In [1]:
```python
import numpy as np
import pandas as pd
import os
import glob
import seaborn as sns
import matplotlib.pyplot as plt
from pathlib import Path
from functools import reduce
from datetime import datetime
from termcolor import colored
from pickle import dump

from sklearn.preprocessing import Binarizer, OneHotEncoder, PowerTransformer, MinMaxScaler,
StandardScaler, FunctionTransformer
from sklearn.model_selection import train_test_split, GridSearchCV, RandomizedSearchCV,
ShuffleSplit, cross_val_score, StratifiedShuffleSplit
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.decomposition import PCA
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn import linear_model
from sklearn.pipeline import Pipeline
from sklearn import set_config
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.compose import ColumnTransformer
from sklearn.compose import make_column_selector as selector
from sklearn.feature_selection import SelectFromModel

from xgboost import XGBRegressor

from yellowbrick.regressor import residuals_plot
from yellowbrick.regressor import prediction_error

set_config(display="diagram")
pd.set_option('display.max_columns', None)
pd.set_option('display.float_format', lambda x: '%.3f' % x)
```

Load the train data

Since offline training is one time process, hence no special code was writing to grab data from folder. Also due to shortage of time. In future this process can also be automated so that training workflow can exceute more quickly

In [2]:
```python
raw_excel_dff = pd.read_excel(r"C:\Users\kumar\OneDrive\Desktop\Akshat\insurance\Data\Data 08-
10-2021.xlsx", engine='openpyxl')
excel_dff = raw_excel_dff.copy()
```

Data Prepratiion

1. Outlier Detection

The Indentified outliers in columns **Incurred** and **Capped Incurred** with lower limit of 5th percentile and upper limit of 95th percentile is replaced with respective 5th and 95th percentile values respectively. This method will force variable towards a more normal disttribution and helps in reducing kurtosis as well.

In [3]:
```python
def outlier_removal(X, outlier_cutoff = 0.01):
    """
    Impute the outliers with 5th and 95th percentile

    Parameters
    ----------
    outlier_cutoff : stope or start quantile range.range. default = 0.01

    Return
    ------
    a dataframe without outliers

    Note:
    This function is setup for only "Incurred" and "Capped Incurred" columns. Since these two
are only identified outlier columns during data exploration process
    """

    outlier_columns = ["Incurred", "Capped Incurred"]
    out_new_dff = X[X.columns.intersection(outlier_columns)].reset_index(drop=True)

    out_new_dff.pipe(lambda x:x.clip(lower=x.quantile(outlier_cutoff), upper=x.quantile(1-
outlier_cutoff), axis=1, inplace=True))

    X.drop(outlier_columns, axis=1, inplace=True)
    X = pd.merge(X, out_new_dff, left_index=True, right_index=True)

    return X
```

In [4]:
```python
# Execute outlier removal function for "Incurred" and "Capped Incurred" columns
excel_dff = outlier_removal(excel_dff)
```

2. Converting Date Columns

Date columns doesn't help in molde training process. Therefore, converting it into:

- Year : Year of loss
- Month : Month of loss
- Weekend : If loss is on weekend

Also, converted Inception to loss to Months since loss, to reduce range of column. Removed other non-useful columns identified during data exploration process

In [5]:
```python
# Adding columns for "Date_of_loss" column (Month, Weekend)
excel_dff['Month'] = pd.DatetimeIndex(excel_dff['date_of_loss']).month
excel_dff['Weekend'] = np.where((pd.to_datetime(excel_dff['date_of_loss']).dt.dayofweek) > 4, 1,
0)

excel_dff['MSL'] = round(excel_dff['Inception_to_loss']/30, 0) # Months since loss

excel_dff.drop(["date_of_loss",'Loss_code','Loss_description','TP_type_insd_pass_front',
'TP_type_pass_multi'], axis = 1, inplace=True, errors="ignore")
```

3. Split Data

Splitting training dataset into test and train before doing any futher preprocessing steps to data leakage. Split is performed using **StratifiedShuffleSplit** so that training and test data represent similar distribution. Due to lack of data, the test set is 20%

In [6]:
```python
# Split Dataset for Training and Test set

excel_dff["Incurred_cat"] = pd.cut(excel_dff["Incurred"],
                               bins = [-np.inf, 0., 25027., 50055., 75082., np.inf],
                               labels = range(1, 6))

split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=1234)
for train_index, test_index in split.split(excel_dff, excel_dff["Incurred_cat"]):
    strat_train_set = excel_dff.loc[train_index].reset_index(drop=True)
    strat_test_set = excel_dff.loc[test_index].reset_index(drop=True)

print(f"The original data contains {excel_dff.shape[0]} rows and {excel_dff.shape[1]} columns")
print(f"\nTraning data contains {strat_train_set.shape[0]} rows")
print(f"Test data contains {strat_test_set.shape[0]} rows")

# Saving test data for future use
strat_test_set.to_excel(r"C:\Users\kumar\OneDrive\Desktop\Akshat\insurance\Input\Insurance.xlsx",
 index = False)
```

```
The original data contains 7691 rows and 45 columns

Traning data contains 6152 rows
Test data contains 1539 rows
```

4. Partition Train dataset to seprate features from target

In below code cell, target **Incurred** values are seperated from features input into seperate datasets. This is done to train regression model on features data and target "Incurred" (ground truths).

In [7]:
```python
features = strat_train_set.drop(['Incurred', 'Claim Number', 'Incurred_cat'], axis = 1)
target = strat_train_set['Incurred']

# Drop ID Column and save it for future use
id_col = strat_train_set['Claim Number']
```

Pipeline

1. Feature Engineering Pipeline

All the columns created during data exploration task were added in pipeline after creating custom **DataframeFunctionTransformer** class. Main advantage of creating this pipeline is to add it in final predictive pipeline and utilize it in future test set

In [8]:
```python
class DataframeFunctionTransformer():
    """
    Pipeline class that can take only user defined function with fit and transform functionality

    Parameters
    ----------
    func : can take any user defined function and apply over pandas dataframe (required)

    Return
    ------
    a pandas dataframe
    """
    def __init__(self, func):
        self.func = func

    def transform(self, input_df, **transform_params):
        return self.func(input_df)

    def fit(self, X, y=None, **fit_params):
        return self


# ==================================================================================
# Feature engineering function, new columns can be added or drop easily in pipeline
# ==================================================================================
def add_columns(X):
    """"
    Add featues to dataframe

    Parameters
    ----------
    X : a pandas dataframe

    Return
    ------
    a pandas dataframe
    """

    def flag_int(dff, col_list):
        # This function add flag columns
        binarizer = Binarizer(threshold=0, copy = True)

        for columns in col_list:
            dff[f'{columns}_flag'] =  binarizer.fit_transform(dff[columns].values.reshape(-1,
1))

        return dff

    tp_cols = [col for col in X if col.startswith('TP_')] # columns starting with "TP_" will be
used for flag

    X = flag_int(X, tp_cols) # passing list of "TP_" columns to flag function


    # ADD MORE COLUMNS IF REQUIRED

    X['TP_injury_flag'] = np.where((X['TP_injury_whiplash'] > 0) | (X['TP_injury_traumatic'] >
0) | (X['TP_injury_fatality'] > 0) | (X['TP_injury_unclear'] > 0), 1, 0)
    X['TP_insd_pass_injury'] = np.where((X['TP_type_insd_pass_back'] > 0) & (X['TP_injury_flag']
> 0), 1, 0)

    X['Vehicle_mobile'] = np.where(X['Vehicle_mobile'].str.lower().isin(['n/k']) == True,
'missing', X['Vehicle_mobile'].str.lower())
    X['PH_considered_TP_at_fault'] =
np.where(X['PH_considered_TP_at_fault'].str.lower().isin(['n/k', '#']) == True, 'missing',
X['PH_considered_TP_at_fault'].str.lower())
    X['Location_of_incident'] = np.where(X['Location_of_incident'].str.lower().isin(['n/k', 'not
applicable']) == True, 'missing', X['Location_of_incident'].str.lower())
    X['Weather_conditions'] = np.where(X['Weather_conditions'].str.lower() == 'snow,ice,fog',
'chilly', X['Weather_conditions'].str.lower())
    X['Weather_conditions'] = np.where(X['Weather_conditions'].isin(['n/a', 'n/k']) |
X['Weather_conditions'].isnull() == True, 'missing', X['Weather_conditions'])


    # numeric continuous columns conversion to float data type
    numerics = ['int16', 'int32', 'int64', 'float16', 'float32', 'float64']
    int_list = X.select_dtypes(include=numerics).columns
    int_cols = [col for col in X[int_list] if X[col].nunique() > 2]
    int_cols =  [*int_cols, 'TP_type_cyclist', 'TP_type_pedestrian']


    # Binary Flag columns conversion to int data type
    int_flag = [col for col in X[int_list] if X[col].nunique() <= 2]
    int_flag_remove = ['TP_type_cyclist', 'TP_type_pedestrian']
    int_flag = list(set(int_flag) - set(int_flag_remove))


    # Object columns conversion to category data type
    cat_list = X.select_dtypes(exclude=numerics).columns
    cat_cols = [col for col in X[cat_list]]

    X[int_cols] = X[int_cols].apply(lambda x: x.astype('float64'))
    X[int_flag] = X[int_flag].apply(lambda x: x.astype('int64'))
    X[cat_cols] = X[cat_cols].apply(lambda x: x.astype('category'))

    return X
```

2. Feature Normalizer Pipeline

This Pipeline is combination of:

- Feature Engineering Pipeline - Created in above step
- Numeric Transformer - Numeric columns are first **normalized** using **MinMaxScaler** class of sklearn and then **standardized** using **PowerTransformer** class of sklearn with **yeo-johson** method
- Categorical Transformer - One Hot Encoding is used for categorical data since there aren't much unique categories for respective feature

Lastly, all theree Pipelines are connected using **ColumnTransformer** from sklearn with "remainder = passthrough" argument so that any untreated feature can also passthrough pipeline without dropping

In [9]:
```python
# used new column custom class for pipeline
new_col_pipeline = Pipeline([
    ("NewColumns", DataframeFunctionTransformer(add_columns))
])

# numeric column normalizer and standardizer pipeline
scaler = MinMaxScaler()
power = PowerTransformer(method='yeo-johnson', standardize = True)
numeric_transformer = Pipeline(steps=[('MinMax', scaler), ('Power', power)])

# categorical features standardizer pipeline
categorical_transformer = OneHotEncoder(handle_unknown='ignore')

# combining all three pipelines with Column Transformer
column_preprocess = ColumnTransformer(remainder = "passthrough",
    transformers = [
    ("NumScale", numeric_transformer, selector(dtype_include = "float64")),
    ("CatTransformer", categorical_transformer, selector(dtype_include = "category"))
])
```

3. Full Pipeline

This is a final predictive pipeline which will be used to train algorithm on training dataset and predict on test dataset. This pipeline contains number of steps:

- Feature Normalizer Pipeline - All feature engineering pipeline are combined in this, fist is "new column" and the "feature scaling"
- PCA Pipeline - This is used for feature reduction, 47 components are used which explain 99% of variance in data
- Regression Pipeline - XGBoost model is used with best parameters found during GridSearchCV (with 5 Cross Validations) at time of data exploration

In [11]:
```python
full_pipe = Pipeline(steps=[
    ("NewColumns", new_col_pipeline),
    ("ScaleColumns", column_preprocess),
    ("pca", PCA(n_components=0.99)),
    ("dt", XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=0.6,
             colsample_bynode=1, colsample_bytree=0.8, gamma=0, gpu_id=0,
             importance_type='gain', interaction_constraints='',
             learning_rate=0.03, max_delta_step=0, max_depth=10,
             min_child_weight=10, monotone_constraints='()',
             n_estimators=1000, n_jobs=8, num_parallel_tree=1, random_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=0.5,
             tree_method='gpu_hist', validate_parameters=1))
])
```

4. Target Feature Pipeline

The traget feature which was forced normalized by removing outliers is standardized using **PowerTransformer** class from sklearn with **yeo-johnson** method. This will help in converging algorithm faster.

In [12]:
```python
power = PowerTransformer(method='yeo-johnson', standardize = True)
target_pipeline = Pipeline(steps=[('p', power)])
target_pipeline.fit(target.values.reshape(-1, 1)) # reshape target column since 1D array is
required for Y_true parameter of algorithm
```

Out[12]:
```
Pipeline
PowerTransformer
```

Fit Regression Pipeline

The Pipeline created in step 2 is executed for features and target column from training set

In [20]:
```python
full_pipe.fit(features, target_pipeline.transform(target.values.reshape(-1, 1)))
```

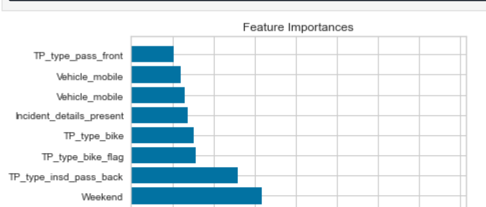
```
[16:35:34] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.4.0/src/learner.cc:573:
Parameters: { "verbose" } might not be used.

  This may not be accurate due to some parameters are only used in language bindings but
  passed down to XGBoost core.  Or some parameters are not used but slip through this
  verification. Please open an issue if you find above cases.
```

Out[20]:
```
Pipeline
NewColumns: Pipeline
DataframeFunctionTransformer
ScaleColumns: ColumnTransformer
NumScale          CatTransformer    remainder
MinMaxScaler      OneHotEncoder     passthrough
PowerTransformer
PCA
XGBRegressor
```

Visualization

In [14]:
```python
model = full_pipe.steps[2][1]
n_pcs= model.components_.shape[0]
initial_feature_names = features.columns
most_important = [np.abs(model.components_[i]).argmax() for i in range(n_pcs)]
most_important_names = [initial_feature_names[most_important[i]] for i in range(n_pcs)]
zipped_feats = zip(most_important_names, full_pipe.steps[3][1].feature_importances_)
zipped_feats = sorted(zipped_feats, key=lambda x: x[1], reverse=True)
features_col, importances = zip(*zipped_feats)
top_features = features_col[:10]
top_importances = importances[:10]
plt.title("Feature Importances")
plt.barh(range(len(top_importances)), top_importances, color="b", align="center")
plt.yticks(range(len(top_importances)), top_features)
plt.xlabel("Relative Importance")
plt.show()
```



Pickle Predictive and Target Pipeline

Both trained (**Regression** and **Target**) pipelines are saved in pickle format for future use with new unseen data

In [15]:
```python
# Pickle Predictive Pipeline
dump(full_pipe, open("model.pkl", "wb"))

# Pickle Target Pipeline
dump(target_pipeline, open("target.pkl", "wb"))
```

In [ ]:

Test Data Prepration

- Partition test data to seprate feature and target
- Seprate ID column for future use

In [16]:
```python
features_testdata = strat_test_set.drop(['Incurred', 'Claim Number', 'Incurred_cat'], axis = 1)
target_testdata = strat_test_set['Incurred']

# Drop ID Column and save it for future use
id_col_testdata = strat_test_set['Claim Number']
```

Use Trained Predictive Pipeline

In [17]:
```python
predictions_test = full_pipe.predict(features_testdata)
```

In [18]:
```python
y_pred = pd.DataFrame(target_pipeline.inverse_transform(predictions_test.reshape(-1,1)), columns
= ["predictions"])
y_actuals = pd.DataFrame(target_testdata , columns = ["actuals"])

data_comb = [y_pred, y_actuals]

y_check = pd.concat([id_col_testdata, y_pred, target_testdata], axis = 1)

mae = mean_absolute_error(target_pipeline.inverse_transform(predictions_test.reshape(-1,1)),
target_testdata)
print(f"Mean Absolute Error of Test Data: {round(mae, 2)}")
```

```
Mean Absolute Error of Test Data: 2699.52
```

In [19]:
```python
y_check.head(50)
```

Out[19]:

	Claim Number	predictions	Incurred
0	6689	22.611	0.000
1	2237	14798.183	9571.048
2	1349	3826.262	2890.385
3	1180	3086.135	3008.016
4	7513	10.602	0.000
5	5391	4.127	0.000
6	3335	14.669	0.000
7	3960	21001.740	65023.748
8	1306	2940.443	2235.702
9	6981	18.775	0.000
10	1537	37566.215	38252.543
11	7455	137.216	469.503
12	7182	23469.426	39784.121
13	755	18878.713	20859.307
14	3673	2477.953	2241.172
15	4914	19130.346	14668.627
16	2427	4.489	0.000
17	1181	4643.222	4707.087
18	1354	8504.921	8572.740
19	6214	10950.959	6591.310
20	171	142.196	580.995
21	4498	0.365	0.000
22	622	3465.154	3678.713
23	6567	5081.177	4798.259
24	4139	49.011	0.000
25	2213	111.852	68.001
26	7656	5551.409	6960.651
27	2351	26863.809	24182.278
28	7618	13.060	0.000
29	961	312.584	1299.678
30	5089	2650.599	2751.460
31	4317	19.284	0.000
32	4920	0.676	0.000
33	4736	946.696	1289.860
34	5954	449.900	1476.582
35	4038	11.547	23.418
36	2639	3188.211	4006.935
37	4273	57.255	0.000
38	2972	22.630	0.000
39	5966	3.960	0.000
40	3615	131.303	724.255
41	6499	0.520	0.000
42	7327	17.667	260.424
43	2905	287.102	711.716
44	1986	47.689	0.000
45	6625	24687.859	45531.190
46	6527	29205.807	18425.232
47	3936	46.156	427.757
48	1154	61.333	82.284
49	1110	800.392	1131.109

In [21]:
```python
output_path = r"C:\Users\kumar\OneDrive\Desktop\Akshat\insurance\Output"
now = datetime.now()
y_check.to_excel(str(output_path) + r"/Incurance Ultimate Claim - Data Load " +
now.strftime("%d%B%y") + ".xlsx", index = False, header = True)
```

In [ ]: