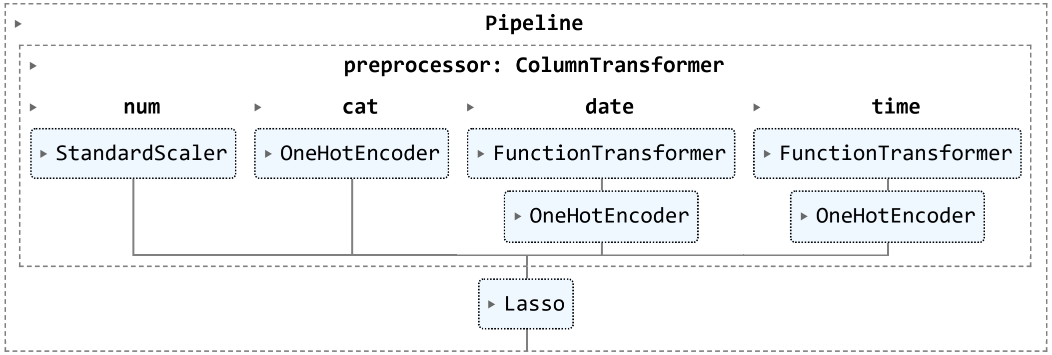
```
lasso_pipeline = Pipeline([
    ('preprocessor',full_pipeline2),
    ('regressor',Lasso())
])

param_grid_lasso = {
    'regressor__alpha':np.linspace(0.1,0.5,1000)
}
kf = KFold(n_splits=10, shuffle=True, random_state=42)
lasso_grid = GridSearchCV(lasso_pipeline,param_grid=param_grid_lasso,cv=kf,scoring='r2')
lasso_grid.fit(X2_train,t2_train)
best_params_grid_search_poly_lasso = lasso_grid.best_params_
print("Best hyperparamaters for GridsearchCV for Linear Regression with lasso:", best_params_grid_search_poly_lasso)
```

```
Best hyperparamaters for GridsearchCV for Linear Regression with lasso: {'regressor__alpha': 0.2881881881881882}
```

In [30]:

```
model2_lasso = Pipeline([
    ('preprocessor',full_pipeline2),
    ('regressor',Lasso(alpha= best_params_grid_search_poly_lasso['regressor__alpha']))
]).fit(X2_train,t2_train)
model2_lasso
```

Out[30]:



Impact of features on models ability to predict 'Unit price'

In [31]:
```
date_feature2_names = list(full_pipeline.transformers_[2][1].named_steps['encoder'].get_feature_names_out(date_feature2))
time_feature2_names = list(full_pipeline.transformers_[3][1].named_steps['encoder'].get_feature_names_out(time_feature2))
num_feature2_names = num_features2  # Since num_features is predefined
cat_feature2_names = full_pipeline2.transformers_[1][1].named_steps['encoder'].get_feature_names_out(cat_features2)
```

In [32]:
```
coefficients = lr_pipeline2.named_steps['lin_reg'].coef_
feature_names = np.concatenate([
    num_feature2_names,
    cat_feature2_names,
    date_feature2_names,
    time_feature2_names
])
coef_df = pd.DataFrame({'Feature name': feature_names, 'Coefficient value': coefficients})
coef_df['AbsCoefficient'] = coef_df['Coefficient value'].abs()
coef_df = coef_df.sort_values(by='AbsCoefficient', ascending=False)
print("Coefiiceints of linear regression")
# Display sorted coefficients by absolute value
coef_df
```

```
Coefiiceints of linear regression
```

Out[32]:

	Feature name	Coefficient value	AbsCoefficient
0	Quantity	-23.374382	23.374382
1	Total	11.079626	11.079626
2	cogs	11.079626	11.079626
3	gross income	11.079626	11.079626
26	Date_Tuesday	-2.260858	2.260858
22	Date_Monday	1.629256	1.629256
19	Payment_Credit card	-1.487510	1.487510
27	Date_Wednesday	1.412690	1.412690
30	Time_Morning	1.275701	1.275701
28	Time_Afternoon	-1.116084	1.116084
29	Time_Evening	-0.884502	0.884502
18	Payment_Cash	0.825014	0.825014
31	Time_Night	0.724886	0.724886
13	Product line_Fashion accessories	0.668900	0.668900
20	Payment_Ewallet	0.662496	0.662496
23	Date_Saturday	-0.643900	0.643900
16	Product line_Home and lifestyle	-0.567832	0.567832
7	Branch_C	-0.545217	0.545217
9	Customer type_Normal	-0.523654	0.523654
8	Customer type_Member	0.523654	0.523654
24	Date_Sunday	-0.472172	0.472172
4	Rating	0.461121	0.461121
15	Product line_Health and beauty	0.445950	0.445950
10	Gender_Female	-0.429418	0.429418
11	Gender_Male	0.429418	0.429418
17	Product line_Sports and travel	-0.392299	0.392299
5	Branch_A	0.297906	0.297906
25	Date_Thursday	0.296182	0.296182

	Feature name	Coefficient value	AbsCoefficient
6	Branch_B	0.247311	0.247311
14	Product line_Food and beverages	-0.180634	0.180634
21	Date_Friday	0.038802	0.038802
12	Product line_Electronic accessories	0.025915	0.025915

In [33]:

```
coefficients = model2_lasso.named_steps['regressor'].coef_
feature_names = np.concatenate([
    num_feature2_names,
    cat_feature2_names,
    date_feature2_names,
    time_feature2_names
])
coef_df = pd.DataFrame({'Feature name': feature_names, 'Coefficient value': coefficients})
coef_df['AbsCoefficient'] = coef_df['Coefficient value'].abs()
coef_df = coef_df.sort_values(by='AbsCoefficient', ascending=False)
print("Coefiiceints of linear regression with lasso")
# Display sorted coefficients by absolute value
coef_df
```

```
Coefiiceints of linear regression with lasso
```

Out[33]:

	Feature name	Coefficient value	AbsCoefficient
1	Total	32.244177	32.244177
0	Quantity	-22.425996	22.425996
19	Payment_Credit card	-0.756274	0.756274
26	Date_Tuesday	-0.107249	0.107249
4	Rating	0.078173	0.078173
28	Time_Afternoon	-0.072728	0.072728
30	Time_Morning	0.000000	0.000000
29	Time_Evening	-0.000000	0.000000
27	Date_Wednesday	0.000000	0.000000
17	Product line_Sports and travel	-0.000000	0.000000
24	Date_Sunday	-0.000000	0.000000
23	Date_Saturday	-0.000000	0.000000
22	Date_Monday	0.000000	0.000000
21	Date_Friday	0.000000	0.000000
20	Payment_Ewallet	0.000000	0.000000
18	Payment_Cash	0.000000	0.000000
25	Date_Thursday	0.000000	0.000000
16	Product line_Home and lifestyle	-0.000000	0.000000
15	Product line_Health and beauty	0.000000	0.000000
14	Product line_Food and beverages	-0.000000	0.000000
13	Product line_Fashion accessories	0.000000	0.000000
12	Product line_Electronic accessories	-0.000000	0.000000
11	Gender_Male	0.000000	0.000000
10	Gender_Female	-0.000000	0.000000
9	Customer type_Normal	-0.000000	0.000000
8	Customer type_Member	0.000000	0.000000
7	Branch_C	-0.000000	0.000000
6	Branch_B	0.000000	0.000000

	Feature name	Coefficient value	AbsCoefficient
5	Branch_A	0.000000	0.000000
3	gross income	0.000000	0.000000
2	cogs	0.000000	0.000000
31	Time_Night	0.000000	0.000000

In [34]:
```
with open('model2_lr.pkl','wb') as f:
    pickle.dump(model2_lr,f)

with open('model2_lasso.pkl','wb') as f:
    pickle.dump(model2_lasso,f)

with open('X2_test.pkl', 'wb') as f:
    pickle.dump(X2_test, f)

with open('t2_test.pkl', 'wb') as f:
    pickle.dump(t2_test, f)
```

1. How is the unit price affected by gross income, quantity, and other variables like day, timeslot, and product line in general?

- In the model linear regression without lasso, unit price is affected the most by 'Quantity' followed by 'Total','cogs','gross income' equally. in the categoreis day, timeslot, and product line, unit price is most affected on Tuesday, Morning and Fashion accessories repectively.
- In model linear regression with lasso, Unit price is most affected by 'Total' and followed by 'Quantity'. Using Lasso regularization reduces the weights of most of the features but the affect by Tuesday and Afternoon categories exist is small weights.

4. Logistic regression to classify gender

In [35]:
```
## Use logistic regression to study the relationship between gender, product line, payment and gross income for branch C
# To classify Gender, Use 1 to represent male and 0 to represent to represent non_male(female)
```

In [36]:
```
data_branch_C = data[data['Branch']=='C']
X3= data_branch_C.drop(columns=['Gender','Branch'])
t3 = data_branch_C['Gender'].apply(lambda x: 1 if x == 'Male' else 0)

X3_train,X3_test,t3_train,t3_test = train_test_split(X3,t3,test_size=0.2, random_state=1, shuffle=True,stratify=t3)
X3_train.shape,X3_test.shape
```

Out[36]:
```
((262, 11), (66, 11))
```

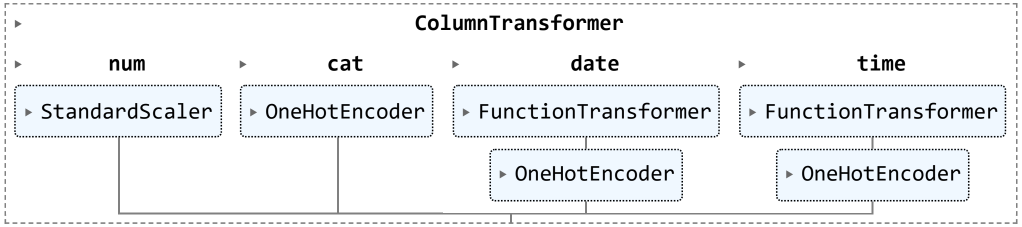
In [37]:
```
date_feature3 = ['Date']
time_feature3 = ['Time']
num_cat_data3 = X3_train.drop(columns=['Date','Time']) #to exclude date and time features of other features
```

```
num_features3 = [col for col in num_cat_data3.columns if num_cat_data3[col].dtype != "object"]
cat_features3 = [col for col in num_cat_data3.columns if num_cat_data3[col].dtype == "object"]
print("Categorical features:",cat_features3)
print("Numerical features:",num_features3)
```

```
Categorical features: ['Customer type', 'Product line', 'Payment']
Numerical features: ['Unit price', 'Quantity', 'Total', 'cogs', 'gross income', 'Rating']
```

In [38]:
```
full_pipeline3 = ColumnTransformer([
    ('num', num_pipeline, num_features3),  # Process numeric features
    ('cat', cat_pipeline, cat_features3),  # Process categorical features
    ('date', date_pipeline, date_feature3),  # Process the 'Date' column
    ('time', time_pipeline, time_feature3)  # Process the 'Time' column
])
full_pipeline3
```

Out[38]:



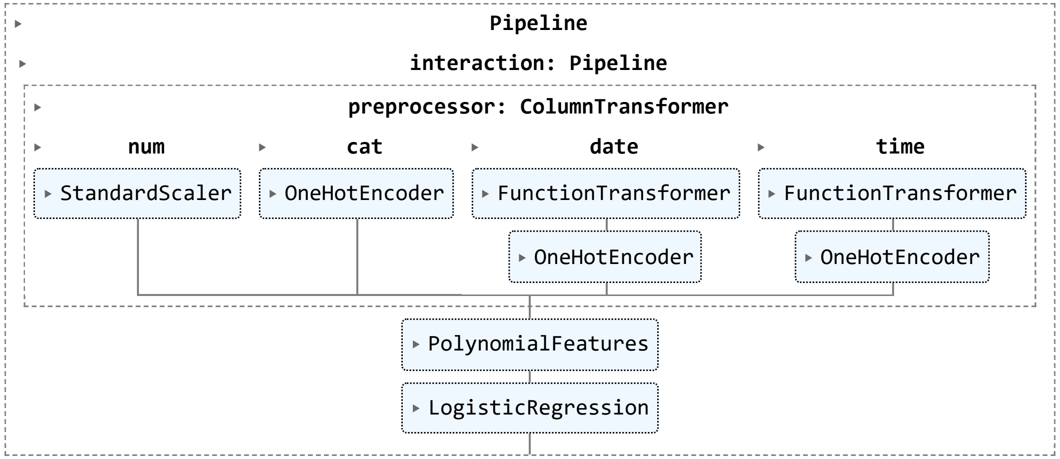
In [39]:
```
interaction_pipeline = Pipeline([
    ('preprocessor', full_pipeline3),
    ('poly', PolynomialFeatures(degree=2, interaction_only=True, include_bias=False))  # Interaction terms only
])

log_reg_pipeline = Pipeline([
    ('interaction', interaction_pipeline),
    ('log_reg', LogisticRegression(penalty=None,max_iter=10000))
])
```

In [40]:
```
param_grid={'log_reg__C':[0.01,0.1,1,10,100], 'log_reg__solver':['lbfgs','saga', 'liblinear']}
grid_search = GridSearchCV(log_reg_pipeline,param_grid,cv=10)
grid_search.fit(X3_train,t3_train)
best_param = grid_search.best_params_
print(best_param)
```

```
{'log_reg__C': 0.01, 'log_reg__solver': 'lbfgs'}
```

In [41]:
```
model3 = Pipeline([
    ('interaction',interaction_pipeline),
    ('log_reg',LogisticRegression(penalty=None, solver=best_param['log_reg__solver'],max_iter=10000,C = best_param['log_reg__C']))
])
model3.fit(X3_train,t3_train)
```

Out[41]:



In [42]:

```
cat_feature_names = list(full_pipeline3.transformers_[1][1].named_steps['encoder'].get_feature_names_out(cat_features3))
num_feature_names = num_features3
date_feature_names = list(full_pipeline3.transformers_[2][1].named_steps['encoder'].get_feature_names_out(date_feature3))
time_feature_names = list(full_pipeline3.transformers_[3][1].named_steps['encoder'].get_feature_names_out(time_feature3))
interaction_feature_names = interaction_pipeline.named_steps['poly'].get_feature_names_out(
    input_features=num_feature_names + cat_feature_names + date_feature_names + time_feature_names)
#Extract the coefficients from the trained logistic regression model
coefficients = model3.named_steps['log_reg'].coef_[0]

# Create a dataframe for feature names and coefficients
coef_df = pd.DataFrame({'Feature name': interaction_feature_names, 'Coefficient value': coefficients})

# Sort coefficients by absolute value to identify the most informative features
coef_df['AbsCoefficient'] = coef_df['Coefficient value'].abs()
coef_df = coef_df.sort_values(by='AbsCoefficient', ascending=False)
print("Coefficeints of logistic regression to classify gender")
# Display sorted coefficients by absolute value
coef_df
```

```
Coefficeints of logistic regression to classify gender
```

Out[42]:

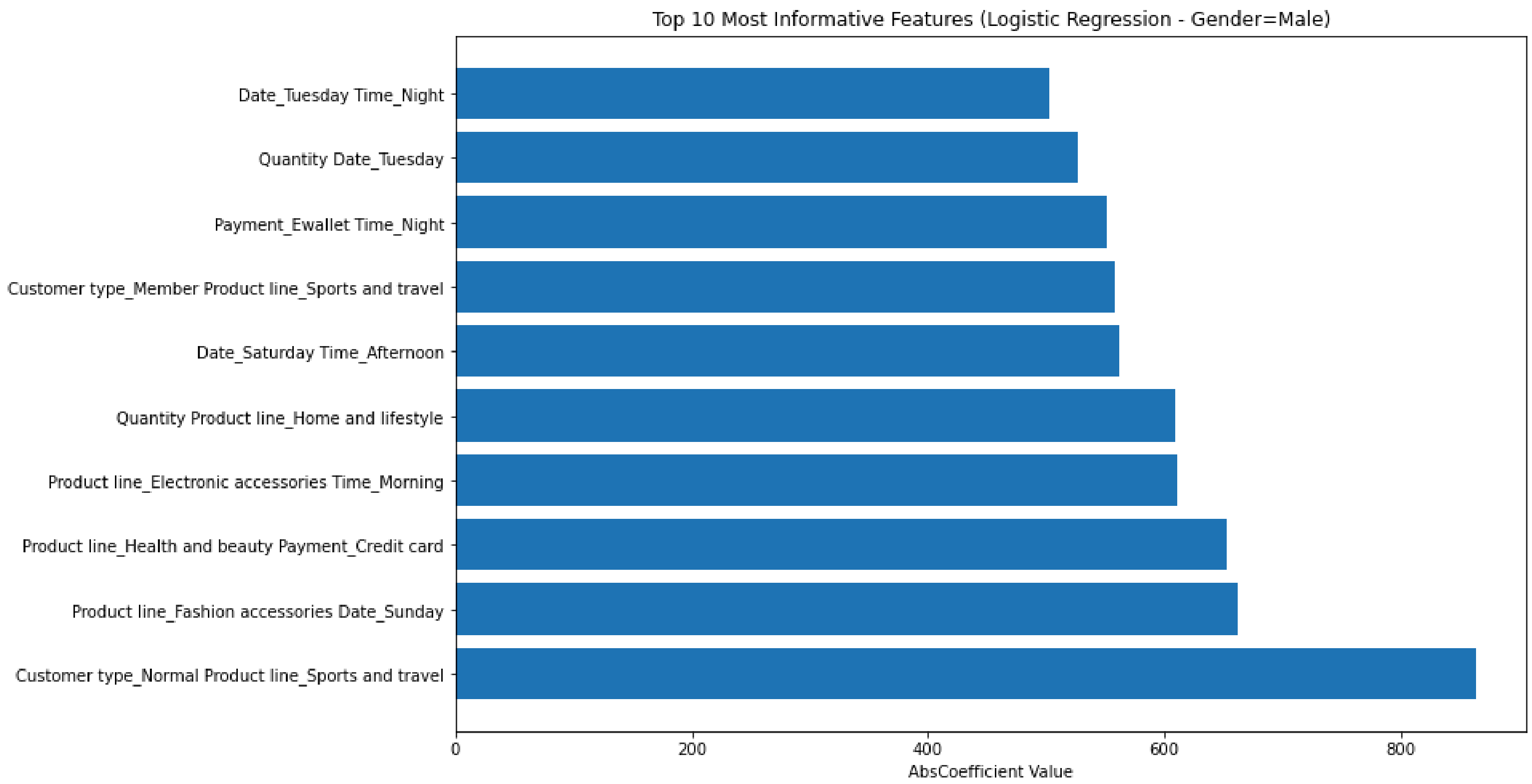
	Feature name	Coefficient value	AbsCoefficient
201	Customer type_Normal Product line_Sports and t...	-863.245115	863.245115
245	Product line_Fashion accessories Date_Sunday	-662.686730	662.686730
273	Product line_Health and beauty Payment_Credit ...	652.443479	652.443479
233	Product line_Electronic accessories Time_Morning	611.208800	611.208800
65	Quantity Product line_Home and lifestyle	-609.496929	609.496929
...	...	...	...
364	Date_Monday Date_Tuesday	0.000000	0.000000
315	Payment_Cash Payment_Credit card	0.000000	0.000000
175	Customer type_Member Customer type_Normal	0.000000	0.000000
370	Date_Saturday Date_Sunday	0.000000	0.000000
405	Time_Morning Time_Night	0.000000	0.000000

406 rows × 3 columns

2. Which attributes are the most informative?

In [43]:

```
plt.figure(figsize=(12, 8))
plt.barh(coef_df['Feature name'][:10], coef_df['AbsCoefficient'][:10])  # Top 10 most informative features
plt.xlabel('AbsCoefficient Value')
plt.title('Top 10 Most Informative Features (Logistic Regression - Gender=Male)')
plt.show()

# Print out the most informative features
print("Top 10 Most Informative Features for Gender=Male classification:")
coef_df.head(10)
```




```
Top 10 Most Informative Features for Gender=Male classification:
```

Out[43]:

	Feature name	Coefficient value	AbsCoefficient
201	Customer type_Normal Product line_Sports and t...	-863.245115	863.245115
245	Product line_Fashion accessories Date_Sunday	-662.686730	662.686730
273	Product line_Health and beauty Payment_Credit ...	652.443479	652.443479
233	Product line_Electronic accessories Time_Morning	611.208800	611.208800
65	Quantity Product line_Home and lifestyle	-609.496929	609.496929
374	Date_Saturday Time_Afternoon	561.429587	561.429587
181	Customer type_Member Product line_Sports and t...	557.383628	557.383628
350	Payment_Ewallet Time_Night	551.056433	551.056433
75	Quantity Date_Tuesday	-526.979850	526.979850
395	Date_Tuesday Time_Night	502.983010	502.983010

In [44]:
```
with open('model3.pkl','wb') as f:
    pickle.dump(model3,f)

with open('X3_test.pkl', 'wb') as f:
    pickle.dump(X3_test, f)

with open('t3_test.pkl', 'wb') as f:
    pickle.dump(t3_test, f)
```

5. Logistic regression to classify Customer type

In [45]:
```
X4= data_branch_C.drop(columns=['Customer type','Branch'])
t4 = data_branch_C['Customer type'].apply(lambda x: 1 if x == 'Normal' else 0)

X4_train,X4_test,t4_train,t4_test = train_test_split(X4,t4,test_size=0.2, random_state=1, shuffle=True,stratify=t4)
X4_train.shape,X4_test.shape
```

Out[45]:
```
((262, 11), (66, 11))
```

In [46]:
```
date_feature4 = ['Date']
time_feature4 = ['Time']
num_cat_data4 = X4_train.drop(columns=['Date','Time']) #to exclude date and time features of other features
num_features4 = [col for col in num_cat_data4.columns if num_cat_data4[col].dtype != "object"]
cat_features4 = [col for col in num_cat_data4.columns if num_cat_data4[col].dtype == "object"]
print("Categorical features:",cat_features4)
print("Numerical features:",num_features4)
```

```
Categorical features: ['Gender', 'Product line', 'Payment']
Numerical features: ['Unit price', 'Quantity', 'Total', 'cogs', 'gross income', 'Rating']
```

In [47]:
```
full_pipeline4 = ColumnTransformer([
    ('num', num_pipeline, num_features4),  # Process numeric features
    ('cat', cat_pipeline, cat_features4),  # Process categorical features
    ('date', date_pipeline, date_feature4),  # Process the 'Date' column
    ('time', time_pipeline, time_feature4)  # Process the 'Time' column
])
```

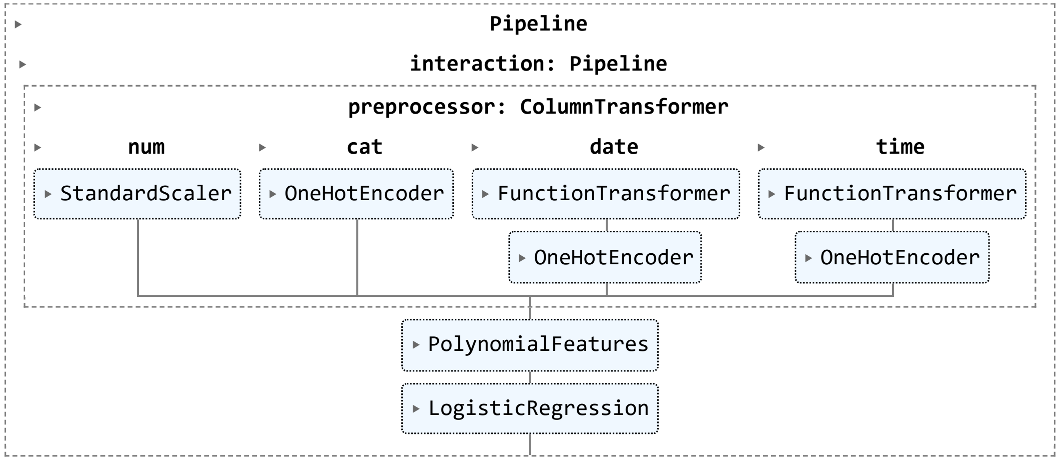
In [48]:
```
interaction_pipeline2 = Pipeline([
    ('preprocessor', full_pipeline4),
    ('poly', PolynomialFeatures(degree=2, interaction_only=True, include_bias=False))  # Interaction terms only
])

log_reg_pipeline2 = Pipeline([
    ('interaction', interaction_pipeline2),
    ('log_reg', LogisticRegression(penalty=None,max_iter=10000))
])
```

In [49]:
```python
param_grid={'log_reg__C':[0.01,0.1,1,10,100], 'log_reg__solver':['lbfgs','saga', 'liblinear']}
grid_search = GridSearchCV(log_reg_pipeline2,param_grid,cv=10)
grid_search.fit(X4_train,t4_train)
best_param = grid_search.best_params_
print(best_param)
```

```
{'log_reg__C': 0.01, 'log_reg__solver': 'lbfgs'}
```

In [50]:
```python
model4 = Pipeline([
    ('interaction',interaction_pipeline2),
    ('log_reg',LogisticRegression(penalty=None, solver=best_param['log_reg__solver'],max_iter=10000,C = best_param['log_reg__C']))
])
model4.fit(X4_train,t4_train)
```

Out[50]:



In [51]:
```python
#Extract the coefficients from the trained logistic regression model
coefficients = model4.named_steps['log_reg'].coef_[0]

cat_feature_names = list(full_pipeline4.transformers_[1][1].named_steps['encoder'].get_feature_names_out(cat_features4))
num_feature_names = num_features4
date_feature_names = list(full_pipeline4.transformers_[2][1].named_steps['encoder'].get_feature_names_out(date_feature4))
time_feature_names = list(full_pipeline4.transformers_[3][1].named_steps['encoder'].get_feature_names_out(time_feature4))
interaction_feature_names = interaction_pipeline2.named_steps['poly'].get_feature_names_out(
    input_features=num_feature_names + cat_feature_names + date_feature_names + time_feature_names)

# Create a dataframe for feature names and coefficients
coef_df = pd.DataFrame({'Feature name': interaction_feature_names, 'Coefficient value': coefficients})

coef_df['AbsCoefficient'] = coef_df['Coefficient value'].abs()
coef_df = coef_df.sort_values(by='AbsCoefficient', ascending=False)
print("Coefficeints of logistic regression to classify Customer type")
# Display sorted coefficients by absolute value
coef_df
```

```
Coefficeints of logistic regression to classify Customer type
```

Out[51]:

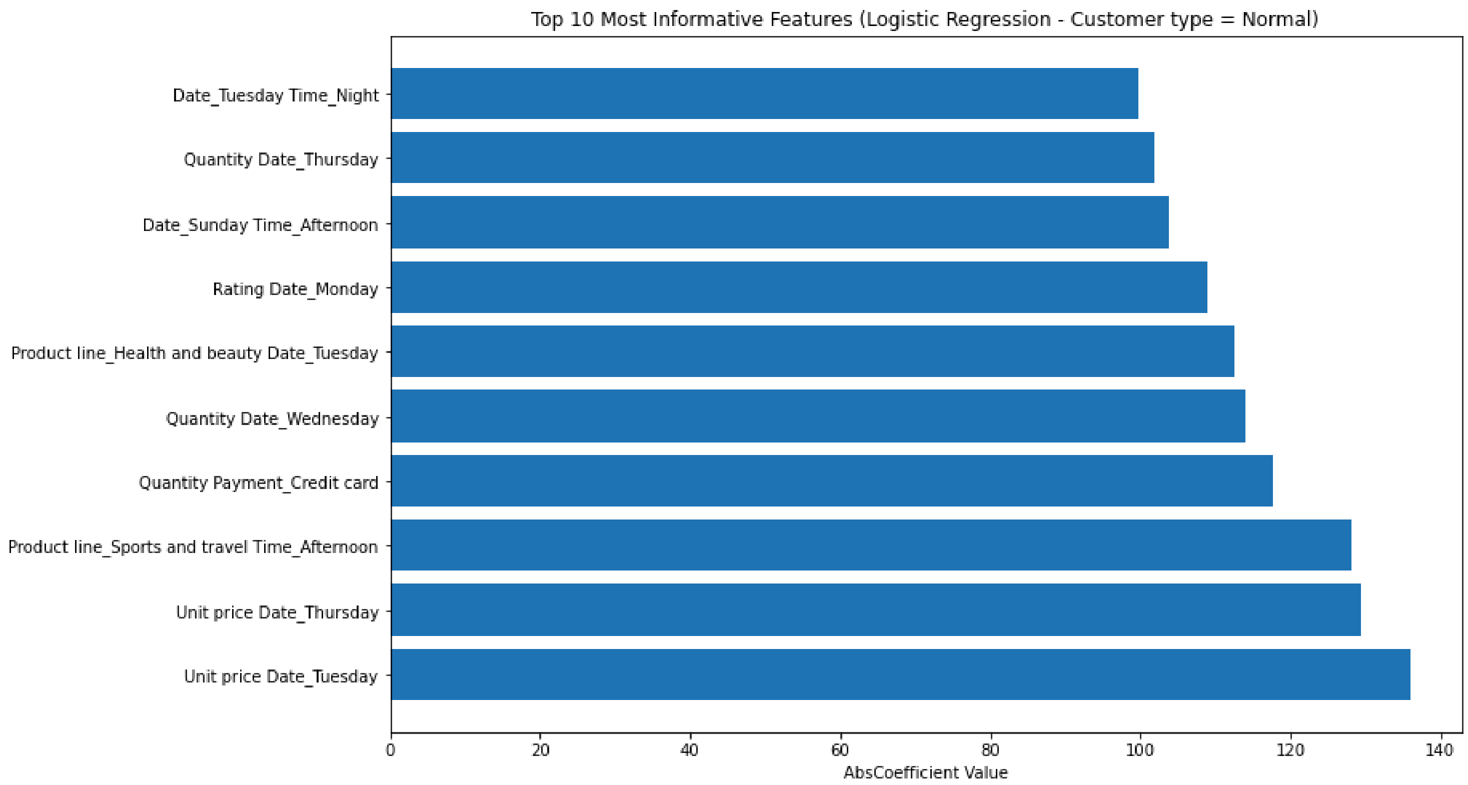
	Feature name	Coefficient value	AbsCoefficient
49	Unit price Date_Tuesday	-136.043526	136.043526
48	Unit price Date_Thursday	129.472702	129.472702
311	Product line_Sports and travel Time_Afternoon	-128.181779	128.181779
68	Quantity Payment_Credit card	-117.716967	117.716967
76	Quantity Date_Wednesday	-114.057021	114.057021
...	...	...	...
286	Product line_Home and lifestyle Product line_S...	0.000000	0.000000
378	Date_Sunday Date_Thursday	0.000000	0.000000
379	Date_Sunday Date_Tuesday	0.000000	0.000000
380	Date_Sunday Date_Wednesday	0.000000	0.000000
405	Time_Morning Time_Night	0.000000	0.000000

406 rows × 3 columns

2.Which attributes are the most informative?

In [52]:

```python
plt.figure(figsize=(12, 8))
plt.barh(coef_df['Feature name'][:10], coef_df['AbsCoefficient'][:10])  # Top 10 most informative features
plt.xlabel('AbsCoefficient Value')
plt.title('Top 10 Most Informative Features (Logistic Regression - Customer type = Normal)')
plt.show()

# Print out the most informative features
print("Top 10 Most Informative Features for Customer type = Normal classification:")
coef_df.head(10)
```




```
Top 10 Most Informative Features for Customer type = Normal classification:
```

Out[52]:

	Feature name	Coefficient value	AbsCoefficient
49	Unit price Date_Tuesday	-136.043526	136.043526
48	Unit price Date_Thursday	129.472702	129.472702
311	Product line_Sports and travel Time_Afternoon	-128.181779	128.181779
68	Quantity Payment_Credit card	-117.716967	117.716967
76	Quantity Date_Wednesday	-114.057021	114.057021
280	Product line_Health and beauty Date_Tuesday	112.417962	112.417962
165	Rating Date_Monday	-108.865755	108.865755
381	Date_Sunday Time_Afternoon	-103.701788	103.701788
74	Quantity Date_Thursday	101.784768	101.784768
395	Date_Tuesday Time_Night	-99.711887	99.711887

In [53]:
```
with open('model4.pkl','wb') as f:
    pickle.dump(model4,f)

with open('X4_test.pkl', 'wb') as f:
    pickle.dump(X4_test, f)

with open('t4_test.pkl', 'wb') as f:
    pickle.dump(t4_test, f)
```

6a. Classifiers to predict day of purchase

Classifier 1: Decision Tree classifier

In [54]:
```
from sklearn.model_selection import cross_val_score, StratifiedKFold
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score,make_scorer
from scipy import stats
```

In [55]:
```
X= data.copy()
X['DayofWeek'] = pd.to_datetime(X['Date']).dt.day_name()
X5 = X.drop(columns=['Date','DayofWeek'])
t5 = X['DayofWeek']
X5_train,X5_test,t5_train,t5_test = train_test_split(X5,t5,test_size=0.2,random_state=1,stratify=t5)
X5_train
```

Out[55]:

	Branch	Customer type	Gender	Product line	Unit price	Quantity	Total	Time	Payment	cogs	gross income	Rating
646	C	Normal	Male	Health and beauty	70.21	6	442.3230	14:58	Cash	421.26	21.0630	7.4
561	C	Normal	Male	Food and beverages	89.20	10	936.6000	15:42	Credit card	892.00	44.6000	4.4
163	C	Normal	Male	Sports and travel	76.40	2	160.4400	19:42	Ewallet	152.80	7.6400	6.5
49	C	Member	Female	Fashion accessories	82.63	10	867.6150	17:08	Ewallet	826.30	41.3150	7.9
83	C	Member	Female	Food and beverages	80.36	4	337.5120	18:45	Credit card	321.44	16.0720	8.3
...	...	...	...	...	...	...	...	...	...	...	...	...
559	A	Member	Female	Home and lifestyle	72.42	3	228.1230	16:54	Ewallet	217.26	10.8630	8.2
833	A	Member	Male	Health and beauty	91.30	1	95.8650	14:42	Ewallet	91.30	4.5650	9.2
784	C	Member	Female	Health and beauty	10.16	5	53.3400	13:08	Ewallet	50.80	2.5400	4.1
278	C	Member	Male	Fashion accessories	70.99	10	745.3950	16:28	Cash	709.90	35.4950	5.7
346	A	Member	Male	Electronic accessories	71.95	1	75.5475	12:14	Cash	71.95	3.5975	7.3

800 rows × 12 columns

In [56]:

```
time_feature5 = ['Time']
num_cat_data5 = X5.drop(columns = ['Time'])
num_features5 = [col for col in num_cat_data5.columns if num_cat_data5[col].dtype != "object"]
cat_features5 = [col for col in num_cat_data5.columns if num_cat_data5[col].dtype == "object"]
print("Numerical features:",num_features5)
print("Categorical features:",cat_features5)
```

```
Numerical features: ['Unit price', 'Quantity', 'Total', 'cogs', 'gross income', 'Rating']
Categorical features: ['Branch', 'Customer type', 'Gender', 'Product line', 'Payment']
```

In [57]:

```
full_pipeline5 = ColumnTransformer([
    ('num', num_pipeline, num_features5),  # Process numeric features
    ('cat', cat_pipeline, cat_features5),  # Process categorical features
    ('time', time_pipeline, time_feature5)  # Process the 'Time' column
])
```

In [58]:

```
decision_pipeline = Pipeline(steps=[
    ('preprocessor',full_pipeline5),
    ('classifier', DecisionTreeClassifier(random_state=1))
])

decision_param_grid = {
    'classifier__criterion':['gini','entropy'],
    'classifier__max_depth': [15, 20, 30, None],
    'classifier__min_samples_split': [2, 5, 10],
    'classifier__min_samples_leaf': [2, 4, 6, 10]
```

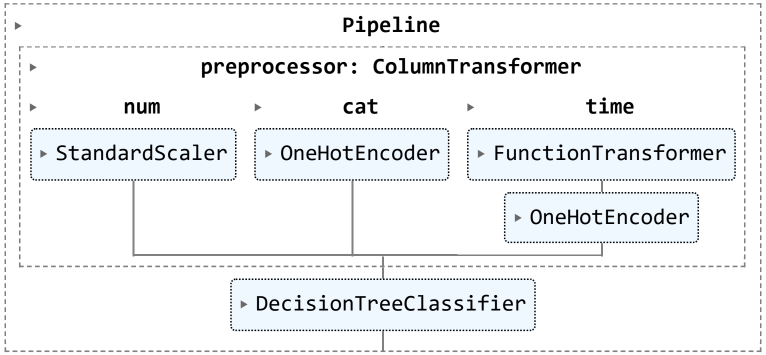
```python
}

kf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
grid_search = GridSearchCV(decision_pipeline,decision_param_grid,cv=kf,scoring='accuracy')
grid_search.fit(X5_train,t5_train)
best_param = grid_search.best_params_
print(best_param)
```

```
{'classifier__criterion': 'gini', 'classifier__max_depth': 15, 'classifier__min_samples_leaf': 6, 'classifier__min_samples_split': 2}
```

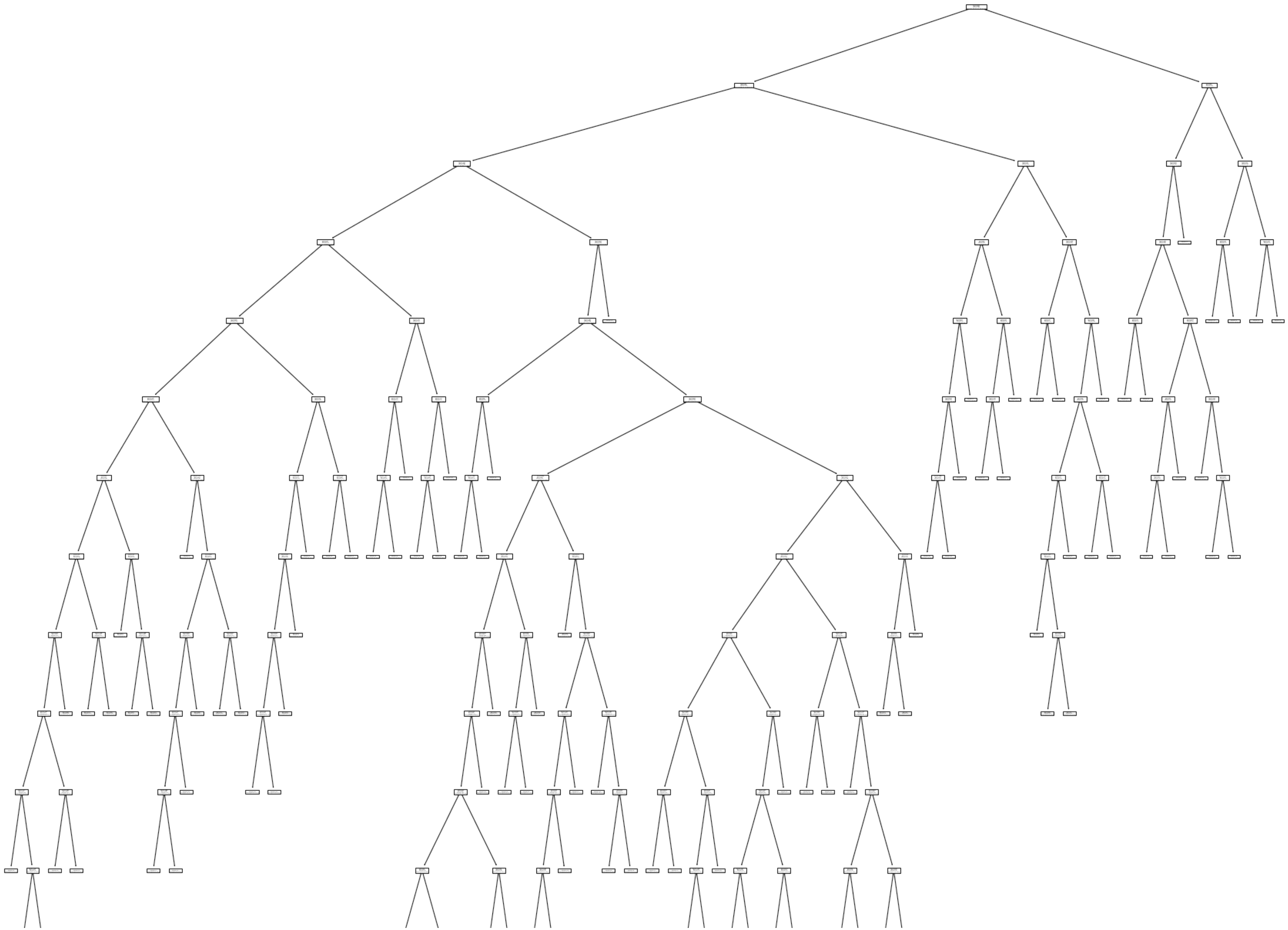
Using stratifiedKfold we can ensure the best Cross validation strategy and using GridsearchCV, we can find the best parameters for optimal performance.

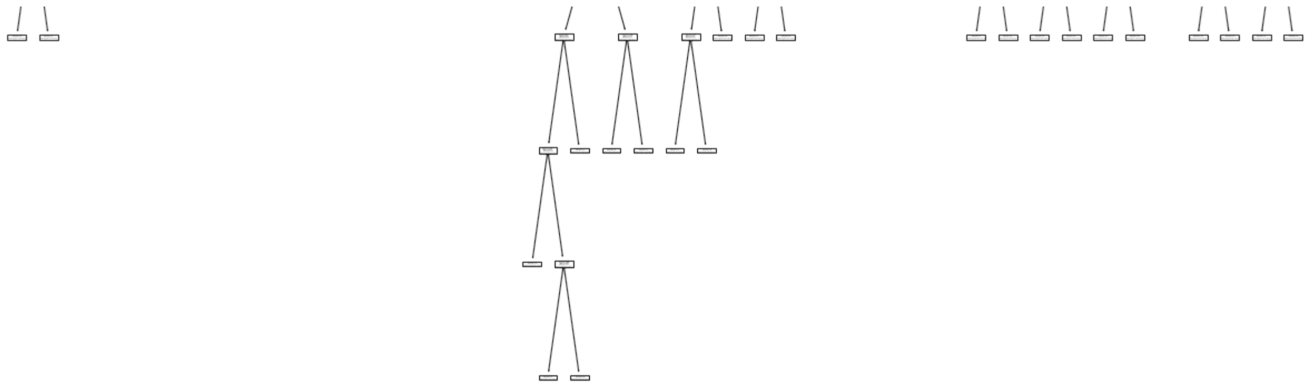
In [59]:
```python
model5 = Pipeline([
    ('preprocessor',full_pipeline5),
    ('classifier',DecisionTreeClassifier(criterion=best_param['classifier__criterion'],max_depth=best_param['classifier__max_depth'],
                                        min_samples_leaf=best_param['classifier__min_samples_leaf'],min_samples_split= best_param['classifier__min_samples_split'
])
model5.fit(X5_train,t5_train)
```

Out[59]:



In [60]:
```python
from sklearn.tree import plot_tree
tree_model = model5.named_steps['classifier']
plt.figure(figsize=(30,30))
plot_tree(tree_model)
plt.show()
```





In [61]:
```
with open('model5.pkl','wb') as f:
    pickle.dump(model5,f)

with open('X5_test.pkl', 'wb') as f:
    pickle.dump(X5_test, f)

with open('t5_test.pkl', 'wb') as f:
    pickle.dump(t5_test, f)
```

6b. Classifiers to predict day of purchase

2. Random Forest classifier

In [62]:
```
rf_pipeline = Pipeline(steps=[
    ('preprocessor', full_pipeline5),
    ('classifier', RandomForestClassifier(random_state=1))
])

rf_param_grid = {
    'classifier__criterion':['gini','entropy'],
    'classifier__n_estimators': [50, 100, 200],
    'classifier__max_depth': [10, 20, None],
    'classifier__min_samples_split': [2, 5, 10],
    'classifier__min_samples_leaf': [1, 2, 4]
}

kf = StratifiedKFold(n_splits=5, shuffle=True, random_state=1)
grid_search = GridSearchCV(rf_pipeline,rf_param_grid,cv=kf,scoring='accuracy')
grid_search.fit(X5_train,t5_train)
best_param = grid_search.best_params_
print(best_param)
```

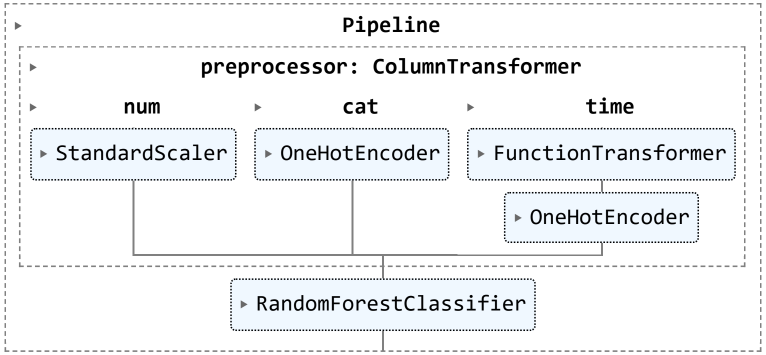
```
{'classifier__criterion': 'entropy', 'classifier__max_depth': 10, 'classifier__min_samples_leaf': 2, 'classifier__min_samples_split': 2, 'classifier__n_estimator
s': 50}
```

Using stratifiedKfold we can ensure the best Cross validation strategy and using GridsearchCV, we can find the best parameters for optimal performance.

In [63]:

```
model6 = Pipeline([
    ('preprocessor',full_pipeline5),
    ('classifier',RandomForestClassifier(n_estimators=best_param['classifier__n_estimators'],criterion=best_param['classifier__criterion'],
                                         max_depth=best_param['classifier__max_depth'], min_samples_split=best_param['classifier__min_samples_split'],
                                         min_samples_leaf=best_param['classifier__min_samples_leaf'], random_state=1))
])
model6.fit(X5_train,t5_train)
```

Out[63]:



In [64]:

```
with open('model6.pkl','wb') as f:
    pickle.dump(model6,f)
```

In [ ]: