In [1]:

```
# install the opendatasets package
!pip install opendatasets

import opendatasets as od

# download the dataset (this is a Kaggle dataset)
# during download you will be required to input your Kaggle username and password
od.download("https://www.kaggle.com/mlg-ulb/creditcardfraud")
```

```
Requirement already satisfied: opendatasets in c:\users\hp\anaconda3\lib\site-packages (0.1.22)
Requirement already satisfied: kaggle in c:\users\hp\anaconda3\lib\site-packages (from opendatasets) (1.5.12)
Requirement already satisfied: tqdm in c:\users\hp\anaconda3\lib\site-packages (from opendatasets) (4.62.3)
Requirement already satisfied: click in c:\users\hp\anaconda3\lib\site-packages (from opendatasets) (8.0.3)
Requirement already satisfied: colorama in c:\users\hp\anaconda3\lib\site-packages (from click->opendatasets) (0.4.4)
Requirement already satisfied: python-dateutil in c:\users\hp\anaconda3\lib\site-packages (from kaggle->opendatasets) (2.8.2)
Requirement already satisfied: requests in c:\users\hp\anaconda3\lib\site-packages (from kaggle->opendatasets) (2.26.0)
Requirement already satisfied: python-slugify in c:\users\hp\anaconda3\lib\site-packages (from kaggle->opendatasets) (5.0.2)
Requirement already satisfied: six>=1.10 in c:\users\hp\anaconda3\lib\site-packages (from kaggle->opendatasets) (1.16.0)
Requirement already satisfied: urllib3 in c:\users\hp\anaconda3\lib\site-packages (from kaggle->opendatasets) (1.26.7)
Requirement already satisfied: certifi in c:\users\hp\anaconda3\lib\site-packages (from kaggle->opendatasets) (2021.10.8)
Requirement already satisfied: text-unidecode>=1.3 in c:\users\hp\anaconda3\lib\site-packages (from python-slugify->kaggle->open
datasets) (1.3)
Requirement already satisfied: charset-normalizer~=2.0.0 in c:\users\hp\anaconda3\lib\site-packages (from requests->kaggle->open
datasets) (2.0.4)
Requirement already satisfied: idna<4,>=2.5 in c:\users\hp\anaconda3\lib\site-packages (from requests->kaggle->opendatasets) (3.
2)
Skipping, found downloaded files in ".\creditcardfraud" (use force=True to force download)
```

In [2]:

```
# Snap ML is available on PyPI. To install it simply run the pip command below.
!pip install snapml
```

```
Collecting snapml
  Downloading snapml-1.11.1-cp39-cp39-win_amd64.whl (1.1 MB)
Requirement already satisfied: scipy in c:\users\hp\anaconda3\lib\site-packages (from snapml) (1.7.1)
Requirement already satisfied: scikit-learn in c:\users\hp\anaconda3\lib\site-packages (from snapml) (0.24.2)
Requirement already satisfied: numpy>=1.18.5 in c:\users\hp\anaconda3\lib\site-packages (from snapml) (1.20.3)
Requirement already satisfied: joblib>=0.11 in c:\users\hp\anaconda3\lib\site-packages (from scikit-learn->snapml) (1.1.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\hp\anaconda3\lib\site-packages (from scikit-learn->snapml) (2.2.
0)
Installing collected packages: snapml
Successfully installed snapml-1.11.1
```

In [3]:
```python
# Import the libraries we need to use in this lab
from __future__ import print_function
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import normalize, StandardScaler
from sklearn.utils.class_weight import compute_sample_weight
from sklearn.metrics import roc_auc_score
import time
import warnings
warnings.filterwarnings('ignore')
```

In [4]:
```python
# read the input data
raw_data = pd.read_csv('creditcardfraud/creditcard.csv')
print("There are " + str(len(raw_data)) + " observations in the credit card fraud dataset.")
print("There are " + str(len(raw_data.columns)) + " variables in the dataset.")

# display the first rows in the dataset
raw_data.head()
```

```
There are 284807 observations in the credit card fraud dataset.
There are 31 variables in the dataset.
```

Out[4]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	V25
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.018307	0.277838	-0.110474	0.066928	0.128539
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	...	-0.225775	-0.638672	0.101288	-0.339846	0.167170
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...	0.247998	0.771679	0.909412	-0.689281	-0.327642
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...	-0.108300	0.005274	-0.190321	-1.175575	0.647376
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...	-0.009431	0.798278	-0.137458	0.141267	-0.206010

5 rows × 31 columns

In [5]:
```
n_replicas = 10

# inflate the original dataset
big_raw_data = pd.DataFrame(np.repeat(raw_data.values, n_replicas, axis=0), columns=raw_data.columns)

print("There are " + str(len(big_raw_data)) + " observations in the inflated credit card fraud dataset.")
print("There are " + str(len(big_raw_data.columns)) + " variables in the dataset.")

# display first rows in the new dataset
big_raw_data.head()
```

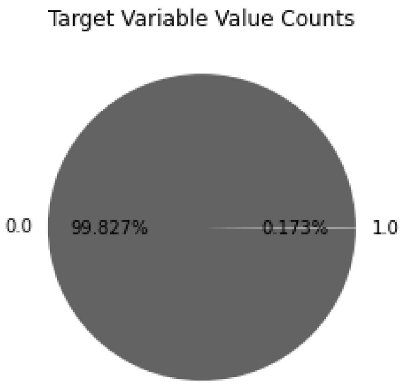
```
There are 2848070 observations in the inflated credit card fraud dataset.
There are 31 variables in the dataset.
```

Out[5]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	V25	
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.018307	0.277838	-0.110474	0.066928	0.128539	-0.1
1	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.018307	0.277838	-0.110474	0.066928	0.128539	-0.1
2	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.018307	0.277838	-0.110474	0.066928	0.128539	-0.1
3	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.018307	0.277838	-0.110474	0.066928	0.128539	-0.1
4	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.018307	0.277838	-0.110474	0.066928	0.128539	-0.1

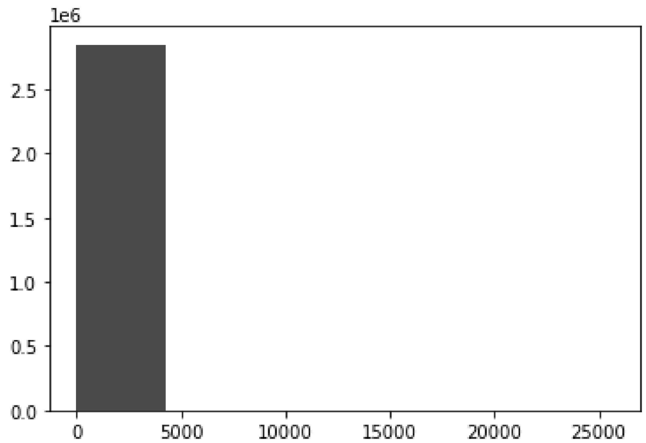
5 rows × 31 columns

In [6]:
```
# get the set of distinct classes
labels = big_raw_data.Class.unique()

# get the count of each class
sizes = big_raw_data.Class.value_counts().values

# plot the class value counts
fig, ax = plt.subplots()
ax.pie(sizes, labels=labels, autopct='%1.3f%%')
ax.set_title('Target Variable Value Counts')
plt.show()
```



In [7]:

```
# we provide our solution here
plt.hist(big_raw_data.Amount.values, 6, histtype='bar', facecolor='g')
plt.show()

print("Minimum amount value is ", np.min(big_raw_data.Amount.values))
print("Maximum amount value is ", np.max(big_raw_data.Amount.values))
print("90% of the transactions have an amount less or equal than ", np.percentile(raw_data.Amount.values, 90))
```




```
Minimum amount value is  0.0
Maximum amount value is  25691.16
90% of the transactions have an amount less or equal than  203.0
```

In [8]:
```
# data preprocessing such as scaling/normalization is typically useful for
# linear models to accelerate the training convergence

# standardize features by removing the mean and scaling to unit variance
big_raw_data.iloc[:, 1:30] = StandardScaler().fit_transform(big_raw_data.iloc[:, 1:30])
data_matrix = big_raw_data.values

# X: feature matrix (for this analysis, we exclude the Time variable from the dataset)
X = data_matrix[:, 1:30]

# y: labels vector
y = data_matrix[:, 30]

# data normalization
X = normalize(X, norm="l1")

# print the shape of the features matrix and the labels vector
print('X.shape=', X.shape, 'y.shape=', y.shape)
```

```
X.shape= (2848070, 29) y.shape= (2848070,)
```

In [9]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42, stratify=y)
print('X_train.shape=', X_train.shape, 'Y_train.shape=', y_train.shape)
print('X_test.shape=', X_test.shape, 'Y_test.shape=', y_test.shape)
```

```
X_train.shape= (1993649, 29) Y_train.shape= (1993649,)
X_test.shape= (854421, 29) Y_test.shape= (854421,)
```

In [10]:
```
# compute the sample weights to be used as input to the train routine so that
# it takes into account the class imbalance present in this dataset
w_train = compute_sample_weight('balanced', y_train)

# import the Decision Tree Classifier Model from scikit-learn
from sklearn.tree import DecisionTreeClassifier

# for reproducible output across multiple function calls, set random_state to a given integer value
sklearn_dt = DecisionTreeClassifier(max_depth=4, random_state=35)

# train a Decision Tree Classifier using scikit-learn
t0 = time.time()
sklearn_dt.fit(X_train, y_train, sample_weight=w_train)
sklearn_time = time.time()-t0
print("[Scikit-Learn] Training time (s):  {0:.5f}".format(sklearn_time))
```

```
[Scikit-Learn] Training time (s):  23.14271
```

In [11]:

```python
# if not already computed,
# compute the sample weights to be used as input to the train routine so that
# it takes into account the class imbalance present in this dataset
# w_train = compute_sample_weight('balanced', y_train)

# import the Decision Tree Classifier Model from Snap ML
from snapml import DecisionTreeClassifier

# Snap ML offers multi-threaded CPU/GPU training of decision trees, unlike scikit-learn
# to use the GPU, set the use_gpu parameter to True
# snapml_dt = DecisionTreeClassifier(max_depth=4, random_state=45, use_gpu=True)

# to set the number of CPU threads used at training time, set the n_jobs parameter
# for reproducible output across multiple function calls, set random_state to a given integer value
snapml_dt = DecisionTreeClassifier(max_depth=4, random_state=45, n_jobs=4)

# train a Decision Tree Classifier model using Snap ML
t0 = time.time()
snapml_dt.fit(X_train, y_train, sample_weight=w_train)
snapml_time = time.time()-t0
print("[Snap ML] Training time (s):  {0:.5f}".format(snapml_time))
```

```
[Snap ML] Training time (s):  2.51329
```

In [12]:
```python
# Snap ML vs Scikit-Learn training speedup
training_speedup = sklearn_time/snapml_time
print('[Decision Tree Classifier] Snap ML vs. Scikit-Learn speedup : {0:.2f}x '.format(training_speedup))

# run inference and compute the probabilities of the test samples
# to belong to the class of fraudulent transactions
sklearn_pred = sklearn_dt.predict_proba(X_test)[:,1]

# evaluate the Compute Area Under the Receiver Operating Characteristic
# Curve (ROC-AUC) score from the predictions
sklearn_roc_auc = roc_auc_score(y_test, sklearn_pred)
print('[Scikit-Learn] ROC-AUC score : {0:.3f}'.format(sklearn_roc_auc))

# run inference and compute the probabilities of the test samples
# to belong to the class of fraudulent transactions
snapml_pred = snapml_dt.predict_proba(X_test)[:,1]

# evaluate the Compute Area Under the Receiver Operating Characteristic
# Curve (ROC-AUC) score from the prediction scores
snapml_roc_auc = roc_auc_score(y_test, snapml_pred)
print('[Snap ML] ROC-AUC score : {0:.3f}'.format(snapml_roc_auc))
```

```
[Decision Tree Classifier] Snap ML vs. Scikit-Learn speedup : 9.21x
[Scikit-Learn] ROC-AUC score : 0.966
[Snap ML] ROC-AUC score : 0.966
```

In [13]:
```python
# import the linear Support Vector Machine (SVM) model from Scikit-Learn
from sklearn.svm import LinearSVC

# instatiate a scikit-learn SVM model
# to indicate the class imbalance at fit time, set class_weight='balanced'
# for reproducible output across multiple function calls, set random_state to a given integer value
sklearn_svm = LinearSVC(class_weight='balanced', random_state=31, loss="hinge", fit_intercept=False)

# train a linear Support Vector Machine model using Scikit-Learn
t0 = time.time()
sklearn_svm.fit(X_train, y_train)
sklearn_time = time.time() - t0
print("[Scikit-Learn] Training time (s):  {0:.2f}".format(sklearn_time))
```

```
[Scikit-Learn] Training time (s):  54.31
```

In [14]:
```python
# import the Support Vector Machine model (SVM) from Snap ML
from snapml import SupportVectorMachine

# in contrast to scikit-learn's LinearSVC, Snap ML offers multi-threaded CPU/GPU training of SVMs
# to use the GPU, set the use_gpu parameter to True
# snapml_svm = SupportVectorMachine(class_weight='balanced', random_state=25, use_gpu=True, fit_intercept=False)

# to set the number of threads used at training time, one needs to set the n_jobs parameter
snapml_svm = SupportVectorMachine(class_weight='balanced', random_state=25, n_jobs=4, fit_intercept=False)
# print(snapml_svm.get_params())

# train an SVM model using Snap ML
t0 = time.time()
model = snapml_svm.fit(X_train, y_train)
snapml_time = time.time() - t0
print("[Snap ML] Training time (s):  {0:.2f}".format(snapml_time))
```

```
[Snap ML] Training time (s):  7.30
```

In [15]:
```python
# compute the Snap ML vs Scikit-Learn training speedup
training_speedup = sklearn_time/snapml_time
print('[Support Vector Machine] Snap ML vs. Scikit-Learn training speedup : {0:.2f}x '.format(training_speedup))

# run inference using the Scikit-Learn model
# get the confidence scores for the test samples
sklearn_pred = sklearn_svm.decision_function(X_test)

# evaluate accuracy on test set
acc_sklearn  = roc_auc_score(y_test, sklearn_pred)
print("[Scikit-Learn] ROC-AUC score:   {0:.3f}".format(acc_sklearn))

# run inference using the Snap ML model
# get the confidence scores for the test samples
snapml_pred = snapml_svm.decision_function(X_test)

# evaluate accuracy on test set
acc_snapml  = roc_auc_score(y_test, snapml_pred)
print("[Snap ML] ROC-AUC score:   {0:.3f}".format(acc_snapml))
```

```
[Support Vector Machine] Snap ML vs. Scikit-Learn training speedup : 7.44x
[Scikit-Learn] ROC-AUC score:   0.984
[Snap ML] ROC-AUC score:   0.985
```

In [16]:
```
# get the confidence scores for the test samples
sklearn_pred = sklearn_svm.decision_function(X_test)
snapml_pred  = snapml_svm.decision_function(X_test)

# import the hinge_loss metric from scikit-learn
from sklearn.metrics import hinge_loss

# evaluate the hinge loss from the predictions
loss_snapml = hinge_loss(y_test, snapml_pred)
print("[Snap ML] Hinge loss:   {0:.3f}".format(loss_snapml))

# evaluate the hinge loss metric from the predictions
loss_sklearn = hinge_loss(y_test, sklearn_pred)
print("[Scikit-Learn] Hinge loss:   {0:.3f}".format(loss_snapml))

# the two models should give the same Hinge loss
```

```
[Snap ML] Hinge loss:   0.228
[Scikit-Learn] Hinge loss:   0.228
```

In [ ]:
```
```