In [1]:
```
# Load libraries
import matplotlib
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.patches as mpatches
import matplotlib as mpl
from sklearn.preprocessing import StandardScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import RandomizedSearchCV
from sklearn.feature_selection import SelectFromModel
from sklearn.neighbors import KNeighborsClassifier
import seaborn as sns
from sklearn import metrics
from scipy.stats import pearsonr
from scipy.stats import spearmanr
import math
from sklearn.model_selection import train_test_split
from scipy.cluster.hierarchy import linkage, fcluster
from sklearn.cluster import KMeans, DBSCAN
```

In [2]:
```
# Get training and testing data
train_data = pd.read_csv('train_data.csv', delimiter='\t', index_col=0
)
test_data  = pd.read_csv('test_data.csv',  delimiter='\t', index_col=0
)
# Drop ID, chocolate, the ficticious drug Semer, and legal substances
train_data.drop(columns=['ID', 'Choc', 'Semer', 'Alcohol', 'Nicotine',
'Caff', 'Legalh'], inplace=True)
test_data.drop (columns=['ID', 'Choc', 'Semer', 'Alcohol', 'Nicotine',
'Caff', 'Legalh'], inplace=True)

# Convert categories to integers
for column in train_data.loc[:, 'Amphet':]:
    train_data[column] = train_data[column].astype('category').cat.cod
es
    train_data[column] = train_data[column].astype('int32')
for column in test_data.loc[:, 'Amphet':]:
    test_data[column]  = test_data[column].astype('category').cat.code
s
    test_data[column]  = test_data[column].astype('int32')

train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1319 entries, 1287 to 684
Data columns (total 25 columns):
Age          1319 non-null float64
Gender       1319 non-null float64
Education    1319 non-null float64
Country      1319 non-null float64
Ethnicity    1319 non-null float64
Nscore       1319 non-null float64
Escore       1319 non-null float64
Oscore       1319 non-null float64
Ascore       1319 non-null float64
Cscore       1319 non-null float64
Impulsive    1319 non-null float64
SS           1319 non-null float64
Amphet       1319 non-null int32
Amyl         1319 non-null int32
Benzos       1319 non-null int32
Cannabis     1319 non-null int32
Coke         1319 non-null int32
Crack        1319 non-null int32
Ecstacy      1319 non-null int32
Heroin       1319 non-null int32
Ketamine     1319 non-null int32
LSD          1319 non-null int32
Meth         1319 non-null int32
Mushrooms    1319 non-null int32
VSA          1319 non-null int32
dtypes: float64(12), int32(13)
memory usage: 200.9 KB
```

In [3]:
```
def is_drug_user(row):
    row = row['Amphet':]
    num_zeros = (row == 0).astype(bool).sum()
    if num_zeros == row.size:
        return False
    return True

# Add 'Drug User' column
train_data['Drug User'] = train_data.apply(is_drug_user, axis=1)
test_data['Drug User']  = test_data.apply (is_drug_user, axis=1)
train_data.info()
```

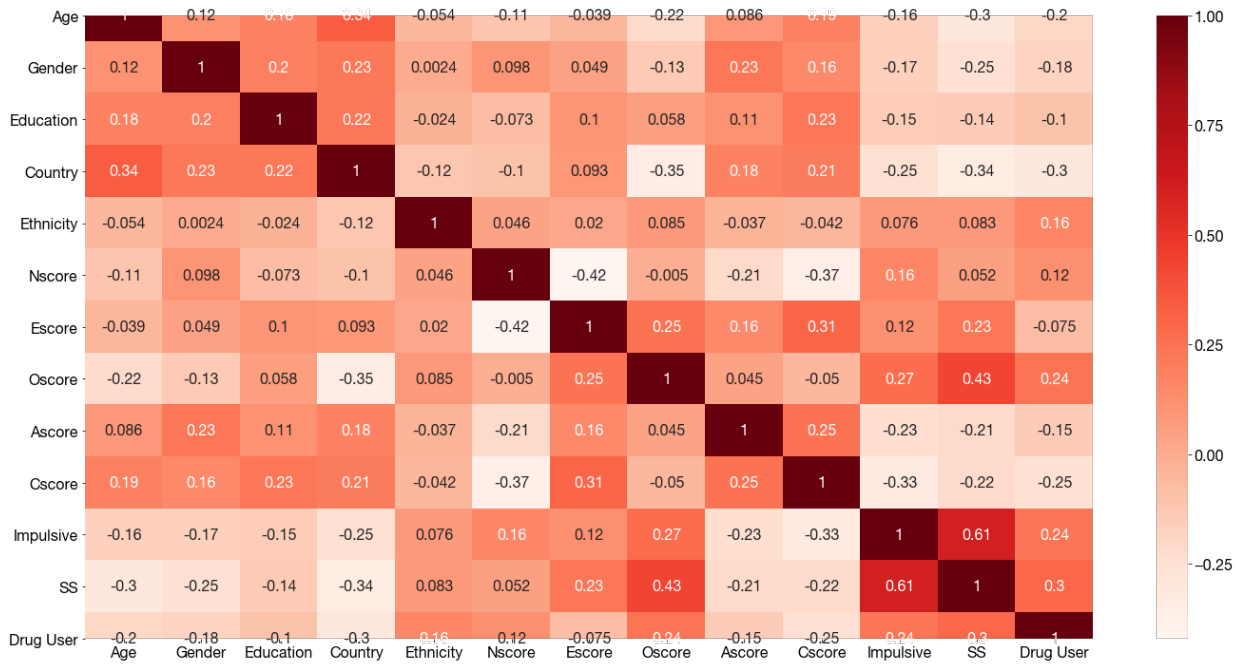
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1319 entries, 1287 to 684
Data columns (total 26 columns):
Age          1319 non-null float64
Gender       1319 non-null float64
Education    1319 non-null float64
Country      1319 non-null float64
Ethnicity    1319 non-null float64
Nscore       1319 non-null float64
Escore       1319 non-null float64
Oscore       1319 non-null float64
Ascore       1319 non-null float64
Cscore       1319 non-null float64
Impulsive    1319 non-null float64
SS           1319 non-null float64
Amphet       1319 non-null int32
Amyl         1319 non-null int32
Benzos       1319 non-null int32
Cannabis     1319 non-null int32
Coke         1319 non-null int32
Crack        1319 non-null int32
Ecstacy      1319 non-null int32
Heroin       1319 non-null int32
Ketamine     1319 non-null int32
LSD          1319 non-null int32
Meth         1319 non-null int32
Mushrooms    1319 non-null int32
VSA          1319 non-null int32
Drug User    1319 non-null bool
dtypes: bool(1), float64(12), int32(13)
memory usage: 202.2 KB
```

In [4]:
```
# Examine input variables
matplotlib.rc('font', family='Helvetica Neue', size=16)
fig  = plt.gcf()
fig.set_size_inches(20, 10)
corr = train_data.drop(columns=['Amphet',
                                'Amyl',
                                'Benzos',
                                'Cannabis',
                                'Coke',
                                'Crack',
                                'Ecstacy',
                                'Heroin',
                                'Ketamine',
                                'LSD',
                                'Meth',
                                'Mushrooms',
                                'VSA']).corr()
sns.heatmap(corr, annot=True, cmap=plt.cm.Reds)
plt.tight_layout()
plt.savefig('figures/heatmap.png', dpi=300)

# Correlation with output variable
corr_target = abs(corr['Drug User'])

# Select relevant variables
variables   = corr_target[corr_target > corr_target.loc['Age':'SS'].me
dian()]
variables   = variables.loc['Age':'SS'].index.values
var_indices = [train_data.columns.get_loc(variable) for variable in va
riables]
print('Relevant variables (corr > %.3f):'%corr_target.loc['Age':'SS'].
median(), variables)
```

```
Relevant variables (corr > 0.192): ['Age' 'Country' 'Oscore' 'Cscore
' 'Impulsive' 'SS']
```



In [5]:

```python
drop_cols = ['Amphet', 'Amyl', 'Benzos', 'Cannabis',
             'Coke', 'Crack', 'Ecstacy', 'Heroin',
             'Ketamine', 'LSD', 'Meth', 'Mushrooms',
             'VSA', 'Drug User']
x_train = train_data.drop(columns=drop_cols)
x_test  = test_data.drop (columns=drop_cols)
y_train = train_data['Drug User']
y_test  = test_data ['Drug User']

# Standardize training and testing data
scaler         = StandardScaler()
x_train_scaled = scaler.fit_transform(x_train)
x_test_scaled  = scaler.fit_transform(x_test)
```

In [6]:
```
# Build a decision tree classifier to classify people as drug users or
non-users
classifier = DecisionTreeClassifier(criterion='entropy', random_state=
0)
classifier.fit(x_train_scaled[:, var_indices], y_train)
```

Out[6]:
```
DecisionTreeClassifier(class_weight=None, criterion='entropy', max_d
epth=None,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split
=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=0, splitter='best')
```

In [7]:
```
# Show the structure of the decision tree classifier
print(classifier.tree_.__getstate__()['nodes'])
len(classifier.tree_.__getstate__()['nodes'])
```

```
[(  1,  88,  1,  0.37104077, 0.61578458, 1319, 1.319e+03)
 (  2,  33,  1, -1.03708935, 0.21804385,  603, 6.030e+02)
 (  3,   4,  3, -0.71024391, 0.09916557,  389, 3.890e+02)
 ( -1,  -1, -2, -2.        , 0.        ,  124, 1.240e+02)
 (  5,   6,  4, -0.48617859, 0.1350362 ,  265, 2.650e+02)
 ( -1,  -1, -2, -2.        , 0.        ,   66, 6.600e+01)
 (  7,  16,  0, -0.6268507 , 0.16932446,  199, 1.990e+02)
 (  8,   9,  2,  1.30229104, 0.07360348,  112, 1.120e+02)
 ( -1,  -1, -2, -2.        , 0.        ,   89, 8.900e+01)
 ( 10,  15,  2,  1.5078187 , 0.25801867,   23, 2.300e+01)
 ( 11,  12,  4,  0.75859267, 0.54356444,    8, 8.000e+00)
 ( -1,  -1, -2, -2.        , 0.        ,    6, 6.000e+00)
 ( 13,  14,  3,  0.49862912, 1.        ,    2, 2.000e+00)
 ( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
 ( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
 ( -1,  -1, -2, -2.        , 0.        ,   15, 1.500e+01)
 ( 17,  30,  3,  1.46841699, 0.2690553 ,   87, 8.700e+01)
 ( 18,  25,  5, -0.37598695, 0.22028327,   85, 8.500e+01)
 ( 19,  24,  2,  1.41152394, 0.65002242,   12, 1.200e+01)
 ( 20,  23,  4, -0.00517242, 0.43949699,   11, 1.100e+01)
 ( 21,  22,  3,  0.22490337, 0.81127812,    4, 4.000e+00)
 ( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
 ( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
 ( -1,  -1, -2, -2.        , 0.        ,    7, 7.000e+00)
 ( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
 ( 26,  29,  2, -0.66125342, 0.10441908,   73, 7.300e+01)
 ( 27,  28,  5,  1.40527081, 0.81127812,    4, 4.000e+00)
 ( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
 ( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
 ( -1,  -1, -2, -2.        , 0.        ,   69, 6.900e+01)
```

```
( 31,  32,  2,  1.70191941, 1.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( 34,  59,  5, -0.70359236, 0.38346413,  214, 2.140e+02)
( 35,  58,  3,  2.89427984, 0.81127812,   36, 3.600e+01)
( 36,  57,  3,  1.2207939 , 0.77551266,   35, 3.500e+01)
( 37,  38,  2, -2.10688007, 0.83664074,   30, 3.000e+01)
( -1,  -1, -2, -2.        , 0.        ,    4, 4.000e+00)
( 39,  56,  0,  1.65218514, 0.89049164,   26, 2.600e+01)
( 40,  41,  2, -1.75221407, 0.85545081,   25, 2.500e+01)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( 42,  43,  2, -1.05371639, 0.81127812,   24, 2.400e+01)
( -1,  -1, -2, -2.        , 0.        ,    5, 5.000e+00)
( 44,  45,  5, -1.8749342 , 0.89974376,   19, 1.900e+01)
( -1,  -1, -2, -2.        , 0.        ,    4, 4.000e+00)
( 46,  47,  4, -1.10488191, 0.97095059,   15, 1.500e+01)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
( 48,  51,  3, -1.12799984, 0.81127812,   12, 1.200e+01)
( 49,  50,  0,  0.21027907, 0.91829583,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( 52,  55,  2, -0.53011969, 0.50325833,    9, 9.000e+00)
( 53,  54,  0, -0.6268507 , 1.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    7, 7.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    5, 5.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( 60,  61,  3, -0.4606221 , 0.23919262,  178, 1.780e+02)
( -1,  -1, -2, -2.        , 0.        ,   76, 7.600e+01)
( 62,  87,  3,  0.85076225, 0.36078057,  102, 1.020e+02)
( 63,  86,  2,  1.97521383, 0.42806963,   80, 8.000e+01)
( 64,  65,  4, -0.00517242, 0.38774318,   79, 7.900e+01)
( -1,  -1, -2, -2.        , 0.        ,   31, 3.100e+01)
( 66,  85,  2,  0.62622762, 0.54356444,   48, 4.800e+01)
( 67,  84,  4,  1.16431427, 0.68403844,   33, 3.300e+01)
( 68,  73,  3,  0.06268557, 0.79504028,   25, 2.500e+01)
( 69,  70,  0,  0.21027907, 0.41381685,   12, 1.200e+01)
( -1,  -1, -2, -2.        , 0.        ,    9, 9.000e+00)
( 71,  72,  2, -0.65939173, 0.91829583,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
( 74,  81,  3,  0.50337908, 0.9612366 ,   13, 1.300e+01)
( 75,  80,  0,  0.21027907, 0.91829583,    6, 6.000e+00)
( 76,  77,  2,  0.19164676, 0.91829583,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( 78,  79,  5,  0.2593739 , 1.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
```

```
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
( 82,  83,  5, -0.06127545, 0.59167278,    7, 7.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    6, 6.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    8, 8.000e+00)
( -1,  -1, -2, -2.        , 0.        ,   15, 1.500e+01)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,   22, 2.200e+01)
( 89, 390,  5, -0.06127545, 0.81348426,  716, 7.160e+02)
( 90, 153,  3, -0.20422167, 0.92869829,  433, 4.330e+02)
( 91, 152,  0,  2.51666594, 0.69734097,  117, 1.170e+02)
( 92,  93,  3, -1.84134251, 0.66657836,  115, 1.150e+02)
( -1,  -1, -2, -2.        , 0.        ,    7, 7.000e+00)
( 94, 125,  5, -0.70359236, 0.69128987,  108, 1.080e+02)
( 95, 102,  0, -0.6268507 , 0.81127812,   52, 5.200e+01)
( 96, 101,  4,  0.75859267, 0.97095059,   10, 1.000e+01)
( 97, 100,  2, -0.72547463, 0.81127812,    8, 8.000e+00)
( 98,  99,  4, -2.08610392, 0.91829583,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    5, 5.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
(103, 124,  4, -0.48617859, 0.65002242,   42, 4.200e+01)
(104, 121,  0,  1.65218514, 0.79732651,   29, 2.900e+01)
(105, 120,  0,  0.88757563, 0.72192809,   25, 2.500e+01)
(106, 117,  3, -0.4606221 , 0.87398105,   17, 1.700e+01)
(107, 108,  2, -1.89755994, 0.74959526,   14, 1.400e+01)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
(109, 110,  2, -1.35220063, 0.61938219,   13, 1.300e+01)
( -1,  -1, -2, -2.        , 0.        ,    7, 7.000e+00)
(111, 116,  5, -1.04381639, 0.91829583,    6, 6.000e+00)
(112, 113,  2, -1.13100407, 0.91829583,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
(114, 115,  3, -0.58359382, 1.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
(118, 119,  2, -1.89755994, 0.91829583,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    8, 8.000e+00)
(122, 123,  5, -1.04381639, 1.        ,    4, 4.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,   13, 1.300e+01)
(126, 127,  2, -1.7622633 , 0.54356444,   56, 5.600e+01)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
(128, 129,  4, -0.48617859, 0.49716776,   55, 5.500e+01)
( -1,  -1, -2, -2.        , 0.        ,   12, 1.200e+01)
(130, 133,  3, -1.4426015 , 0.58301942,   43, 4.300e+01)
```

```
(131, 132,  3, -1.57019365, 0.97095059,    5, 5.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
(134, 147,  3, -0.33532771, 0.48546076,   38, 3.800e+01)
(135, 144,  2,  0.94170904, 0.33729007,   32, 3.200e+01)
(136, 143,  5, -0.37598695, 0.2108423 ,   30, 3.000e+01)
(137, 142,  3, -0.76873922, 0.50325833,    9, 9.000e+00)
(138, 141,  0,  0.88757563, 0.81127812,    4, 4.000e+00)
(139, 140,  2, -0.39899582, 1.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    5, 5.000e+00)
( -1,  -1, -2, -2.        , 0.        ,   21, 2.100e+01)
(145, 146,  5, -0.37598695, 1.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
(148, 151,  0,  0.21027907, 0.91829583,    6, 6.000e+00)
(149, 150,  2, -1.20443997, 0.91829583,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
(154, 321,  2, -0.11631877, 0.97205045,  316, 3.160e+02)
(155, 316,  0,  1.65218514, 0.99540013,  213, 2.130e+02)
(156, 253,  3,  0.85076225, 0.99142668,  202, 2.020e+02)
(157, 252,  4,  0.3922534 , 0.95735567,  124, 1.240e+02)
(158, 203,  2, -0.79162669, 0.96995049,  118, 1.180e+02)
(159, 168,  2, -1.75221407, 0.89486923,   61, 6.100e+01)
(160, 167,  3,  0.50337908, 0.97986876,   12, 1.200e+01)
(161, 162,  0,  0.21027907, 0.86312057,    7, 7.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
(163, 164,  4, -1.10488191, 0.65002242,    6, 6.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    4, 4.000e+00)
(165, 166,  2, -2.01397288, 1.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    5, 5.000e+00)
(169, 202,  3,  0.67402029, 0.80309098,   49, 4.900e+01)
(170, 199,  4, -0.00517242, 0.86312057,   42, 4.200e+01)
(171, 186,  5, -1.04381639, 0.82128094,   39, 3.900e+01)
(172, 185,  2, -0.91954565, 0.93666738,   17, 1.700e+01)
(173, 174,  0, -0.6268507 , 0.98522814,   14, 1.400e+01)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
(175, 176,  5, -1.8749342 , 0.9612366 ,   13, 1.300e+01)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
(177, 180,  3,  0.06268557, 1.        ,   10, 1.000e+01)
(178, 179,  5, -1.40861261, 0.81127812,    4, 4.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
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(181, 184,  4, -1.10488191, 0.91829583,    6, 6.000e+00)
(182, 183,  2, -1.55224192, 0.91829583,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
(187, 188,  2, -1.20147705, 0.68403844,   22, 2.200e+01)
( -1,  -1, -2, -2.        , 0.        ,    7, 7.000e+00)
(189, 190,  3, -0.06993568, 0.83664074,   15, 1.500e+01)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
(191, 194,  4, -1.10488191, 0.74959526,   14, 1.400e+01)
(192, 193,  0,  0.21027907, 0.91829583,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
(195, 198,  3,  0.06268557, 0.43949699,   11, 1.100e+01)
(196, 197,  4, -0.48617859, 0.91829583,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    8, 8.000e+00)
(200, 201,  3,  0.19535667, 0.91829583,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    7, 7.000e+00)
(204, 213,  4, -1.10488191, 0.99977797,   57, 5.700e+01)
(205, 206,  0,  0.21027907, 0.93666738,   17, 1.700e+01)
( -1,  -1, -2, -2.        , 0.        ,    5, 5.000e+00)
(207, 212,  2, -0.53012955, 0.41381685,   12, 1.200e+01)
(208, 209,  3,  0.42542024, 0.72192809,    5, 5.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
(210, 211,  5, -0.54245467, 1.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    7, 7.000e+00)
(214, 237,  0,  0.21027907, 0.98370826,   40, 4.000e+01)
(215, 216,  3, -0.06993568, 0.98522814,   21, 2.100e+01)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
(217, 222,  4, -0.48617859, 0.99800088,   19, 1.900e+01)
(218, 221,  3,  0.58981118, 0.91829583,    6, 6.000e+00)
(219, 220,  5, -1.23485631, 0.91829583,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
(223, 224,  5, -0.70359236, 0.9612366 ,   13, 1.300e+01)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
(225, 234,  4, -0.00517242, 1.        ,   10, 1.000e+01)
(226, 233,  0, -0.6268507 , 0.91829583,    6, 6.000e+00)
(227, 228,  2, -0.66125342, 1.        ,    4, 4.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
(229, 230,  3,  0.58981118, 0.91829583,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
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(231, 232,  2, -0.46396762, 1.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
(235, 236,  3,  0.06268557, 0.81127812,    4, 4.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
(238, 251,  2, -0.39899582, 0.83147439,   19, 1.900e+01)
(239, 240,  5, -1.8749342 , 0.94028596,   14, 1.400e+01)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
(241, 242,  5, -0.87734866, 0.89049164,   13, 1.300e+01)
( -1,  -1, -2, -2.        , 0.        ,    5, 5.000e+00)
(243, 248,  2, -0.66125342, 1.        ,    8, 8.000e+00)
(244, 245,  4, -0.48617859, 0.81127812,    4, 4.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
(246, 247,  3,  0.51185234, 1.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
(249, 250,  3,  0.06268557, 0.81127812,    4, 4.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    5, 5.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    6, 6.000e+00)
(254, 263,  3,  1.0380559 , 0.9923985 ,   78, 7.800e+01)
(255, 256,  0, -0.6268507 , 0.77322667,   22, 2.200e+01)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
(257, 262,  2, -0.26371399, 0.6098403 ,   20, 2.000e+01)
(258, 261,  2, -1.35220063, 0.48546076,   19, 1.900e+01)
(259, 260,  0,  0.21027907, 1.        ,    4, 4.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,   15, 1.500e+01)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
(264, 291,  0,  0.21027907, 0.99631652,   56, 5.600e+01)
(265, 290,  4, -0.00517242, 0.91829583,   27, 2.700e+01)
(266, 289,  3,  1.92687446, 0.97602065,   22, 2.200e+01)
(267, 268,  2, -1.75221407, 0.99800088,   19, 1.900e+01)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
(269, 288,  4, -0.48617859, 0.98869941,   16, 1.600e+01)
(270, 271,  2, -1.61691743, 0.99679163,   15, 1.500e+01)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
(272, 287,  5, -0.37598695, 1.        ,   14, 1.400e+01)
(273, 280,  5, -1.04381639, 0.99572745,   13, 1.300e+01)
(274, 279,  5, -1.8749342 , 0.91829583,    6, 6.000e+00)
(275, 276,  3,  1.29844373, 0.91829583,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
(277, 278,  0, -0.6268507 , 1.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
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(281, 286,  3,  1.63621718, 0.86312057,    7, 7.000e+00)
(282, 283,  2, -0.53011969, 0.65002242,    6, 6.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    4, 4.000e+00)
(284, 285,  0, -0.6268507 , 1.        ,    2, 2.000e+00)
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( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    5, 5.000e+00)
(292, 293,  2, -1.61691743, 0.97844933,   29, 2.900e+01)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
(294, 315,  3,  2.18686354, 0.99572745,   26, 2.600e+01)
(295, 296,  2, -1.27491295, 1.        ,   24, 2.400e+01)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
(297, 298,  2, -0.91954565, 0.99403021,   22, 2.200e+01)
( -1,  -1, -2, -2.        , 0.        ,    4, 4.000e+00)
(299, 314,  3,  1.72043622, 0.99107606,   18, 1.800e+01)
(300, 301,  5, -1.40861261, 0.954434  ,   16, 1.600e+01)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
(302, 307,  2, -0.66125342, 0.98522814,   14, 1.400e+01)
(303, 306,  2, -0.79162669, 0.72192809,    5, 5.000e+00)
(304, 305,  3,  1.38266277, 1.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
(308, 313,  3,  1.54606682, 0.99107606,    9, 9.000e+00)
(309, 312,  0,  0.88757563, 0.86312057,    7, 7.000e+00)
(310, 311,  5, -1.04381639, 1.        ,    4, 4.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
(317, 318,  3,  0.86131394, 0.84535094,   11, 1.100e+01)
( -1,  -1, -2, -2.        , 0.        ,    7, 7.000e+00)
(319, 320,  4, -1.73034325, 0.81127812,    4, 4.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
(322, 361,  3,  1.0380559 , 0.8575588 ,  103, 1.030e+02)
(323, 348,  3,  0.50337908, 0.74551784,   66, 6.600e+01)
(324, 347,  0,  1.65218514, 0.877962  ,   37, 3.700e+01)
(325, 338,  4, -0.48617859, 0.85240518,   36, 3.600e+01)
(326, 337,  2,  0.77426478, 0.97095059,   20, 2.000e+01)
(327, 332,  3,  0.19535667, 0.99750255,   17, 1.700e+01)
(328, 331,  0,  0.21027907, 0.81127812,    8, 8.000e+00)
(329, 330,  5, -0.37598695, 0.91829583,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
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( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    5, 5.000e+00)
(333, 334,  0, -0.2940312 , 0.91829583,    9, 9.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
(335, 336,  5, -1.40861261, 0.59167278,    7, 7.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    6, 6.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
(339, 340,  4, -0.00517242, 0.54356444,   16, 1.600e+01)
( -1,  -1, -2, -2.        , 0.        ,    7, 7.000e+00)
(341, 346,  2,  1.11812109, 0.76420451,    9, 9.000e+00)
(342, 345,  2,  0.19571585, 0.54356444,    8, 8.000e+00)
(343, 344,  0,  0.88757563, 0.91829583,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
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( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
(349, 360,  2,  0.34604435, 0.47983202,   29, 2.900e+01)
(350, 355,  2,  0.19571585, 0.67229482,   17, 1.700e+01)
(351, 354,  2,  0.04131827, 0.39124356,   13, 1.300e+01)
(352, 353,  3,  0.67402029, 0.72192809,    5, 5.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    4, 4.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    8, 8.000e+00)
(356, 357,  4, -0.48617859, 1.        ,    4, 4.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
(358, 359,  5, -0.37598695, 0.91829583,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,   12, 1.200e+01)
(362, 389,  3,  1.92687446, 0.97402486,   37, 3.700e+01)
(363, 388,  4,  0.3922534 , 0.99403021,   33, 3.300e+01)
(364, 379,  0,  0.88757563, 0.99924925,   31, 3.100e+01)
(365, 378,  4, -0.48617859, 0.93666738,   17, 1.700e+01)
(366, 377,  2,  1.21441585, 0.99572745,   13, 1.300e+01)
(367, 372,  3,  1.54606682, 0.99403021,   11, 1.100e+01)
(368, 371,  2,  0.27100848, 0.65002242,    6, 6.000e+00)
(369, 370,  3,  1.38419795, 0.91829583,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
(373, 374,  4, -1.10488191, 0.72192809,    5, 5.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
(375, 376,  3,  1.72043622, 1.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    4, 4.000e+00)
(380, 383,  4, -1.10488191, 0.94028596,   14, 1.400e+01)
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(381, 382,  2,  0.11635413, 0.81127812,    4, 4.000e+00)
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( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
(384, 385,  3,  1.38419795, 0.72192809,   10, 1.000e+01)
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( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    4, 4.000e+00)
(391, 412,  3,  0.19535667, 0.49852882,  283, 2.830e+02)
(392, 411,  2, -0.11631877, 0.18970512,  172, 1.720e+02)
(393, 410,  5,  0.61550494, 0.35001059,   76, 7.600e+01)
(394, 395,  3, -0.83304617, 0.46899559,   50, 5.000e+01)
( -1,  -1, -2, -2.        , 0.        ,   13, 1.300e+01)
(396, 403,  4,  0.3922534 , 0.57135497,   37, 3.700e+01)
(397, 398,  3, -0.06993568, 0.25801867,   23, 2.300e+01)
( -1,  -1, -2, -2.        , 0.        ,   19, 1.900e+01)
(399, 402,  0,  0.88757563, 0.81127812,    4, 4.000e+00)
(400, 401,  4, -0.84193926, 1.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
(404, 405,  3, -0.71024391, 0.86312057,   14, 1.400e+01)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
(406, 407,  5,  0.2593739 , 0.77934984,   13, 1.300e+01)
( -1,  -1, -2, -2.        , 0.        ,    7, 7.000e+00)
(408, 409,  0,  0.21027907, 1.        ,    6, 6.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,   26, 2.600e+01)
( -1,  -1, -2, -2.        , 0.        ,   96, 9.600e+01)
(413, 468,  2,  0.48921742, 0.78531981,  111, 1.110e+02)
(414, 419,  2, -1.35220063, 0.89974376,   76, 7.600e+01)
(415, 418,  2, -1.61691743, 0.97095059,   10, 1.000e+01)
(416, 417,  5,  0.2593739 , 0.98522814,    7, 7.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    4, 4.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
(420, 441,  0,  0.21027907, 0.84535094,   66, 6.600e+01)
(421, 426,  3,  0.85076225, 0.66096234,   35, 3.500e+01)
(422, 423,  2,  0.34604435, 0.28639696,   20, 2.000e+01)
( -1,  -1, -2, -2.        , 0.        ,   17, 1.700e+01)
(424, 425,  5,  0.44842939, 0.91829583,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
(427, 440,  5,  1.64387596, 0.91829583,   15, 1.500e+01)
(428, 433,  3,  1.72043622, 0.86312057,   14, 1.400e+01)
(429, 430,  2,  0.34604435, 0.54356444,    8, 8.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    6, 6.000e+00)
```

```
(431, 432,  0, -0.6268507 , 1.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
(434, 435,  4, -0.00517242, 1.        ,    6, 6.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
(436, 439,  0, -0.6268507 , 0.81127812,    4, 4.000e+00)
(437, 438,  4,  0.57923037, 1.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
(442, 453,  4, -0.00517242, 0.96290041,   31, 3.100e+01)
(443, 444,  5,  0.2593739 , 0.72192809,   15, 1.500e+01)
( -1,  -1, -2, -2.        , 0.        ,    6, 6.000e+00)
(445, 452,  3,  1.29844373, 0.91829583,    9, 9.000e+00)
(446, 451,  3,  0.85076225, 0.81127812,    8, 8.000e+00)
(447, 450,  2,  0.19571585, 0.97095059,    5, 5.000e+00)
(448, 449,  3,  0.67402029, 0.81127812,    4, 4.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
(454, 455,  0,  0.88757563, 0.98869941,   16, 1.600e+01)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
(456, 461,  2, -0.53012955, 0.99572745,   13, 1.300e+01)
(457, 458,  4,  1.16431427, 0.72192809,    5, 5.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    3, 3.000e+00)
(459, 460,  3,  0.58981118, 1.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
(462, 467,  0,  1.65218514, 0.81127812,    8, 8.000e+00)
(463, 466,  4,  0.3922534 , 0.59167278,    7, 7.000e+00)
(464, 465,  3,  0.85076225, 0.91829583,    3, 3.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    4, 4.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    1, 1.000e+00)
(469, 474,  5,  0.61550494, 0.31599713,   35, 3.500e+01)
(470, 471,  4,  0.3922534 , 0.50325833,   18, 1.800e+01)
( -1,  -1, -2, -2.        , 0.        ,   12, 1.200e+01)
(472, 473,  2,  0.77426478, 0.91829583,    6, 6.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    4, 4.000e+00)
( -1,  -1, -2, -2.        , 0.        ,    2, 2.000e+00)
( -1,  -1, -2, -2.        , 0.        ,   17, 1.700e+01)]
```

Out[7]: 475

In [8]:
```
# The mean accuracy and the 95% confidence interval of 10-fold cross v
alidation
scores = cross_val_score(classifier, x_train_scaled[:, var_indices], y
_train,
                         cv=10, scoring='accuracy')
print('Accuracy: %0.3f (+/- %0.3f)'%(scores.mean(), scores.std() * 2))

# The mean F1 score and the 95% confidence interval of 10-fold cross v
alidation
scores = cross_val_score(classifier, x_train_scaled[:, var_indices], y
_train,
                         cv=10, scoring='f1')
print('F1 score: %0.3f (+/- %0.3f)'%(scores.mean(), scores.std() * 2))
```

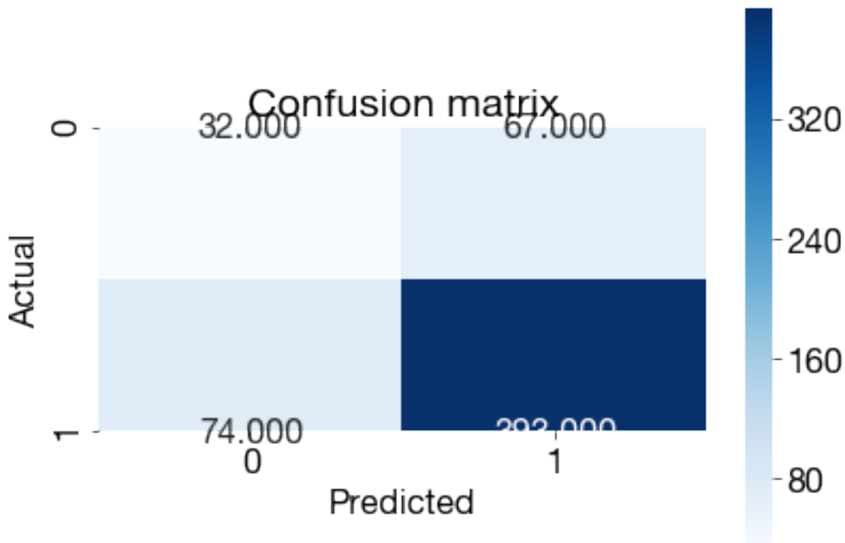
```
Accuracy: 0.790 (+/- 0.082)
F1 score: 0.874 (+/- 0.054)
```

In [9]:
```
# Feature importances (aka Gini importance)
count = 0
print('Gini importance:')
for (variable, feature_importance) in sorted(zip(variables,
    classifier.feature_importances_), key=lambda x: x[1], reverse=True
):
    count += 1
    print('(%d)' % count, '%0.3f,'%feature_importance, variable)
```

```
Gini importance:
(1) 0.243, Cscore
(2) 0.203, Oscore
(3) 0.173, SS
(4) 0.135, Country
(5) 0.131, Age
(6) 0.115, Impulsive
```

In [10]:
```
# Predict the class labels for the test set using the decision tree cl
assifier
y_pred = classifier.predict(x_test_scaled[:, var_indices])

# Plot the corresponding confusion matrix
conf_matrix = metrics.confusion_matrix(y_test, y_pred)
sns.heatmap(conf_matrix, annot=True, fmt='.3f', square=True, cmap=plt.
cm.Blues)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Confusion matrix')
plt.tight_layout()
plt.savefig('figures/conf_matrix_dt.png', dpi=300)
```



In [11]:
```
# Compute evaluation metrics for the decision tree classifier
accuracy  = metrics.accuracy_score(y_test, y_pred)
error     = 1 - metrics.accuracy_score(y_test, y_pred)
precision = metrics.precision_score(y_test, y_pred, average=None)
recall    = metrics.recall_score(y_test, y_pred, average=None)
f1_score  = metrics.f1_score(y_test, y_pred, average=None)
print('Accuracy: ', '%0.3f'%accuracy)
print('Error:    ', '%0.3f'%error)
print('Precision:', '[%0.3f'%precision[0], '%0.3f]'%precision[1])
print('Recall:   ', '[%0.3f'%recall[0],    '%0.3f]'%recall[1])
print('F1 score: ', '[%0.3f'%f1_score[0],  '%0.3f]'%f1_score[1])
```

```
Accuracy:  0.751
Error:     0.249
Precision: [0.302 0.854]
Recall:    [0.323 0.842]
F1 score:  [0.312 0.848]
```

In [12]:
```
# Build a k-nearest neighbors classifier to classify people as drug us
ers or non-users
classifier = KNeighborsClassifier(n_neighbors=3)
classifier.fit(x_train_scaled[:, var_indices], y_train)
```

Out[12]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkows
ki',
                     metric_params=None, n_jobs=None, n_neighbors=3,
p=2,
                     weights='uniform')
```

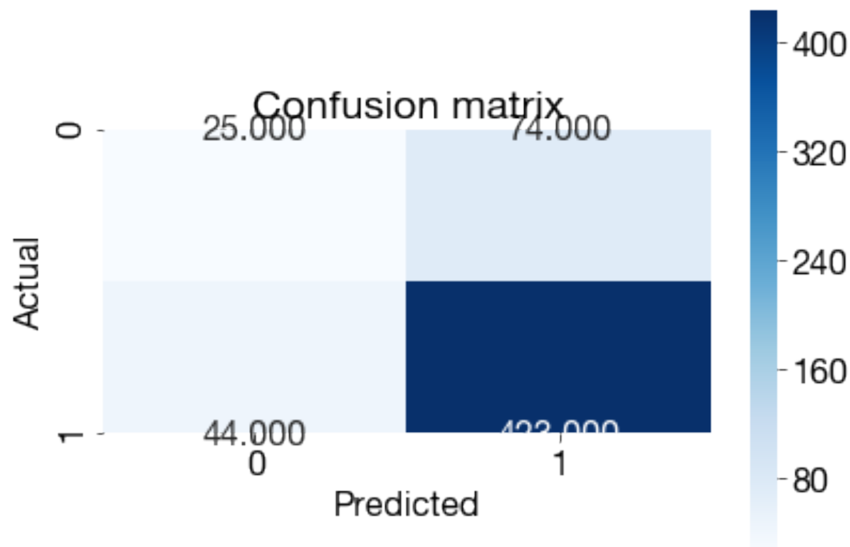
In [13]:
```
# The mean accuracy and the 95% confidence interval of 10-fold cross v
alidation
scores = cross_val_score(classifier, x_train_scaled[:, var_indices], y
_train,
                         cv=10, scoring='accuracy')
print('Accuracy: %0.3f (+/- %0.3f)'%(scores.mean(), scores.std() * 2))

# The mean F1 score and the 95% confidence interval of 10-fold cross v
alidation
scores = cross_val_score(classifier, x_train_scaled[:, var_indices], y
_train,
                         cv=10, scoring='f1')
print('F1 score: %0.3f (+/- %0.3f)'%(scores.mean(), scores.std() * 2))
```

```
Accuracy: 0.809 (+/- 0.060)
F1 score: 0.888 (+/- 0.037)
```

In [14]:
```
# Predict the class labels for the test set using the k-nearest neighb
ors classifier
y_pred = classifier.predict(x_test_scaled[:, var_indices])

# Plot the corresponding confusion matrix
conf_matrix = metrics.confusion_matrix(y_test, y_pred)
sns.heatmap(conf_matrix, annot=True, fmt='.3f', square=True, cmap=plt.
cm.Blues)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Confusion matrix')
plt.tight_layout()
plt.savefig('figures/conf_matrix_knn.png', dpi=300)
```



In [15]:
```
# Compute evaluation metrics for the k-nearest neighbors classifier
accuracy  = metrics.accuracy_score(y_test, y_pred)
error     = 1 - metrics.accuracy_score(y_test, y_pred)
precision = metrics.precision_score(y_test, y_pred, average=None)
recall    = metrics.recall_score(y_test, y_pred, average=None)
f1_score  = metrics.f1_score(y_test, y_pred, average=None)
print('Accuracy: ', '%0.3f'%accuracy)
print('Error:    ', '%0.3f'%error)
print('Precision:', '[%0.3f'%precision[0], '%0.3f]'%precision[1])
print('Recall:   ', '[%0.3f'%recall[0],    '%0.3f]'%recall[1])
print('F1 score: ', '[%0.3f'%f1_score[0],  '%0.3f]'%f1_score[1])
```

```
Accuracy:  0.792
Error:     0.208
Precision: [0.362 0.851]
Recall:    [0.253 0.906]
F1 score:  [0.298 0.878]
```

In [16]:
```
def gender_map(x):
    if math.isclose(x, 0.48246):
        return 'Female'
    else:
        return 'Male'
```

In [17]:
```
def country_map(x):
    countries = [(-0.09765, 'Australia'), (0.24923,'Canada'),
                 (-0.46841,'New Zealand'), (0.21128,'Republic of Ireland
'),
                 (0.96082,'UK'), (-0.57009,'USA'), (-0.28519,'Other')]
    for (value, country) in countries:
        if math.isclose(x, value):
            return country;
    return None
```

In [18]:
```
# Function to determine illegal drug usage per person
def is_drug_user(row):
    row = row['Amphet':]
    num_zeros = (row == 0).astype(bool).sum()
    if num_zeros == row.size:
        return False
    return True
```

In [19]:
```
train_data = pd.read_csv("train_data.csv", delimiter='\t', index_col=0
)
test_data = pd.read_csv("test_data.csv", delimiter='\t', index_col=0)
```

In [20]:
```
def create_plot(ax, data, color='#99004f'):
    usage = data.apply(pd.Series.value_counts, axis=0)
    drug = usage.iloc[:,0].name
    usages = usage.sort_index().iloc[:,0].values
    width = 0.05
    xpos = np.arange(len(usage.index),dtype='float64')
    xpos *= 0.10
    ax.bar(xpos, usages, width=width, color=color)
    rects = ax.patches
    for rect, usage in zip(rects,usages):
        x = rect.get_x() + rect.get_width()/2
        y = rect.get_height() + 0.5
        ax.text(x, y, usage, ha='center',va='bottom', fontsize=5)

    usage_texts = ['Never Used','Decade Ago','Last Decade',
                   'Last Year', 'Last Month',
                   'Last Week', 'Last Day']
    ax.set_ylim(bottom=0, top=1800)
    ax.set_xticks(xpos)
    ax.set_xticklabels(usage_texts)
    ax.tick_params(axis='y', labelsize=4)
    ax.tick_params(axis ='x', labelrotation=15, labelsize=4, width=0.7
)
    ax.text(0.5, 0.9, drug, horizontalalignment='center',
            transform=ax.transAxes, fontsize=9)
```

In [21]:
```
def create_usage_subplots(data):

    colors = ['#99004f', '#007acc', '#009900', '#e67300',
              '#cc0000','#0000b3', '#7a00cc', '#e6e600',
              '#2eb8b8']

    data = data.rename(columns={'Amphet':'Amphetamine', 'Amyl':'Amyl N
itrite',
            'Benzos':'Benzodiazepine','Caff':'Caffeine','Coke':'Cocain
e',
            'Meth':'Methamphetamine'})


    drug_data = data.loc[:,'Alcohol':].apply(lambda series: series.ast
ype(bool).sum(),axis=0)
    drug_data = drug_data.sort_values(ascending=False)
    print(drug_data)
    drugs = drug_data.index.values

    nrows = 5
    ncols= 4
    fig, axs = plt.subplots(nrows=nrows, ncols=ncols, sharex=False, sh
arey=True, figsize=(10,8))
    plt.subplots_adjust(wspace=0.02, hspace= 0.3, top = 0.95)
    color_idx = 0
    i = 0
    for row in range(nrows):
        for col in range(ncols):
            if col != 0:
                axs[row, col].tick_params(axis='y', width=0)
            if i >= len(drugs):
                axs[row, col].set_visible(False)
            else:
                create_plot(axs[row, col], data[[drugs[i]]], colors[co
lor_idx])
            i += 1
            color_idx = (color_idx+1)%len(colors)
    fig.savefig('figures/drugs.png', dpi=300)
    plt.show()
    plt.clf()
```

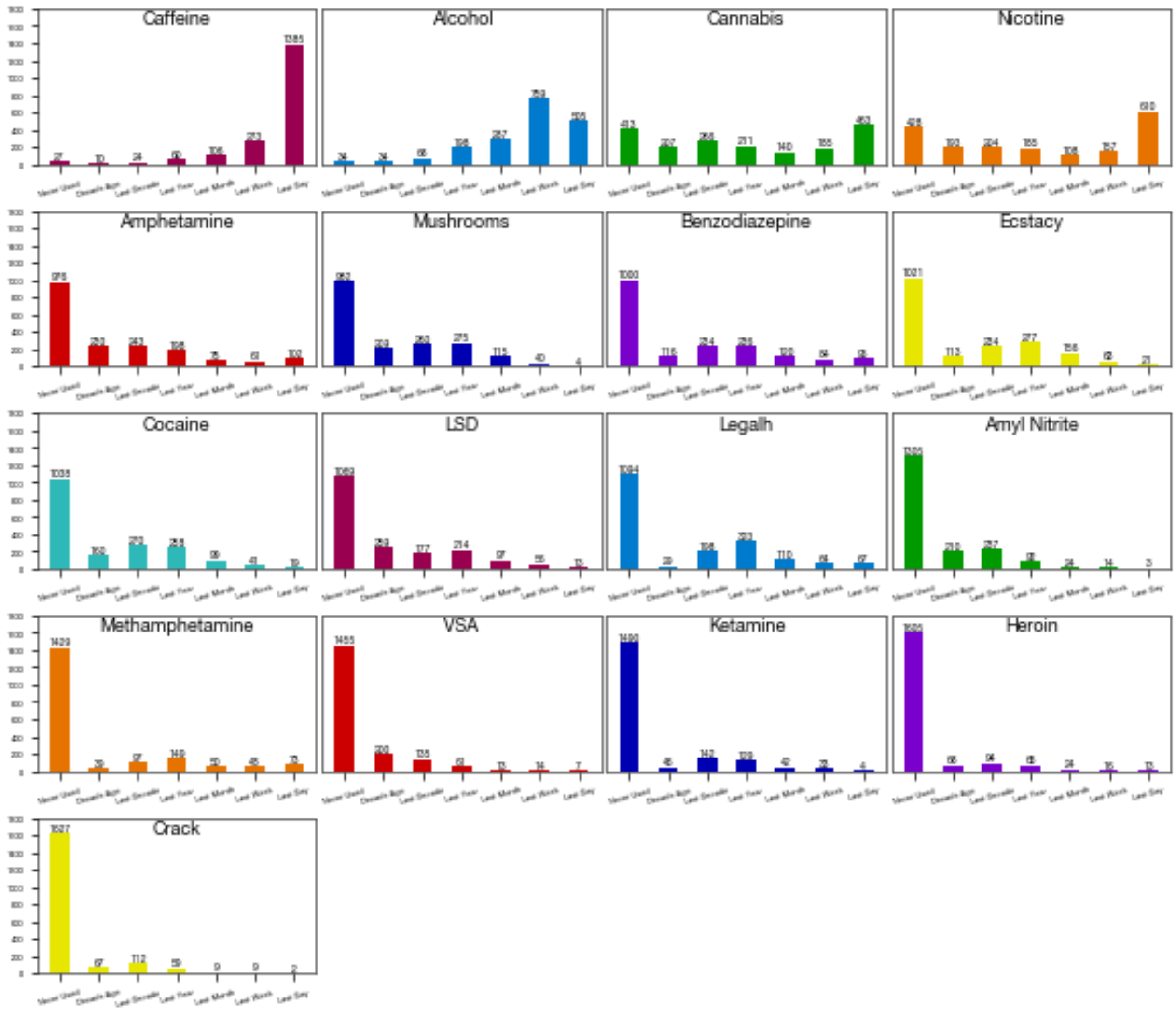
In [22]:
```
plot_data = pd.read_csv('drug_consumption.csv')
mpl.rcParams['axes.linewidth'] = 0.5
```

In [23]:
```
# label encode categorical variables
for column in plot_data.loc[:,'Alcohol':'VSA']:
    # get label encoding for column
    plot_data[column] = plot_data[column].astype('category').cat.codes
    # convert column to numeric type
    plot_data[column] = plot_data[column].astype('int32')
```

In [24]:
```
# drop fake drug
del plot_data['Semer']
# drop ID variable
del plot_data['ID']
# drop chocolate
del plot_data['Choc']
```

In [25]:
```
create_usage_subplots(plot_data)
```

```
Caffeine          1858
Alcohol           1851
Cannabis          1472
Nicotine          1457
Amphetamine        909
Mushrooms          903
Benzodiazepine     885
Ecstacy            864
Cocaine            847
LSD                816
Legalh             791
Amyl Nitrite       580
Methamphetamine    456
VSA                430
Ketamine           395
Heroin             280
Crack              258
dtype: int64
```




```
<Figure size 432x288 with 0 Axes>
```

In [26]:
```
min_score = plot_data.loc[:,'Nscore':'Cscore'].min().values.min()
plot_data.loc[:,'Nscore':'Cscore'] += abs(min_score)
```

In [27]:
```
# Create drug user columns for illegal drug usage
plot_data['Drug User'] = plot_data.drop(['Alcohol', 'Nicotine','Caff',
'Legalh'], axis=1).apply(is_drug_user, axis=1)
plot_data['Gender']= plot_data['Gender'].apply(gender_map)
plot_data['Country']=plot_data['Country'].apply(country_map)
```

In [28]:
```
# Create dataset for drug users
users = plot_data.loc[plot_data['Drug User'] == True]
# Create dataset for non-drug users
nonusers = plot_data.loc[plot_data['Drug User'] == False]
```

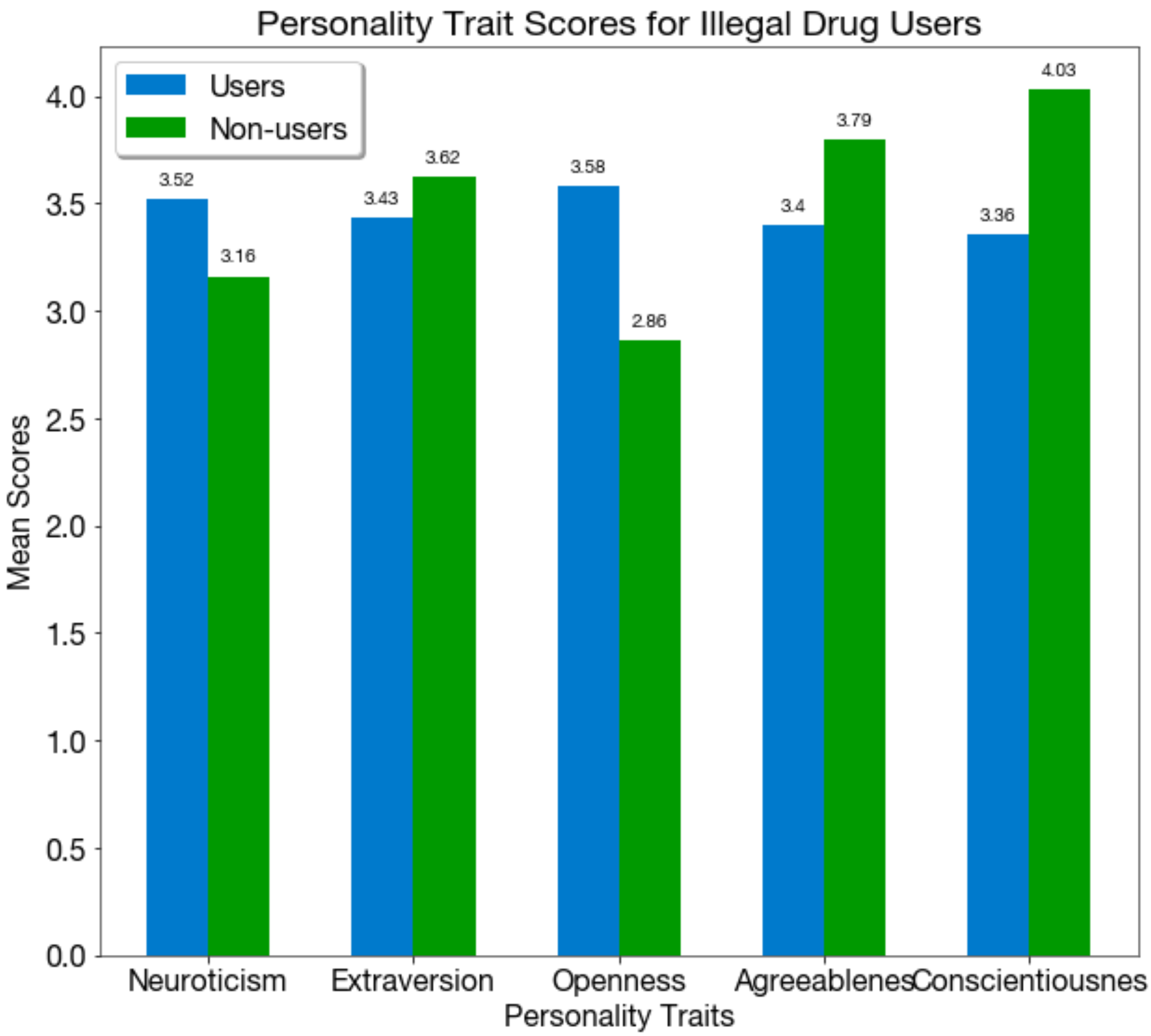
In [29]:
```
# Get data for male drug users
male_users = users.loc[(users['Gender'] == 'Male')]
male_users = male_users.reset_index(drop=True)
```

In [30]:
```
# Get data for female drug users
female_users = users.loc[(users['Gender'] == 'Female')]
female_users = female_users.reset_index(drop=True)
```

In [31]:
```
def create_personality_plot(users, nonusers):
    traits = ['Neuroticism', 'Extraversion', 'Openness',
              'Agreeablenes', 'Conscientiousnes']
    users_scores = users.loc[:,'Nscore':'Cscore'].mean().values
    nonusers_scores = nonusers.loc[:,'Nscore':'Cscore'].mean().values
    width = 0.3
    users_xpos = np.arange(len(users_scores))
    nonusers_xpos = [x + width for x in users_xpos]

    plt.bar(users_xpos, users_scores, width=width, color=['#007acc'],
label='Users')
    plt.bar(nonusers_xpos, nonusers_scores, width=width, color=['#0099
00'], label='Non-users')
    ax = plt.gca()
    rects = ax.patches
    for rect, score in zip(rects[:5],users_scores):
        x = rect.get_x() + rect.get_width()/2
        y = rect.get_height() + 0.05
        ax.text(x, y, np.round(score, 2), ha='center',va='bottom', fon
tsize=10)
    for rect, score in zip(rects[5:],nonusers_scores):
        x = rect.get_x() + rect.get_width()/2
        y = rect.get_height() + 0.05
        ax.text(x, y, np.round(score, 2), ha='center',va='bottom', fon
tsize=10)
    plt.title('Personality Trait Scores for Illegal Drug Users')
    plt.xlabel('Personality Traits')
    plt.ylabel('Mean Scores')
    plt.xticks(users_xpos+width/2, traits)
    plt.legend(loc='upper left',shadow=True)
    fig = plt.gcf()
    fig.set_size_inches(10,9)
    plt.savefig('figures/traits.png', dpi=300)
    plt.show()
    plt.clf()
```

In [32]:
```
create_personality_plot(users, nonusers)
```




```
<Figure size 432x288 with 0 Axes>
```

In [33]:
```
illegal_drugs = plot_data.drop(['Alcohol', 'Nicotine','Caff', 'Legalh'
], axis=1).loc[:, 'Amphet':'VSA']
plot_data['Last Used'] = illegal_drugs.apply(lambda series: series.max
(), axis=1)
males = plot_data.loc[(plot_data['Gender'] == 'Male')]
males = males.reset_index(drop=True)
males.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 943 entries, 0 to 942
Data columns (total 31 columns):
Age          943 non-null float64
Gender       943 non-null object
Education    943 non-null float64
Country      943 non-null object
Ethnicity    943 non-null float64
Nscore       943 non-null float64
Escore       943 non-null float64
Oscore       943 non-null float64
Ascore       943 non-null float64
Cscore       943 non-null float64
Impulsive    943 non-null float64
SS           943 non-null float64
Alcohol      943 non-null int32
Amphet       943 non-null int32
Amyl         943 non-null int32
Benzos       943 non-null int32
Caff         943 non-null int32
Cannabis     943 non-null int32
Coke         943 non-null int32
Crack        943 non-null int32
Ecstacy      943 non-null int32
Heroin       943 non-null int32
Ketamine     943 non-null int32
Legalh       943 non-null int32
LSD          943 non-null int32
Meth         943 non-null int32
Mushrooms    943 non-null int32
Nicotine     943 non-null int32
VSA          943 non-null int32
Drug User    943 non-null bool
Last Used    943 non-null int64
dtypes: bool(1), float64(10), int32(17), int64(1), object(2)
memory usage: 159.4+ KB
```

In [34]:
```
females = plot_data.loc[(plot_data['Gender'] == 'Female')]
females = females.reset_index(drop=True)
```

In [35]:
```
male_freq = males['Last Used'].value_counts().sort_index().values
male_freq
```

Out[35]:
```
array([ 84,  60,  80,  84,  86, 146, 403])
```

In [36]:
```
female_freq = females['Last Used'].value_counts().sort_index().values
female_freq
```

Out[36]:
```
array([216, 110, 161, 105,  56,  78, 216])
```

In [37]:
```
def create_gender_freq_plot(ax, male_freq, female_freq):
    usage_texts = ['Never Used','Decade Ago','Last Decade',
                   'Last Year', 'Last Month',
                   'Last Week', 'Last Day']
    width = 0.3
    males_xpos = np.arange(len(male_freq))
    females_xpos = [x + width for x in males_xpos]
    ax.bar(males_xpos, male_freq, width=width, color=['#2eb8b8'], labe
l='Male')
    ax.bar(females_xpos, female_freq, width=width, color=['#99004f'],
label='Female')
    rects = ax.patches
    for rect, freq in zip(rects[:7], male_freq):
        x = rect.get_x() + rect.get_width()/2
        y = rect.get_height() + 0.05
        ax.text(x, y, freq, ha='center',va='bottom', fontsize=10)
    for rect, freq in zip(rects[7:], female_freq):
        x = rect.get_x() + rect.get_width()/2
        y = rect.get_height() + 0.05
        ax.text(x, y, freq, ha='center',va='bottom', fontsize=10)
    ax.tick_params(axis ='x', labelrotation=15)
    ax.legend(loc='upper left',shadow=True)
    ax.set_xticks(males_xpos+width/2)
    ax.set_xticklabels(usage_texts)
    ax.set_ylabel('Users')
    ax.set_title('Frequency of Illegal Drug Usage by Gender')
```

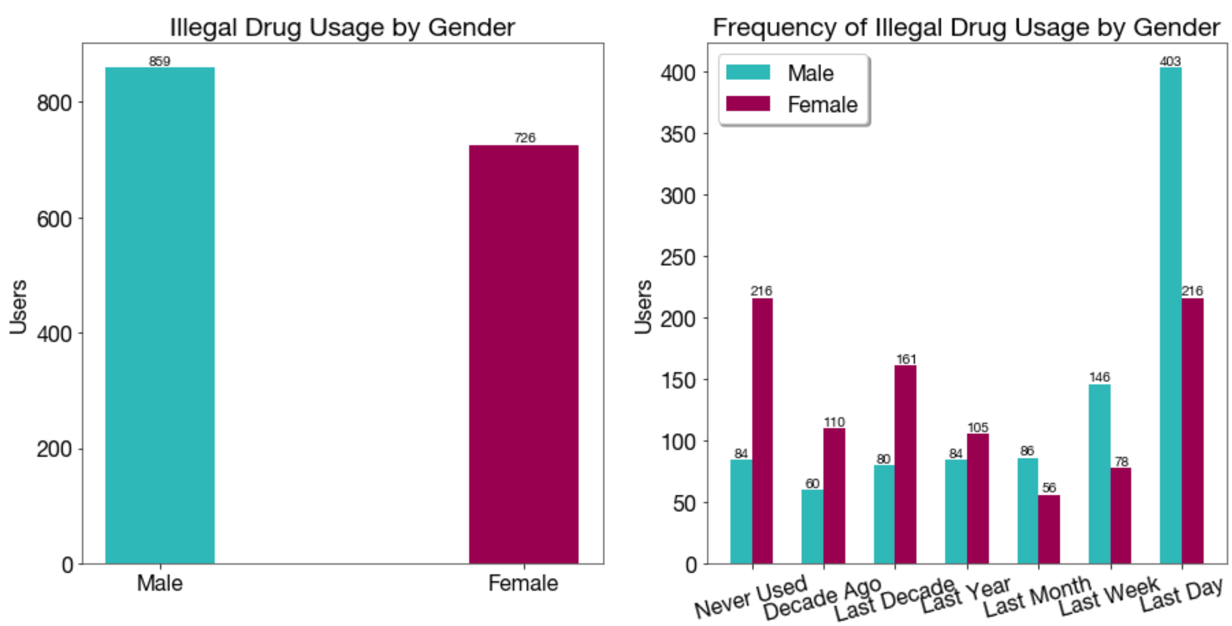
In [38]:
```
def create_gender_plot(ax, male_users, female_users):
    xpos = np.arange(2)
    bars = [len(male_users.index), len(female_users.index)]

    ax.bar(xpos, bars, width=0.3, color=['#2eb8b8','#99004f'], align='
center')

    rects = ax.patches
    for rect, score in zip(rects,bars):
        x = rect.get_x() + rect.get_width()/2
        y = rect.get_height() + 0.05
        ax.text(x, y, np.round(score, 2), ha='center',va='bottom', fon
tsize=10)

    ax.set_xticks(xpos)
    ax.set_xticklabels(['Male', 'Female'])
    ax.set_title('Illegal Drug Usage by Gender')
    ax.set_ylabel('Users')
```

In [39]:
```
fig, (ax1, ax2) = plt.subplots(1, 2, sharey=False, figsize=(15,7))
create_gender_plot(ax1, male_users, female_users)
create_gender_freq_plot(ax2, male_freq, female_freq)
fig.savefig('figures/gender_freq.png', dpi=300)
plt.show()
plt.clf()
```




```
<Figure size 432x288 with 0 Axes>
```

In [40]:
```
train_data = train_data.reset_index(drop=True)
test_data = test_data.reset_index(drop=True)
```

In [41]:
```
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1319 entries, 0 to 1318
Data columns (total 32 columns):
ID           1319 non-null int64
Age          1319 non-null float64
Gender       1319 non-null float64
Education    1319 non-null float64
Country      1319 non-null float64
Ethnicity    1319 non-null float64
Nscore       1319 non-null float64
Escore       1319 non-null float64
Oscore       1319 non-null float64
Ascore       1319 non-null float64
Cscore       1319 non-null float64
Impulsive    1319 non-null float64
SS           1319 non-null float64
Alcohol      1319 non-null object
Amphet       1319 non-null object
Amyl         1319 non-null object
Benzos       1319 non-null object
Caff         1319 non-null object
Cannabis     1319 non-null object
Choc         1319 non-null object
Coke         1319 non-null object
Crack        1319 non-null object
Ecstacy      1319 non-null object
Heroin       1319 non-null object
Ketamine     1319 non-null object
Legalh       1319 non-null object
LSD          1319 non-null object
Meth         1319 non-null object
Mushrooms    1319 non-null object
Nicotine     1319 non-null object
Semer        1319 non-null object
VSA          1319 non-null object
dtypes: float64(12), int64(1), object(19)
memory usage: 329.9+ KB
```

In [42]:
```
# Drop ID, Chocolate, the fake drug Semer, and legal substances
train_data.drop(['ID', 'Choc', 'Semer', 'Alcohol', 'Nicotine', 'Caff',
'Legalh'], axis=1, inplace=True)
test_data.drop(['ID', 'Choc', 'Semer',  'Alcohol', 'Nicotine', 'Caff',
'Legalh'], axis=1, inplace=True)
```

In [43]:
```
for column in train_data.loc[:,'Amphet':]:
    # get label encoding for column
    train_data[column] = train_data[column].astype('category').cat.cod
es.astype('int32')
    test_data[column] = test_data[column].astype('category').cat.codes
.astype('int32')
```

In [44]:
```
# Combine illegal drug usage into a single boolean variable
train_data['Drug User'] = train_data.apply(is_drug_user, axis=1)
test_data['Drug User'] = test_data.apply(is_drug_user, axis=1)
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1319 entries, 0 to 1318
Data columns (total 26 columns):
Age          1319 non-null float64
Gender       1319 non-null float64
Education    1319 non-null float64
Country      1319 non-null float64
Ethnicity    1319 non-null float64
Nscore       1319 non-null float64
Escore       1319 non-null float64
Oscore       1319 non-null float64
Ascore       1319 non-null float64
Cscore       1319 non-null float64
Impulsive    1319 non-null float64
SS           1319 non-null float64
Amphet       1319 non-null int32
Amyl         1319 non-null int32
Benzos       1319 non-null int32
Cannabis     1319 non-null int32
Coke         1319 non-null int32
Crack        1319 non-null int32
Ecstacy      1319 non-null int32
Heroin       1319 non-null int32
Ketamine     1319 non-null int32
LSD          1319 non-null int32
Meth         1319 non-null int32
Mushrooms    1319 non-null int32
VSA          1319 non-null int32
Drug User    1319 non-null bool
dtypes: bool(1), float64(12), int32(13)
memory usage: 192.0 KB
```

In [45]:
```
X_train = train_data.loc[:,'Age':'SS']
y_train = train_data['Drug User']
```

In [46]:
```
# Feature selection
sel = SelectFromModel(RandomForestClassifier(random_state=0), threshol
d=0.05)
sel.fit(X_train, y_train)
selected_feat= X_train.columns[(sel.get_support())]
print(selected_feat.values)
```

```
['Age' 'Education' 'Country' 'Nscore' 'Escore' 'Oscore' 'Ascore' 'Cs
core'
 'Impulsive' 'SS']
```

```
/Users/manasakandimalla/opt/anaconda3/lib/python3.7/site-packages/sk
learn/ensemble/forest.py:245: FutureWarning: The default value of n_
estimators will change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

In [47]:
```
# Grid search for random forest (30,240 base estimators)
max_features = ['auto', 'sqrt']
max_depth = [int(x) for x in np.linspace(5, 100, num = 20)] + [None]
n_estimators = [int(x) for x in np.linspace(start = 100, stop = 1000,
num = 20)]
min_samples_split = [2, 5, 10]
min_samples_leaf = [1, 2, 4]
criterion=['entropy','gini']
bootstrap = [True, False]
grid = {'max_features': max_features,
        'max_depth': max_depth,
        'n_estimators': n_estimators,
        'min_samples_split': min_samples_split,
        'min_samples_leaf': min_samples_leaf,
        'criterion': criterion,
        'bootstrap': bootstrap}
```

In [48]:
```
# Base classifier used for grid search
forest = RandomForestClassifier(random_state=0)
# Use 100 iterations and 10-fold cross-validation, using 4 cores
forest_grid_search = RandomizedSearchCV(estimator = forest, param_dist
ributions = grid,
                              n_iter = 100, cv = 10, verbose=2, rando
m_state=0, n_jobs = 4)
```

In [49]:
```
# Use features selected for training and testing
X_train = train_data[selected_feat.values]
y_train = train_data['Drug User']

X_test = test_data[selected_feat.values]
y_test = test_data['Drug User']
```

In [50]:
```
# Fit features selected to grid search (slow process)
forest_grid_search.fit(X_train, y_train)
```

```
Fitting 10 folds for each of 100 candidates, totalling 1000 fits

[Parallel(n_jobs=4)]: Using backend LokyBackend with 4 concurrent wo
rkers.
[Parallel(n_jobs=4)]: Done  33 tasks      | elapsed:    9.2s
[Parallel(n_jobs=4)]: Done 154 tasks      | elapsed:   39.4s
[Parallel(n_jobs=4)]: Done 357 tasks      | elapsed:  1.6min
[Parallel(n_jobs=4)]: Done 640 tasks      | elapsed:  2.9min
[Parallel(n_jobs=4)]: Done 1000 out of 1000 | elapsed:  4.2min finis
hed
```

Out[50]:
```
RandomizedSearchCV(cv=10, error_score='raise-deprecating',
                   estimator=RandomForestClassifier(bootstrap=True,
                                                    class_weight=Non
e,
                                                    criterion='gini'
,
                                                    max_depth=None,
                                                    max_features='au
to',
                                                    max_leaf_nodes=N
one,
                                                    min_impurity_dec
rease=0.0,
                                                    min_impurity_spl
it=None,
                                                    min_samples_leaf
=1,
                                                    min_samples_spli
t=2,
                                                    min_weight_fract
ion_leaf=0.0,
                                                    n_estimators='wa
rn',
                                                    n_jobs=None,
                                                    oob_s...
                                        'max_depth': [5, 10, 15, 20,
25, 30, 35,
                                                      40, 45, 50, 55
, 60, 65,
                                                      70, 75, 80, 85
, 90, 95,
                                                      100, None],
                                        'max_features': ['auto', 'sq
rt'],
                                        'min_samples_leaf': [1, 2, 4
],
```

```
                                        'min_samples_split': [2, 5,
10],
                                        'n_estimators': [100, 147, 1
94, 242,
                                                         289, 336, 3
84, 431,
                                                         478, 526, 5
73, 621,
                                                         668, 715, 7
63, 810,
                                                         857, 905, 9
52, 1000]},
                   pre_dispatch='2*n_jobs', random_state=0, refit=Tr
ue,
                   return_train_score=False, scoring=None, verbose=2
)
```

In [51]:

```
# Store the dictionary of best parameters
params = forest_grid_search.best_params_
params
```

Out[51]:

```
{'n_estimators': 621,
 'min_samples_split': 10,
 'min_samples_leaf': 4,
 'max_features': 'auto',
 'max_depth': 70,
 'criterion': 'entropy',
 'bootstrap': True}
```

In [52]:

```
search_data = pd.DataFrame(forest_grid_search.cv_results_)
search_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 25 columns):
mean_fit_time              100 non-null float64
std_fit_time               100 non-null float64
mean_score_time            100 non-null float64
std_score_time             100 non-null float64
param_n_estimators         100 non-null object
param_min_samples_split    100 non-null object
param_min_samples_leaf     100 non-null object
param_max_features         100 non-null object
param_max_depth            95 non-null object
param_criterion            100 non-null object
param_bootstrap            100 non-null object
params                     100 non-null object
split0_test_score          100 non-null float64
split1_test_score          100 non-null float64
split2_test_score          100 non-null float64
split3_test_score          100 non-null float64
split4_test_score          100 non-null float64
split5_test_score          100 non-null float64
split6_test_score          100 non-null float64
split7_test_score          100 non-null float64
split8_test_score          100 non-null float64
split9_test_score          100 non-null float64
mean_test_score            100 non-null float64
std_test_score             100 non-null float64
rank_test_score            100 non-null int32
dtypes: float64(16), int32(1), object(8)
memory usage: 19.3+ KB
```

In [53]:
```
# Convert estimators column to integer type
search_data['param_n_estimators'] = search_data['param_n_estimators'].
astype('int32')
```

In [54]:
```
estimators = search_data[['param_n_estimators', 'mean_fit_time', 'mean
_test_score']].sort_values(
    by=['param_n_estimators'])
estimators.head
```

Out[54]:
```
<bound method NDFrame.head of     param_n_estimators  mean_fit_time  
mean_test_score
97                 100       0.174355         0.842305
46                 100       0.168606         0.834723
39                 100       0.166035         0.844579
92                 100       0.186894         0.836240
68                 100       0.171658         0.846096
..                 ...            ...              ...
56                1000       1.653674         0.838514
43                1000       1.637751         0.848370
45                1000       1.596318         0.842305
1                 1000       1.332806         0.846096
75                1000       1.625391         0.845337

[100 rows x 3 columns]>
```

In [55]:
```
max_depths = search_data[['param_max_depth', 'mean_test_score']]
# Remove rows with max depth of None for plotting
max_depths = max_depths[max_depths['param_max_depth'].notnull()]
# Sort values by max depth
max_depths.sort_values(by=['param_max_depth'], inplace=True)
max_depths.reset_index(drop=True, inplace=True)
max_depths.head
```

Out[55]:
```
<bound method NDFrame.head of    param_max_depth  mean_test_score
0                5         0.845337
1                5         0.846096
2                5         0.847612
3                5         0.846096
4                5         0.846854
..             ...              ...
90             100         0.847612
91             100         0.845337
92             100         0.846854
93             100         0.838514
94             100         0.848370

[95 rows x 2 columns]>
```

In [56]:
```
# Plot visuals for grid search
fig, (ax1, ax2, ax3) = plt.subplots(1, 3, sharex=False, sharey=False)
plt.subplots_adjust(wspace=0.3)
fig.set_size_inches(20, 5)

ax1.plot(estimators['param_n_estimators'], estimators['mean_fit_time']
, color='#cc5200')
ax1.set_xlabel('Decision Trees')
ax1.set_ylabel('Mean Training Time (s)')
ax1.set_title('Mean Training Time by Number of Decision Trees', fontdi
ct={'fontsize':10.5})

ax2.plot(estimators['param_n_estimators'], estimators['mean_test_score
'], color='#00b300')
ax2.set_xlabel('Decision Trees')
ax2.set_ylabel('Mean Test Score')
ax2.set_title('Mean Test Score by Number of Decision Trees',fontdict={
'fontsize':10.5})

ax3.plot(max_depths['param_max_depth'], max_depths['mean_test_score'],
color='#007acc')
ax3.set_xlabel('Max Depth of Decision Trees')
ax3.set_ylabel('Mean Test Score')
ax3.set_title('Mean Test Score by Decision Tree Depth',fontdict={'font
size':10.5})
plt.savefig('gridsearch.png', dpi=300)
```

In [57]:
```
# Get mean cross-validation score using best paramaters from grid sear
ch
forest = RandomForestClassifier(n_estimators=params['n_estimators'], m
in_samples_split=params['min_samples_split'],
                                min_samples_leaf=params['min_samples_l
eaf'], max_features=params['max_features'],
                                max_depth=params['max_depth'], bootstr
ap=params['bootstrap'], random_state=0)
```

In [58]:
```
scores = cross_val_score(forest, X_train, y_train, scoring='accuracy',
cv=10)
```

In [59]:
```
print("Mean Accuracy: %f"%(scores.mean()))
```

```
Mean Accuracy: 0.844579
```

In [60]:
```
scores = cross_val_score(forest, X_train, y_train, scoring='f1', cv=10
)
```

In [61]:
```
print("Mean F1 Score: %f"%(scores.mean()))
```

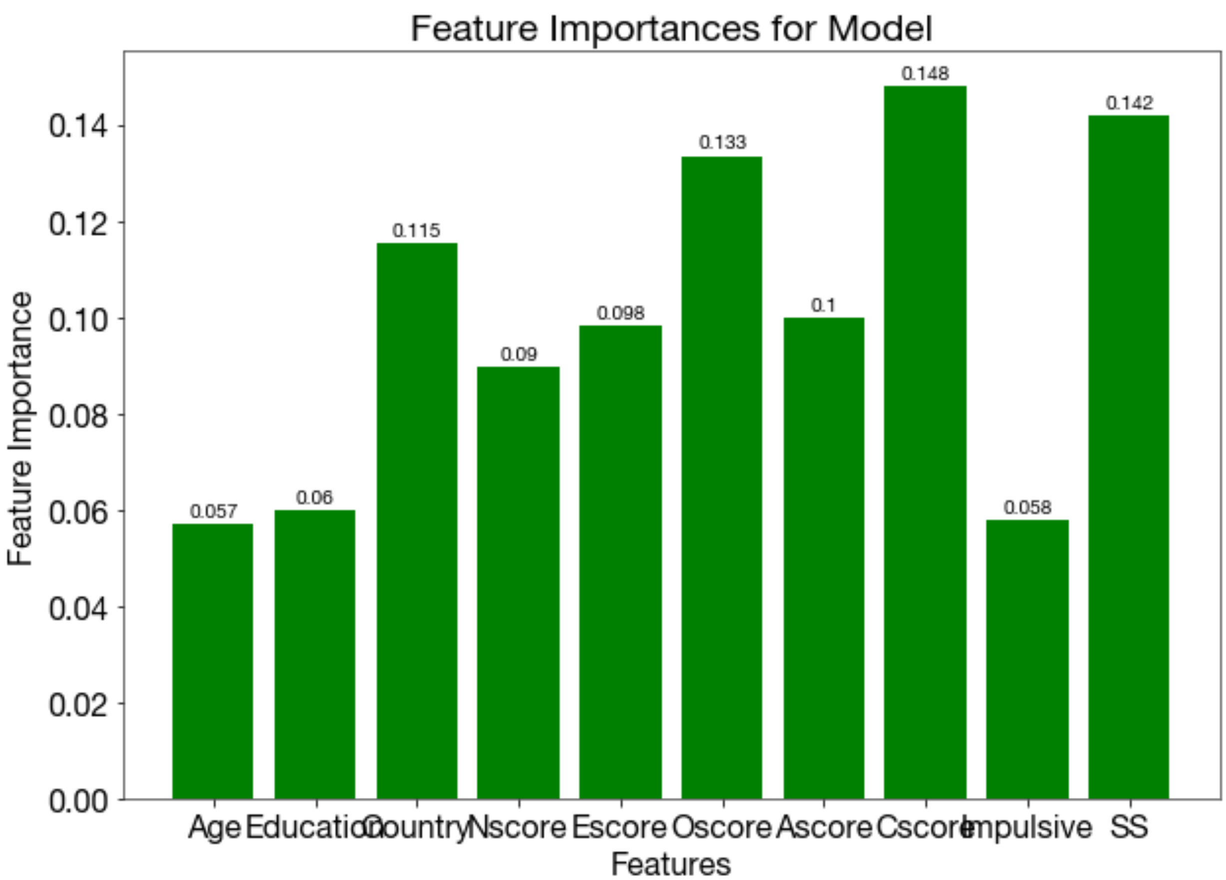
```
Mean F1 Score: 0.913897
```

In [62]:
```
forest = RandomForestClassifier(n_estimators=params['n_estimators'], m
in_samples_split=params['min_samples_split'],
                                min_samples_leaf=params['min_samples_l
eaf'], max_features=params['max_features'],
                                max_depth=params['max_depth'], bootstr
ap=params['bootstrap'], random_state=0)
forest.fit(X_train, y_train)
```

Out[62]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion=
'gini',
                       max_depth=70, max_features='auto', max_leaf_n
odes=None,
                       min_impurity_decrease=0.0, min_impurity_split
=None,
                       min_samples_leaf=4, min_samples_split=10,
                       min_weight_fraction_leaf=0.0, n_estimators=62
1,
                       n_jobs=None, oob_score=False, random_state=0,
verbose=0,
                       warm_start=False)
```

In [63]:
```
plt.bar(np.arange(len(X_train.columns)), forest.feature_importances_,
tick_label=X_train.columns.values, color='g')
fig = plt.gcf()
ax = plt.gca()
rects = ax.patches
for rect, importance in zip(rects, forest.feature_importances_):
    x = rect.get_x() + rect.get_width()/2
    y = rect.get_height() + 0.001
    ax.text(x, y, np.round(importance, 3), ha='center',va='bottom', fo
ntsize=10)
fig.set_size_inches(10,7)
plt.ylabel('Feature Importance')
plt.xlabel('Features')
plt.title('Feature Importances for Model')
```

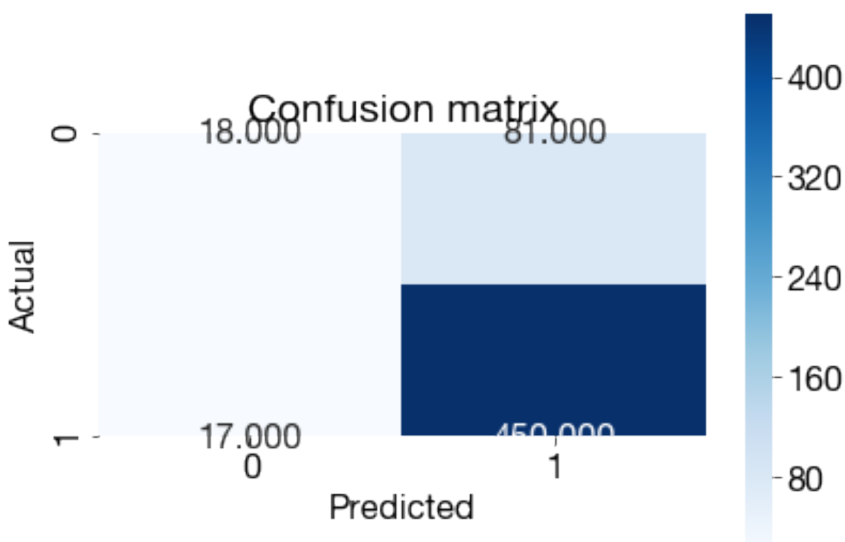
Out[63]:
```
Text(0.5, 1.0, 'Feature Importances for Model')
```



In [64]:
```
# Calculate metrics
y_pred = forest.predict(X_test)
accuracy  = metrics.accuracy_score(y_test, y_pred)
error     = 1 - metrics.accuracy_score(y_test, y_pred)
precision = metrics.precision_score(y_test, y_pred, average=None)
recall    = metrics.recall_score(y_test, y_pred, average=None)
f1_score  = metrics.f1_score(y_test, y_pred, average=None)
print('Accuracy:  ', '%0.3f'%(accuracy))
print('Error:     ', '%0.3f'%(error))
print('Precision: ', precision)
print('Recall:    ', recall)
print('F1 score:  ', f1_score)
```

```
Accuracy:    0.827
Error:       0.173
Precision:   [0.51428571 0.84745763]
Recall:      [0.18181818 0.96359743]
F1 score:    [0.26865672 0.90180361]
```

In [65]:
```
conf_matrix = metrics.confusion_matrix(y_test, y_pred)
sns.heatmap(conf_matrix, annot=True, fmt='.3f', square=True, cmap=plt.
cm.Blues)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Confusion matrix')
plt.tight_layout()
plt.savefig('figures/random_forest_matrix.png', dpi=300)
```



In [ ]:

In [66]:
```
data = pd.read_csv("drug_consumption.csv")
data.head()
```

Out[66]:

	ID	Age	Gender	Education	Country	Ethnicity	Nscore	Escore	Oscore	Ascore
0	1	0.49788	0.48246	-0.05921	0.96082	0.12600	0.31287	-0.57545	-0.58331	-0.91699
1	2	-0.07854	-0.48246	1.98437	0.96082	-0.31685	-0.67825	1.93886	1.43533	0.76096
2	3	0.49788	-0.48246	-0.05921	0.96082	-0.31685	-0.46725	0.80523	-0.84732	-1.62090
3	4	-0.95197	0.48246	1.16365	0.96082	-0.31685	-0.14882	-0.80615	-0.01928	0.59042
4	5	0.49788	0.48246	1.98437	0.96082	-0.31685	0.73545	-1.63340	-0.45174	-0.30172

5 rows × 32 columns

In [67]:
```
#Source: https://drugs.laws.com/list-of-illegal-drugs
#Grouping Illegal and Non-Illegal drugs
illegal_drugs = ['Amphet','Coke','Crack','Ecstacy','Heroin','LSD','Mus
hrooms']
Non_illegal =[i for i in data.columns[13:] if i not in illegal_drugs]
```

In [68]:
```
#Stripping all 'CL' from all the drug columns
for drug in data.columns[13:]:
        data[drug] = data[drug].map(lambda x: int(str(x).lstrip('CL'))
)
```

In [69]:
```
cluster_tab = pd.DataFrame(columns=['Type','Single Linkage','Complete
Linkage','K-Means','DBSCAN'])
```

In [ ]:

In [70]:
```
#Start with Clusters
#Cluster1: Using all the columns
#Cluster1 with Hierarchial clustering single linkage
```

In [71]:
```
variables = data.columns
var_indices = [data.columns.get_loc(variable) for variable in variable
s]
```

In [72]:
```
print(var_indices)
```

```
[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 1
9, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31]
```

In [73]:
```
#Standardizing the data
x = data.iloc[:,var_indices]
scaler = StandardScaler()
x_scaled = scaler.fit_transform(x)
```

In [74]:
```
clustering = linkage(x_scaled,method="single",metric="euclidean")
clusters = fcluster(clustering, 2, criterion = 'maxclust')
clusters = clusters - 1
print(clusters)
```

```
[1 1 1 ... 1 1 1]
```

In [75]:
```
data['clusters'] = clusters
```

In [76]:
```
#Silhouette coefficient
sl_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(sl_sil)
```

```
0.5079507583610615
```

In [77]:
```
#Cluster1 with Hierarchial clustering Complete Linkage
```

In [78]:
```
clustering = linkage(x_scaled,method="complete",metric="euclidean")
clusters = fcluster(clustering, 2, criterion = 'maxclust')
clusters = clusters - 1
print(clusters)
```

```
[1 1 1 ... 1 1 1]
```

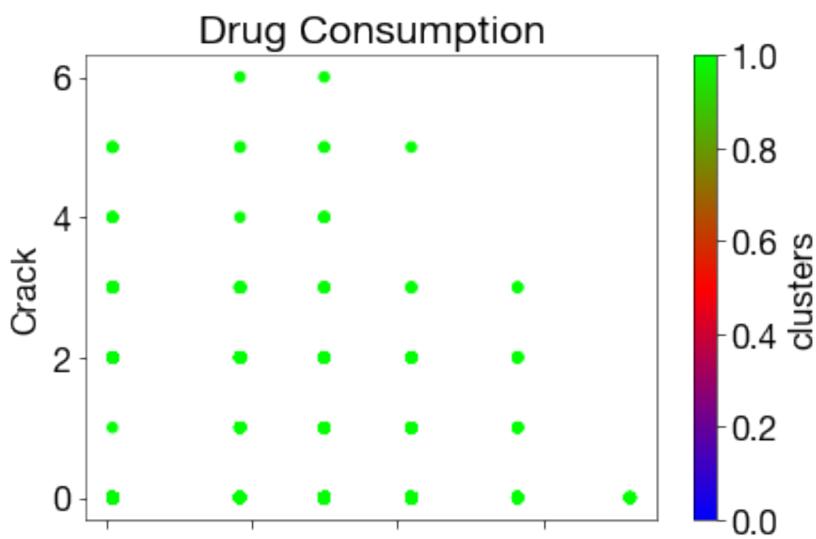
In [79]:
```
data['clusters'] = clusters
```

In [80]:
```
#Silhouette coefficient
cl_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(cl_sil)
```

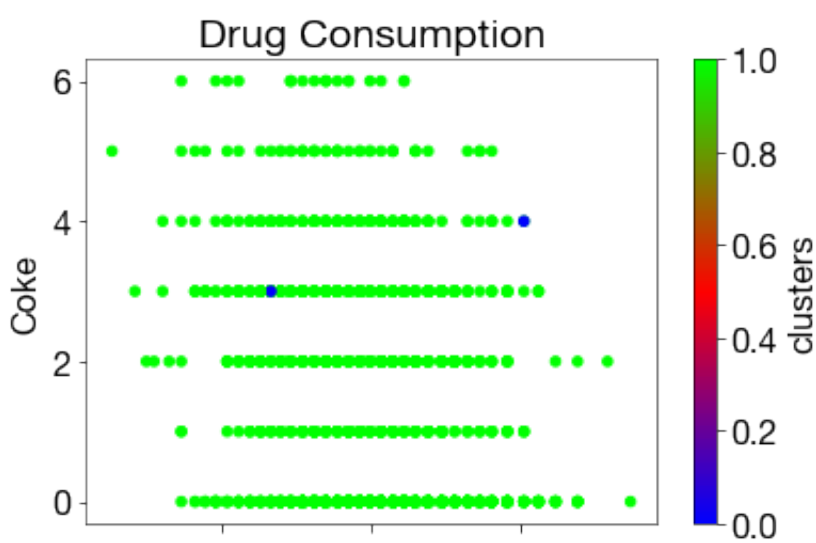
```
0.6629990546490399
```

In [81]:
```
ax = data.plot(kind = 'scatter', x = 'Age', y = 'Crack', c = 'clusters
', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Age', ylabel = 'Crack')
```

Out[81]:
```
[Text(0, 0.5, 'Crack'),
 Text(0.5, 0, 'Age'),
 Text(0.5, 1.0, 'Drug Consumption')]
```

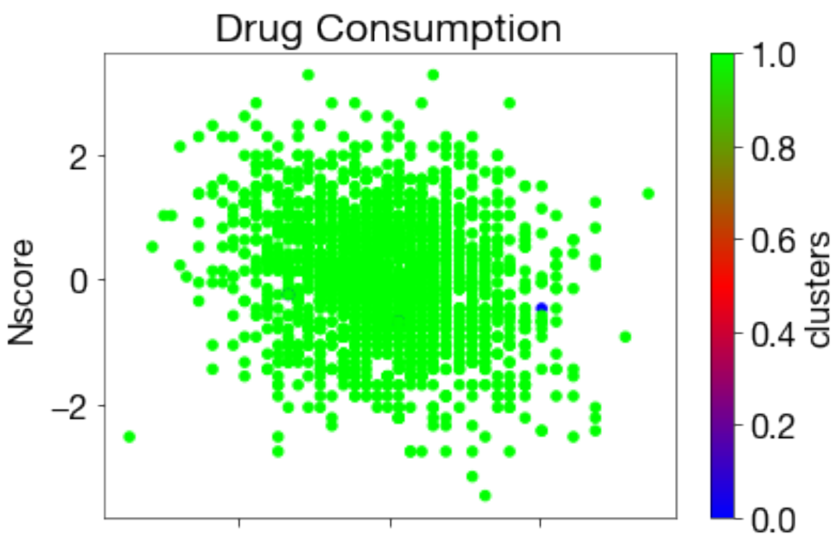


In [82]:
```
ax = data.plot(kind = 'scatter', x = 'Ascore', y = 'Coke', c = 'cluste
rs', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption',ylabel = 'Coke', xlabel = 'Ascore')
plt.savefig('figures/cluster1-AscorevsCoke', dpi=300)
```



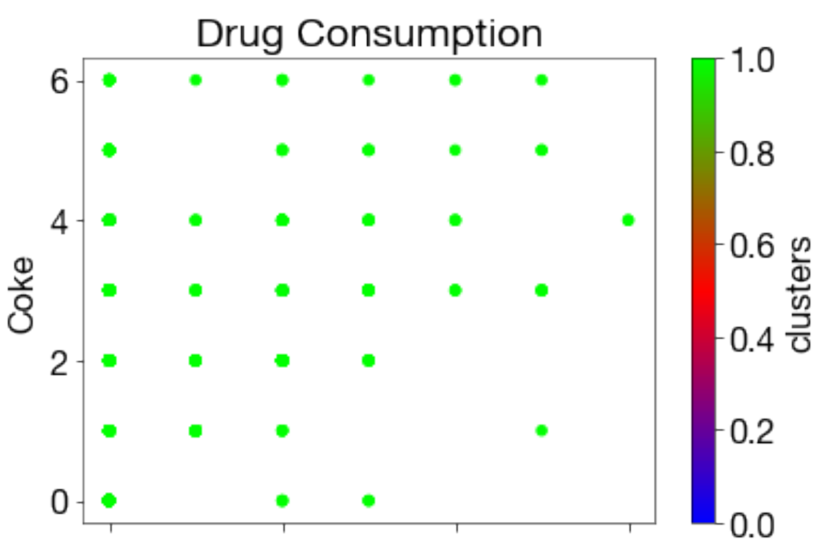
In [83]:
```
ax = data.plot(kind = 'scatter', x = 'Ascore', y = 'Nscore', c = 'clus
ters', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Ascore', ylabel = 'Nscore
')
```

Out[83]:
```
[Text(0, 0.5, 'Nscore'),
 Text(0.5, 0, 'Ascore'),
 Text(0.5, 1.0, 'Drug Consumption')]
```



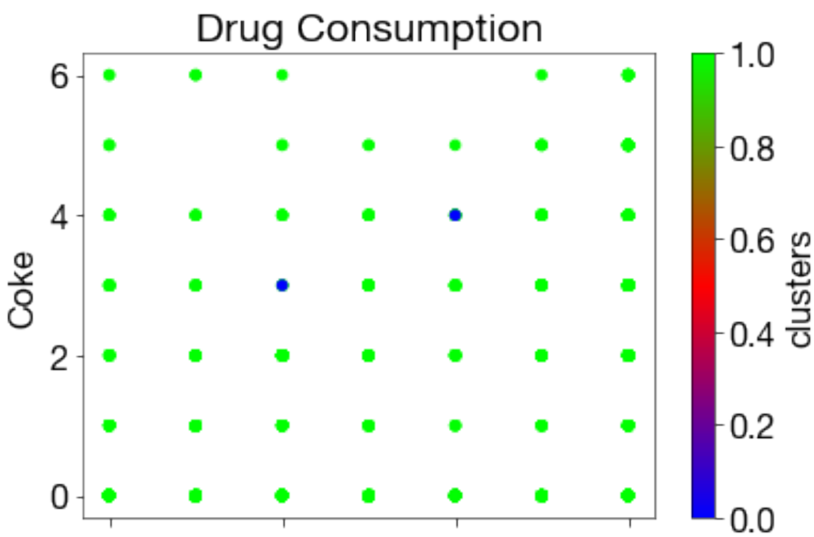
In [84]:
```
ax = data.plot(kind = 'scatter', x = 'Crack', y = 'Coke', c = 'cluster
s', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Crack',ylabel = 'Coke')
```

Out[84]:
```
[Text(0, 0.5, 'Coke'),
 Text(0.5, 0, 'Crack'),
 Text(0.5, 1.0, 'Drug Consumption')]
```



In [85]:
```
ax = data.plot(kind = 'scatter', x = 'Nicotine', y = 'Coke', c = 'clusters', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Nicotine', ylabel = 'Coke')
```

Out[85]:
```
[Text(0, 0.5, 'Coke'),
 Text(0.5, 0, 'Nicotine'),
 Text(0.5, 1.0, 'Drug Consumption')]
```



In [86]:
```
#Cluster1 with K-Means
```

In [87]:
```
clustering = KMeans(n_clusters = 2, init = 'random', n_init = 1, random_state = 0).fit(x_scaled)
clusters = clustering.labels_
print(clusters)
data['clusters'] = clusters
```

```
[0 1 0 ... 1 1 1]
```

In [88]:
```
#Silhouette coefficient
km_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric = "euclidean")
print(km_sil)
```

```
0.18301116784616245
```

In [89]:
```
#Cluster1 with DBSCAN
```

In [90]:
```
clustering = DBSCAN(eps = 2, min_samples = 4, metric = "euclidean").fi
t(x_scaled)
clusters = clustering.labels_
data['clusters'] = clusters
```

In [91]:
```
#Silhouette coefficient
db_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(db_sil)
```

```
-0.1898724108691829
```

In [92]:
```
# print(metrics.adjusted_rand_score(data['clusters']))
# We cannot use rand index cause we do not have anything to compare th
e clusters against
```

In [93]:
```
cluster_tab = cluster_tab.append({'Type':'All Features','Single Linkag
e': sl_sil, 'Complete Linkage':cl_sil,'K-Means':km_sil,'DBSCAN':db_sil
},ignore_index=True)
```

In [ ]:

In [94]:
```
#Cluster2: Using only Non-illegal drugs
```

In [95]:
```
variables = Non_illegal
var_indices = [data.columns.get_loc(variable) for variable in variable
s]
```

In [96]:
```
#Standardizing the data
x = data.iloc[:,var_indices]
scaler = StandardScaler()
x_scaled = scaler.fit_transform(x)
```

In [97]:
```
clustering = linkage(x_scaled,method="single",metric="euclidean")
clusters = fcluster(clustering, 2, criterion = 'maxclust')
clusters = clusters - 1
print(clusters)
```

```
[0 0 0 ... 0 0 0]
```

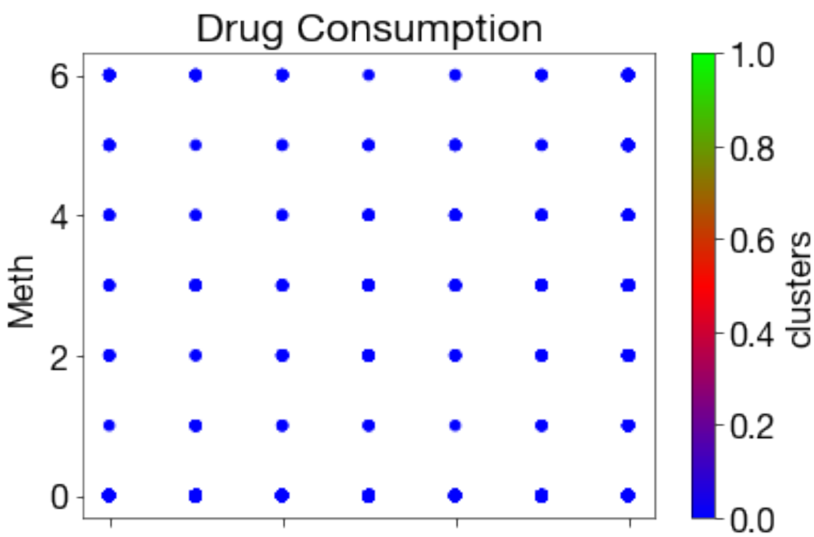
In [98]:
```
data['clusters'] = clusters
```

In [100]:
```
#Silhouette coefficient
sl_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(sl_sil)
```

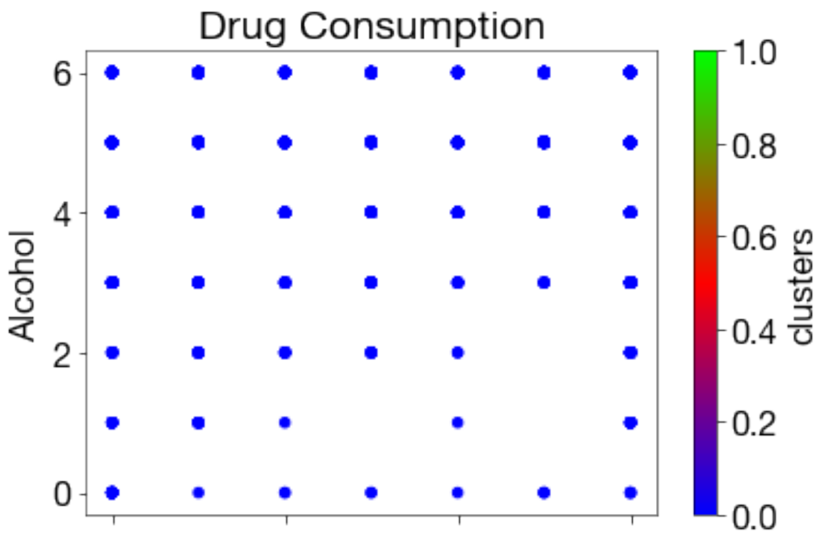
```
0.8233760416358061
```

In [101]:
```
ax = data.plot(kind = 'scatter', x = 'Nicotine', y = 'Meth', c = 'clus
ters', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Nicotine', ylabel = 'Meth
')
```

Out[101]:
```
[Text(0, 0.5, 'Meth'),
 Text(0.5, 0, 'Nicotine'),
 Text(0.5, 1.0, 'Drug Consumption')]
```

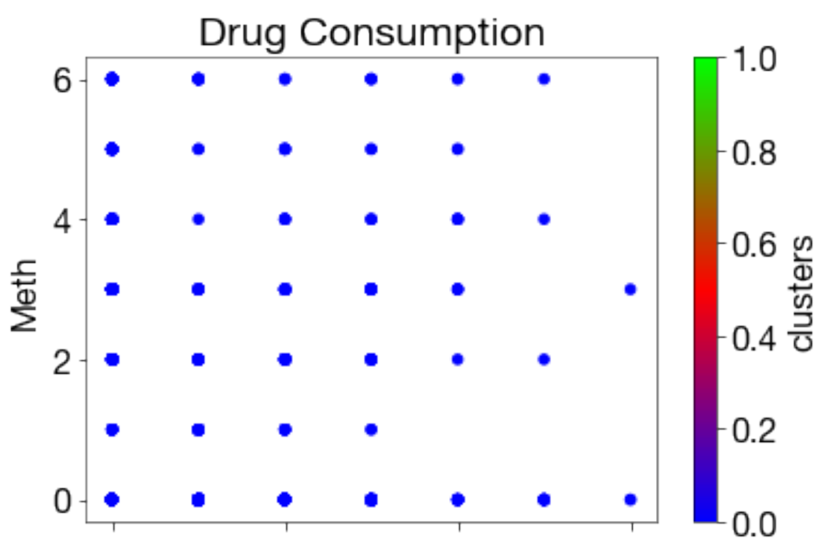


In [102]:
```
ax = data.plot(kind = 'scatter', x = 'Nicotine', y = 'Alcohol', c = 'clusters', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Nicotine', ylabel = 'Alcohol')
plt.savefig('figures/cluster2-NicotineVsAlcohol.png', dpi=300)
```



In [103]:
```
ax = data.plot(kind = 'scatter', x = 'Amyl', y = 'Meth', c = 'clusters', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Amyl', ylabel = 'Meth')
```

Out[103]:
```
[Text(0, 0.5, 'Meth'),
 Text(0.5, 0, 'Amyl'),
 Text(0.5, 1.0, 'Drug Consumption')]
```



In [104]:
```
#Cluster2 with complete Linkage
```

In [105]:
```
clustering = linkage(x_scaled,method="complete",metric="euclidean")
clusters = fcluster(clustering, 2, criterion = 'maxclust')
clusters = clusters - 1
print(clusters)
```

```
[1 1 1 ... 1 1 1]
```

In [106]:
```
data['clusters'] = clusters
```

In [107]:
```
#Silhouette coefficient
cl_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(cl_sil)
```

```
0.7931811284335685
```

In [108]:
```
#Cluster2 with K-Means
```

In [109]:
```
clustering = KMeans(n_clusters = 2, init = 'random', n_init = 1, rando
m_state = 0).fit(x_scaled)
clusters = clustering.labels_
print(clusters)
data['clusters'] = clusters
```

```
[0 1 0 ... 1 1 1]
```

In [110]:
```
#Silhouette coefficient
km_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(km_sil)
```

```
0.22503062682481748
```

In [111]:
```
#Cluster2 with DBSCAN
```

In [112]:
```
clustering = DBSCAN(eps = 2, min_samples = 3, metric = "euclidean").fi
t(x_scaled)
clusters = clustering.labels_
data['clusters'] = clusters
```

In [113]:
```
#Silhouette coefficient
db_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(db_sil)
```

```
0.09401786652049447
```

In [114]:
```
cluster_tab = cluster_tab.append({'Type':'Non_Illegal','Single Linkage
': sl_sil, 'Complete Linkage':cl_sil,'K-Means':km_sil,'DBSCAN':db_sil}
,ignore_index=True)
```

In [ ]:

In [115]:
```
#Cluster3: Using only Illegal drugs
```

In [116]:
```
variables = illegal_drugs
var_indices = [data.columns.get_loc(variable) for variable in variable
s]
print(var_indices)
```

```
[14, 20, 21, 22, 23, 26, 28]
```

In [117]:
```
#Standardizing the data
x = data.iloc[:,var_indices]
scaler = StandardScaler()
x_scaled = scaler.fit_transform(x)
```

In [118]:
```
#Cluster3 using Hierarchial clustering Single Linkage
clustering = linkage(x_scaled,method="single",metric="euclidean")
clusters = fcluster(clustering, 2, criterion = 'maxclust')
clusters = clusters - 1
print(clusters)
```

```
[0 0 0 ... 0 0 0]
```

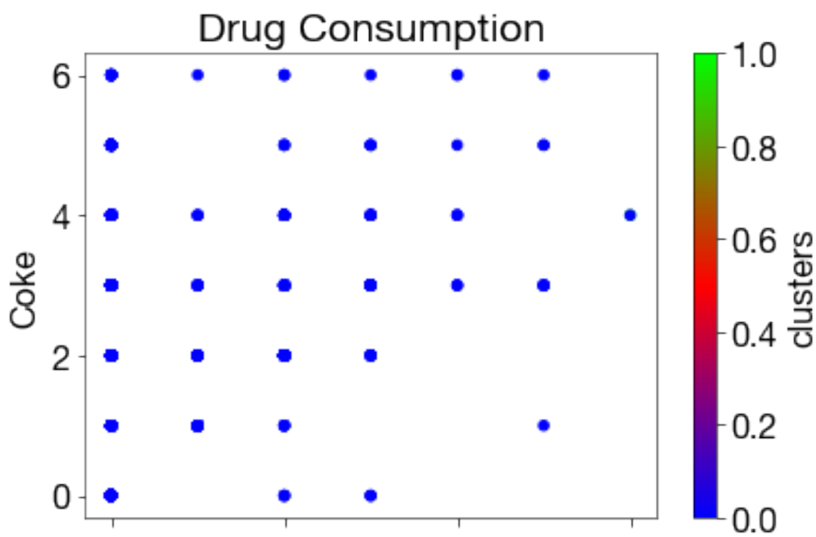
In [119]:
```
data['clusters'] = clusters
```

In [120]:
```
#Silhouette coefficient
sl_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(sl_sil)
```

```
0.6082079307311252
```

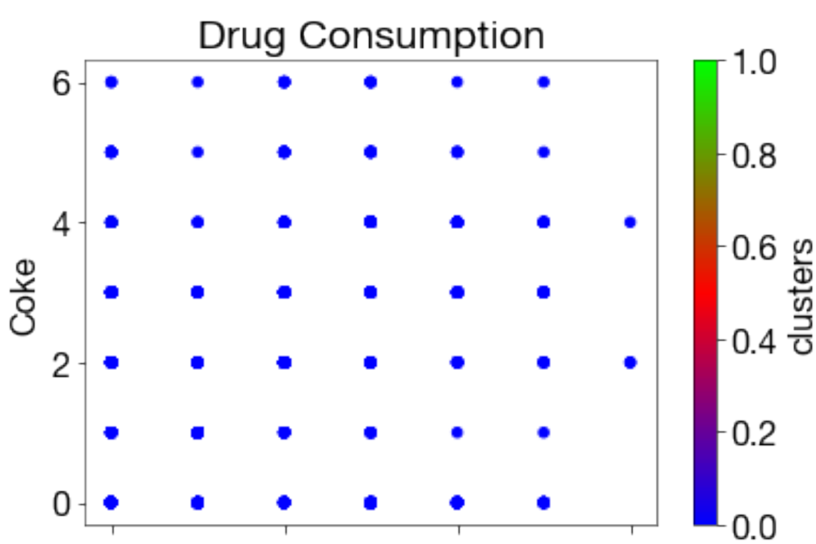
In [121]:
```
ax = data.plot(kind = 'scatter', x = 'Crack', y = 'Coke', c = 'clusters', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Crack', ylabel = 'Coke')
```

Out[121]:
```
[Text(0, 0.5, 'Coke'),
 Text(0.5, 0, 'Crack'),
 Text(0.5, 1.0, 'Drug Consumption')]
```



In [122]:
```
ax = data.plot(kind = 'scatter', x = 'Mushrooms', y = 'Coke', c = 'clusters', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Mushrooms', ylabel = 'Coke')
```

Out[122]:
```
[Text(0, 0.5, 'Coke'),
 Text(0.5, 0, 'Mushrooms'),
 Text(0.5, 1.0, 'Drug Consumption')]
```



In [123]:
```
#Cluster3 using Hierarchial clustering Complete Linkage
```

In [124]:
```
clustering = linkage(x_scaled,method="complete",metric="euclidean")
clusters = fcluster(clustering, 2, criterion = 'maxclust')
clusters = clusters - 1
print(clusters)
```

```
[1 1 1 ... 1 1 1]
```

In [125]:
```
data['clusters'] = clusters
```

In [126]:
```
#Silhouette coefficient
cl_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(cl_sil)
```

```
0.5415889060633275
```

In [127]:
```
#Cluster3 with K-Means
```

In [128]:
```
clustering = KMeans(n_clusters = 2, init = 'random', n_init = 1, rando
m_state = 0).fit(x_scaled)
clusters = clustering.labels_
print(clusters)
data['clusters'] = clusters
```

```
[0 1 0 ... 1 1 1]
```

In [129]:
```
#Silhouette coefficient
km_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(km_sil)
```

```
0.4487703444541595
```

In [130]:
```
#Cluster3 with DBSCAN
```

In [131]:
```
clustering = DBSCAN(eps = 2, min_samples = 3, metric = "euclidean").fi
t(x_scaled)
clusters = clustering.labels_
data['clusters'] = clusters
```

In [132]:
```
#Silhouette coefficient
db_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(db_sil)
```

```
0.5160039017438653
```

In [133]:
```
cluster_tab = cluster_tab.append({'Type':'Illegal','Single Linkage': s
l_sil, 'Complete Linkage':cl_sil,'K-Means':km_sil,'DBSCAN':db_sil},ign
ore_index=True)
```

In [ ]:
```
```

In [134]:
```
#cluster4: Using only the drugs
```

In [135]:
```
variables = illegal_drugs + Non_illegal
var_indices = [data.columns.get_loc(variable) for variable in variable
s]
print(var_indices)
```

```
[14, 20, 21, 22, 23, 26, 28, 13, 15, 16, 17, 18, 19, 24, 25, 27, 29,
30, 31]
```

In [136]:
```
#Standardizing the data
x = data.iloc[:,var_indices]
scaler = StandardScaler()
x_scaled = scaler.fit_transform(x)
```

In [137]:
```
clustering = linkage(x_scaled,method="single",metric="euclidean")
clusters = fcluster(clustering, 2, criterion = 'maxclust')
clusters = clusters - 1
print(clusters)
```

```
[0 0 0 ... 0 0 0]
```

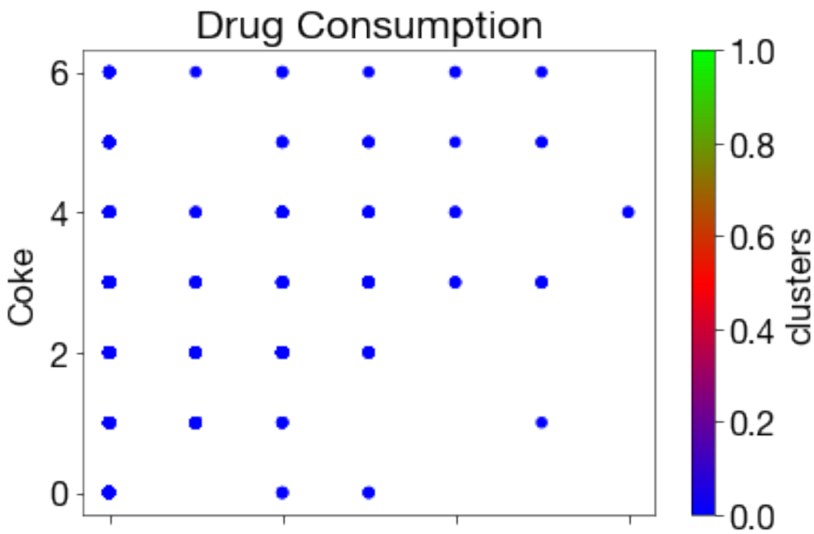
In [138]:
```
data['clusters'] = clusters
```

In [139]:
```
#Silhouette coefficient
sl_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(sl_sil)
```

```
0.7799966615627284
```

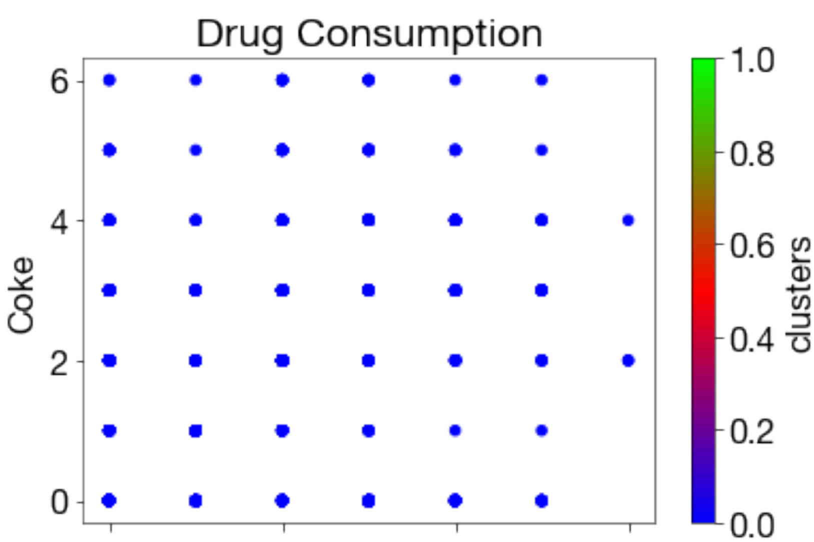
In [140]:
```
ax = data.plot(kind = 'scatter', x = 'Crack', y = 'Coke', c = 'clusters', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Crack', ylabel = 'Coke')
```

Out[140]:
```
[Text(0, 0.5, 'Coke'),
 Text(0.5, 0, 'Crack'),
 Text(0.5, 1.0, 'Drug Consumption')]
```



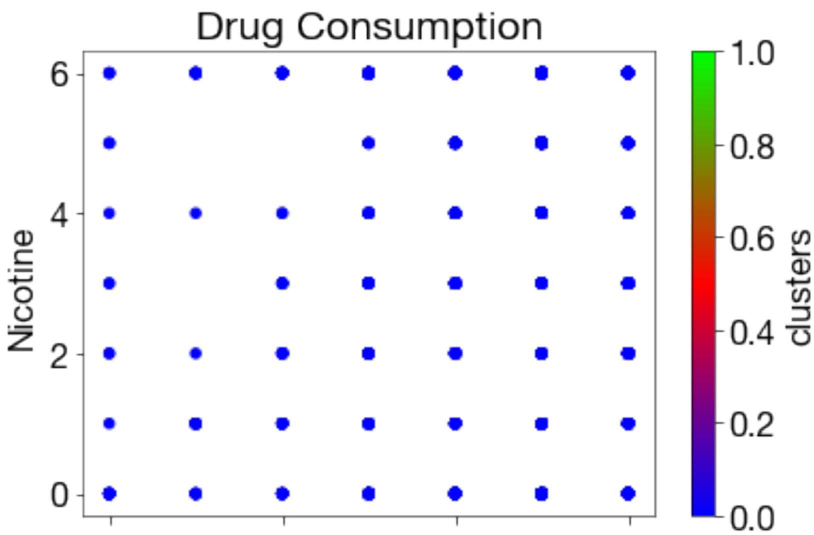
In [141]:
```
ax = data.plot(kind = 'scatter', x = 'Mushrooms', y = 'Coke', c = 'clusters', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Mushrooms', ylabel = 'Coke')
```

Out[141]:
```
[Text(0, 0.5, 'Coke'),
 Text(0.5, 0, 'Mushrooms'),
 Text(0.5, 1.0, 'Drug Consumption')]
```



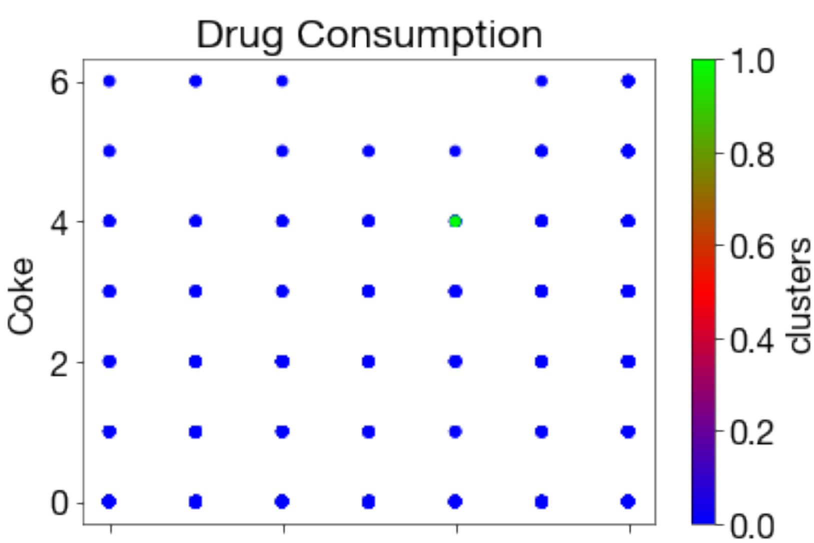
In [142]:
```
ax = data.plot(kind = 'scatter', x = 'Alcohol', y = 'Nicotine', c = 'c
lusters', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Alcohol', ylabel = 'Nicot
ine')
```

Out[142]:
```
[Text(0, 0.5, 'Nicotine'),
 Text(0.5, 0, 'Alcohol'),
 Text(0.5, 1.0, 'Drug Consumption')]
```



In [143]:
```
ax = data.plot(kind = 'scatter', x = 'Nicotine', y = 'Coke', c = 'clus
ters', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Nicotine', ylabel = 'Coke
')
```

Out[143]:
```
[Text(0, 0.5, 'Coke'),
 Text(0.5, 0, 'Nicotine'),
 Text(0.5, 1.0, 'Drug Consumption')]
```



In [144]:
```
#Cluster4 using Hierarchial clustering Complete Linkage
```

In [145]:
```
clustering = linkage(x_scaled,method="complete",metric="euclidean")
clusters = fcluster(clustering, 2, criterion = 'maxclust')
clusters = clusters - 1
print(clusters)
```

```
[1 1 1 ... 1 1 1]
```

In [146]:
```
data['clusters'] = clusters
```

In [147]:
```
#Silhouette coefficient
cl_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(cl_sil)
```

```
0.7432570016576694
```

In [148]:
```
#Cluster4 with K-Means
```

In [149]:
```
clustering = KMeans(n_clusters = 2, init = 'random', n_init = 1, rando
m_state = 0).fit(x_scaled)
clusters = clustering.labels_
print(clusters)
data['clusters'] = clusters
```

```
[0 1 0 ... 1 1 1]
```

In [150]:
```
#Silhouette coefficient
km_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(km_sil)
```

```
0.2684663279061382
```

In [151]:
```
#Cluster4 with DBSCAN
```

In [152]:
```
clustering = DBSCAN(eps = 2, min_samples = 3, metric = "euclidean").fi
t(x_scaled)
clusters = clustering.labels_
data['clusters'] = clusters
```

In [153]:
```
#Silhouette coefficient
db_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(db_sil)
```

```
-0.06633855889724637
```

In [154]:
```
cluster_tab = cluster_tab.append({'Type':'Only Drugs','Single Linkage'
: sl_sil, 'Complete Linkage':cl_sil,'K-Means':km_sil,'DBSCAN':db_sil},
ignore_index=True)
```

In [ ]:

In [155]:
```
#Cluster5: Not using any drugs
```

In [156]:
```
variables = data.columns[0:13]
var_indices = [data.columns.get_loc(variable) for variable in variable
s]
print(var_indices)
```

```
[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12]
```

In [157]:
```
#Standardizing the data
x = data.iloc[:,var_indices]
scaler = StandardScaler()
x_scaled = scaler.fit_transform(x)
```

In [158]:
```
#Cluster5 with Hierarchial clustering with Single Linkage
```

In [159]:
```
clustering = linkage(x_scaled,method='single',metric="euclidean")
clusters = fcluster(clustering, 2, criterion = 'maxclust')
clusters = clusters - 1
print(clusters)
```

```
[0 0 0 ... 0 0 0]
```

In [160]:
```
#Silhouette coefficient
sl_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(sl_sil)
```

```
-0.21114670320992815
```

In [161]:
```
#Cluster5 with Hierarchial Clustering with Complete Linkage
```

In [162]:
```
clustering = linkage(x_scaled,method='complete',metric="euclidean")
clusters = fcluster(clustering, 2, criterion = 'maxclust')
clusters = clusters - 1
print(clusters)
```

```
[1 1 1 ... 1 1 1]
```

In [163]:
```
#Silhouette coefficient
cl_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(cl_sil)
```

```
-0.21114670320992815
```

In [164]:
```
#Cluster 5 with K-Means
```

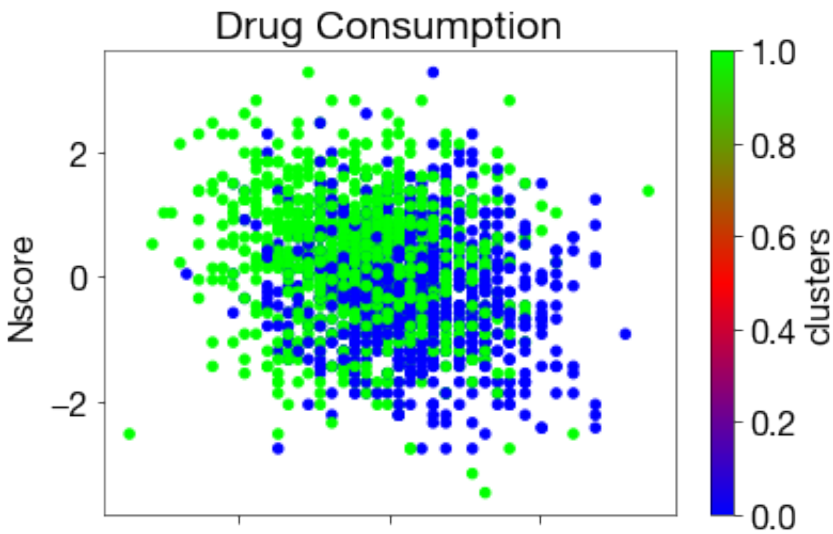
In [165]:
```
clustering = KMeans(n_clusters = 2, init = 'random', n_init = 1, rando
m_state = 0).fit(x_scaled)
clusters = clustering.labels_
print(clusters)
data['clusters'] = clusters
```

```
[0 0 0 ... 1 1 1]
```

In [166]:
```
#Silhouette coefficient
km_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(km_sil)
```

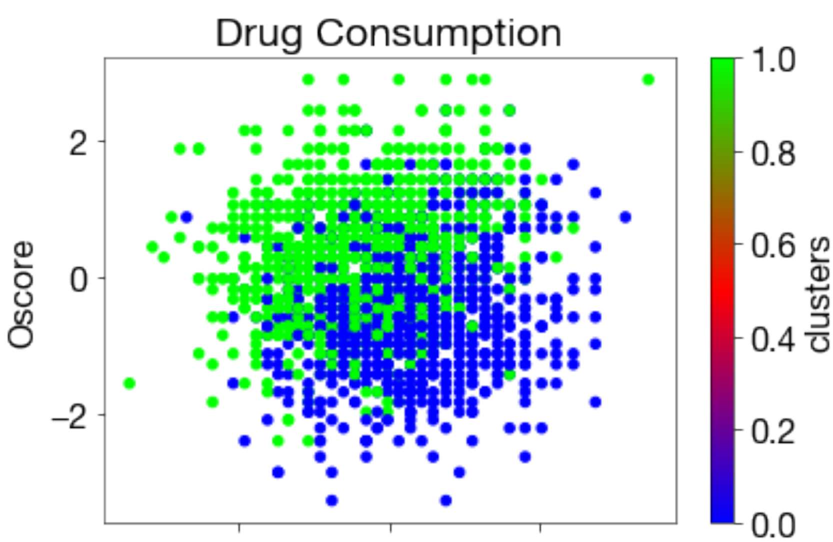
```
0.15804112591503822
```

In [167]:
```
ax = data.plot(kind = 'scatter', x = 'Ascore', y = 'Nscore', c = 'clus
ters', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Ascore', ylabel = 'Nscore
')
plt.savefig('figures/cluster5-AscoreVsNscore.png', dpi=300)
```



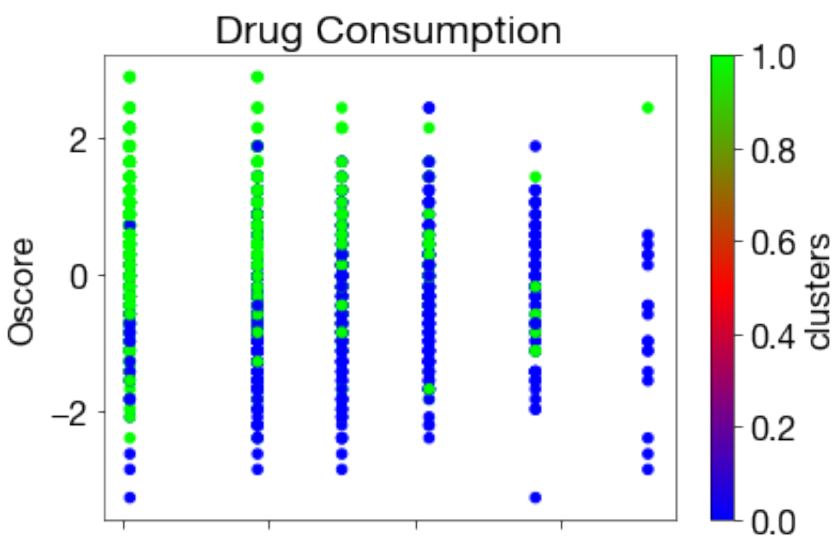
In [168]:
```
ax = data.plot(kind = 'scatter', x = 'Ascore', y = 'Oscore', c = 'clus
ters', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Ascore', ylabel = 'Oscore
')
```

Out[168]:
```
[Text(0, 0.5, 'Oscore'),
 Text(0.5, 0, 'Ascore'),
 Text(0.5, 1.0, 'Drug Consumption')]
```



In [169]:
```
ax = data.plot(kind = 'scatter', x = 'Age', y = 'Oscore', c = 'cluster
s', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Age', ylabel = 'Oscore')
```

Out[169]:
```
[Text(0, 0.5, 'Oscore'),
 Text(0.5, 0, 'Age'),
 Text(0.5, 1.0, 'Drug Consumption')]
```



In [170]:
```
#Cluster5 with DBSCAN
```

In [171]:
```
clustering = DBSCAN(eps = 2, min_samples = 3, metric = "euclidean").fi
t(x_scaled)
clusters = clustering.labels_
data['clusters'] = clusters
```

In [172]:
```
#Silhouette coefficient
db_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(db_sil)
```

```
-0.11510965619210076
```

In [173]:
```
cluster_tab = cluster_tab.append({'Type':'Not Using Drugs','Single Lin
kage': sl_sil, 'Complete Linkage':cl_sil,'K-Means':km_sil,'DBSCAN':db_
sil},ignore_index=True)
```

In [ ]:

In [174]:
```
#Cluster6: Using Personality traits
```

In [175]:
```
variables = data.columns[6:13]
var_indices = [data.columns.get_loc(variable) for variable in variable
s]
print(var_indices)
```

```
[6, 7, 8, 9, 10, 11, 12]
```

In [176]:
```
#Standardizing the data
x = data.iloc[:,var_indices]
scaler = StandardScaler()
x_scaled = scaler.fit_transform(x)
```

In [177]:
```
#Cluster6 with Hierarchial clustering with Single Linkage
```

In [178]:
```
clustering = linkage(x_scaled,method="single",metric="euclidean")
clusters = fcluster(clustering, 2, criterion = 'maxclust')
clusters = clusters - 1
print(clusters)
```

```
[0 0 0 ... 0 0 0]
```

In [179]:
```
#Silhouette coefficient
sl_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(sl_sil)
```

```
-0.32290072471567954
```

In [180]:
```
#Cluster6 with Hierarchial Clustering with Complete Linkage
```

In [181]:
```
clustering = linkage(x_scaled,method='complete',metric="euclidean")
clusters = fcluster(clustering, 2, criterion = 'maxclust')
clusters = clusters - 1
print(clusters)
```

```
[1 1 0 ... 0 0 1]
```

In [182]:
```
#Silhouette coefficient
cl_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(cl_sil)
```

```
-0.32290072471567954
```

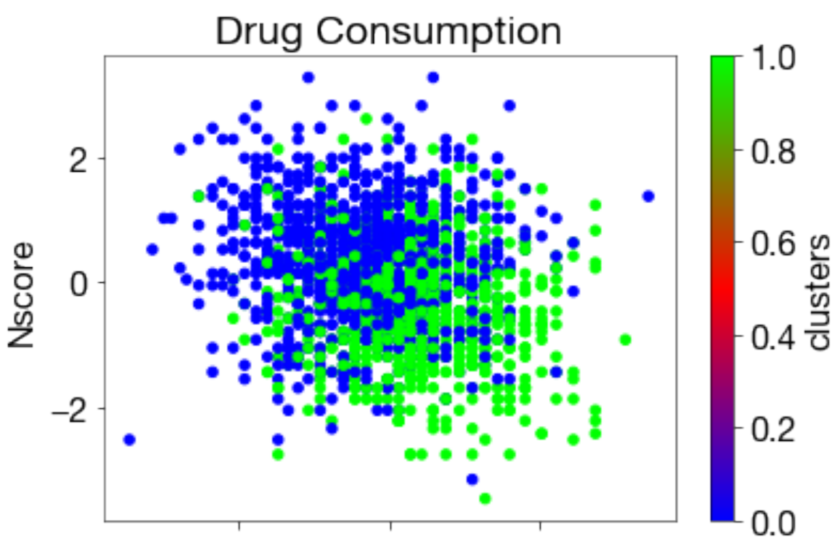
In [183]:
```
#Cluster6 with K-Means
```

In [184]:
```
clustering = KMeans(n_clusters = 2, init = 'random', n_init = 1, rando
m_state = 0).fit(x_scaled)
clusters = clustering.labels_
print(clusters)
data['clusters'] = clusters
```

```
[1 1 1 ... 0 0 0]
```

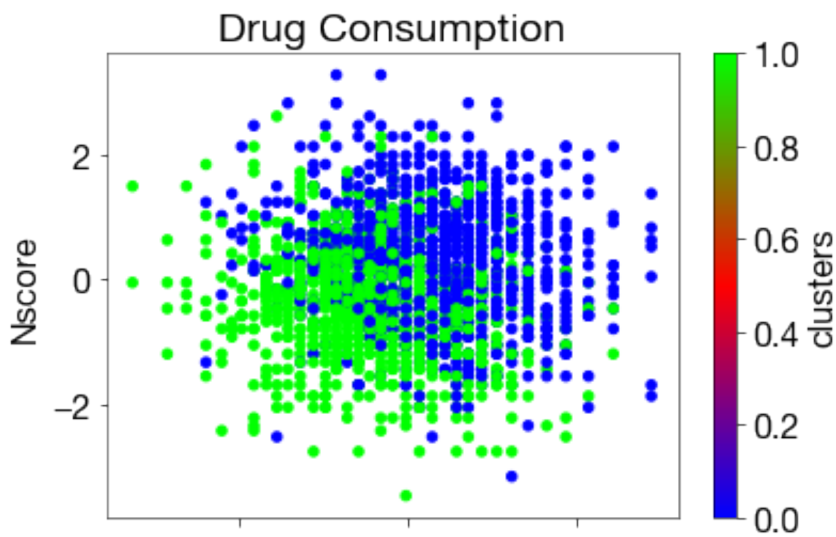
In [185]:
```
ax = data.plot(kind = 'scatter', x = 'Ascore', y = 'Nscore', c = 'clus
ters', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Ascore', ylabel = 'Nscore
')
```

Out[185]:
```
[Text(0, 0.5, 'Nscore'),
 Text(0.5, 0, 'Ascore'),
 Text(0.5, 1.0, 'Drug Consumption')]
```

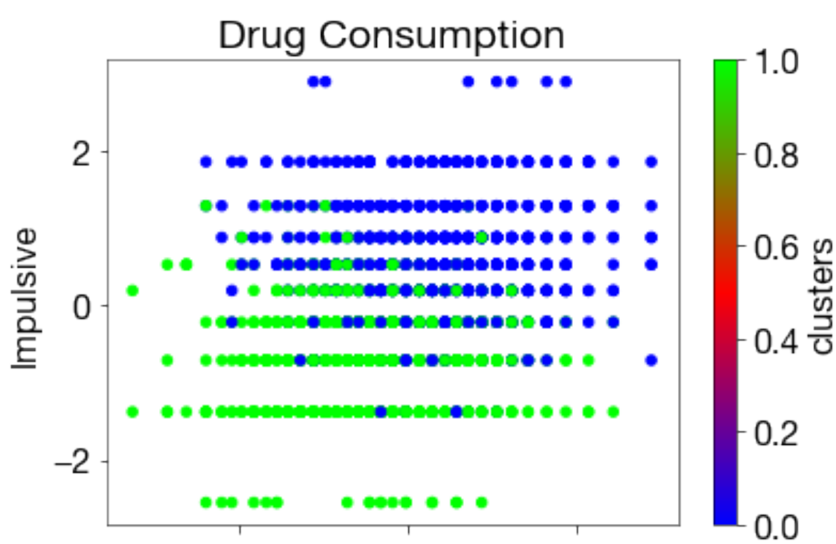


In [186]:
```
ax = data.plot(kind = 'scatter', x = 'Oscore', y = 'Nscore', c = 'clus
ters', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Oscore', ylabel = 'Nscore
')
```

Out[186]:
```
[Text(0, 0.5, 'Nscore'),
 Text(0.5, 0, 'Oscore'),
 Text(0.5, 1.0, 'Drug Consumption')]
```



In [187]:
```
ax = data.plot(kind = 'scatter', x = 'Oscore', y = 'Impulsive', c = 'c
lusters', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Oscore', ylabel = 'Impuls
ive')
plt.savefig('figures/cluster6-OscoreVImpulsive.png', dpi=300)
```



In [188]:
```
#Silhouette coefficient
km_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(km_sil)
```

```
0.1898276389135005
```

In [189]:
```
#Cluster6 with DBSCAN
```

In [190]:
```
clustering = DBSCAN(eps = 2, min_samples = 3, metric = "euclidean").fi
t(x_scaled)
clusters = clustering.labels_
data['clusters'] = clusters
```

In [191]:
```
#Silhouette coefficient
db_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(db_sil)
```

```
0.3122595933194069
```

In [192]:
```
cluster_tab = cluster_tab.append({'Type':'Personality Traits','Single
Linkage': sl_sil, 'Complete Linkage':cl_sil,'K-Means':km_sil,'DBSCAN':
db_sil},ignore_index=True)
```

In [ ]:

In [193]:
```
#Cluster7: Using Personality traits and Non_illegal drugs
```

In [194]:
```
variables = Non_illegal
var_indices = [data.columns.get_loc(variable) for variable in variable
s] + [6,7,8,9,10,11,12]
print(var_indices)
```

```
[13, 15, 16, 17, 18, 19, 24, 25, 27, 29, 30, 31, 6, 7, 8, 9, 10, 11,
12]
```

In [195]:
```
#Standardizing the data
x = data.iloc[:,var_indices]
scaler = StandardScaler()
x_scaled = scaler.fit_transform(x)
```

In [196]:
```
#Cluster7 with Hierarchial Clustering with Single Linkage
```

In [197]:
```
clustering = linkage(x_scaled,method="single",metric="euclidean")
clusters = fcluster(clustering, 2, criterion = 'maxclust')
clusters = clusters - 1
print(clusters)
```

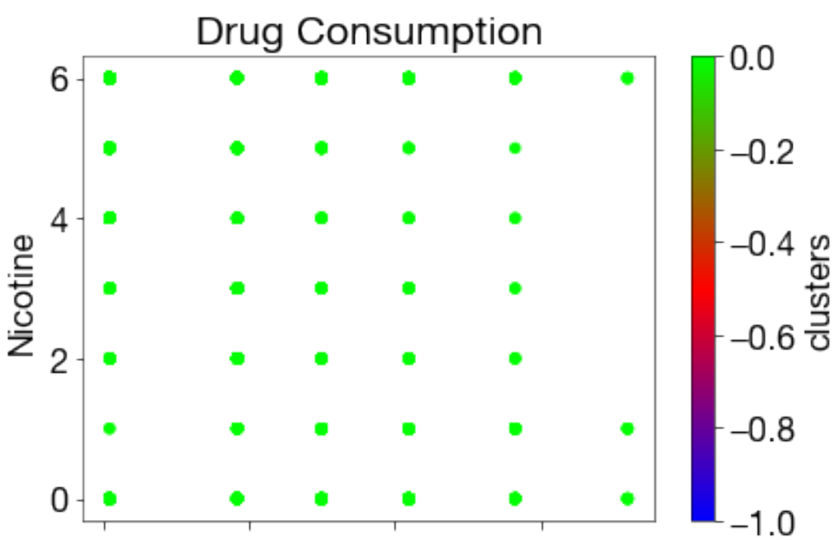
```
[0 0 0 ... 0 0 0]
```

In [198]:
```
#Silhouette coefficient
sl_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(sl_sil)
```

```
0.2200681697633267
```

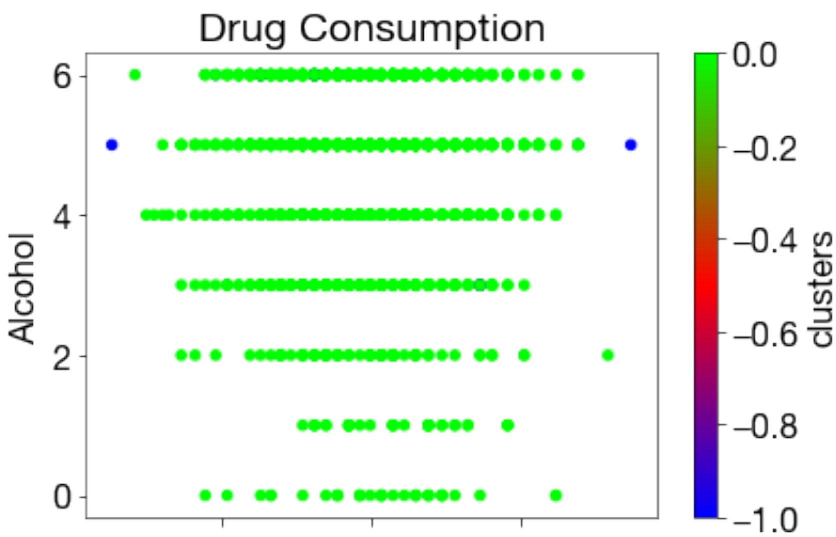
In [199]:
```
ax = data.plot(kind = 'scatter', x = 'Age', y = 'Nicotine', c = 'clust
ers', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Age', ylabel = 'Nicotine'
)
```

Out[199]:
```
[Text(0, 0.5, 'Nicotine'),
 Text(0.5, 0, 'Age'),
 Text(0.5, 1.0, 'Drug Consumption')]
```



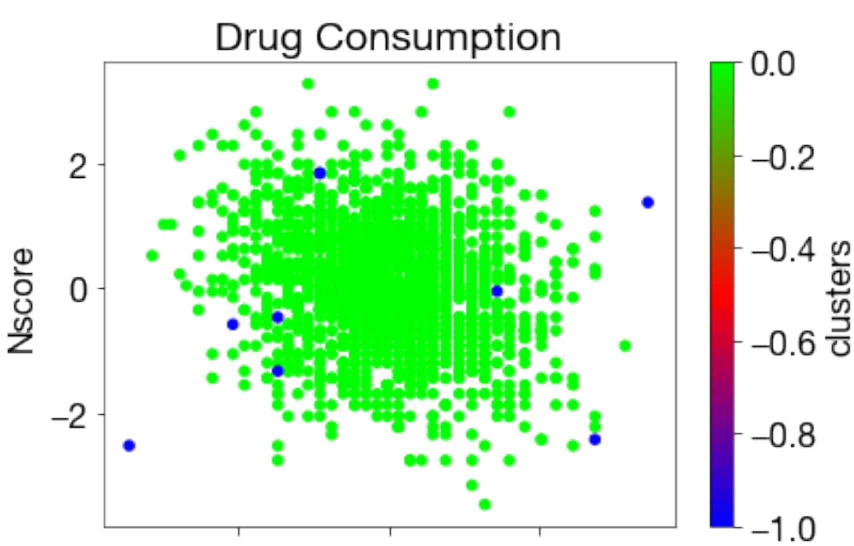
In [200]:
```
ax = data.plot(kind = 'scatter', x = 'Ascore', y = 'Alcohol', c = 'clusters', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Ascore', ylabel = 'Alcohol')
```

Out[200]:
```
[Text(0, 0.5, 'Alcohol'),
 Text(0.5, 0, 'Ascore'),
 Text(0.5, 1.0, 'Drug Consumption')]
```



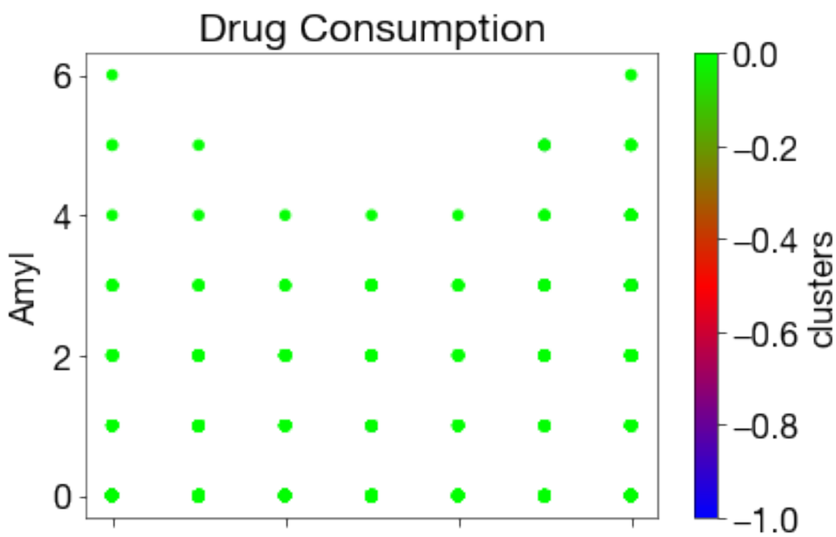
In [201]:
```
ax = data.plot(kind = 'scatter', x = 'Ascore', y = 'Nscore', c = 'clusters', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Ascore', ylabel = 'Nscore')
```

Out[201]:
```
[Text(0, 0.5, 'Nscore'),
 Text(0.5, 0, 'Ascore'),
 Text(0.5, 1.0, 'Drug Consumption')]
```



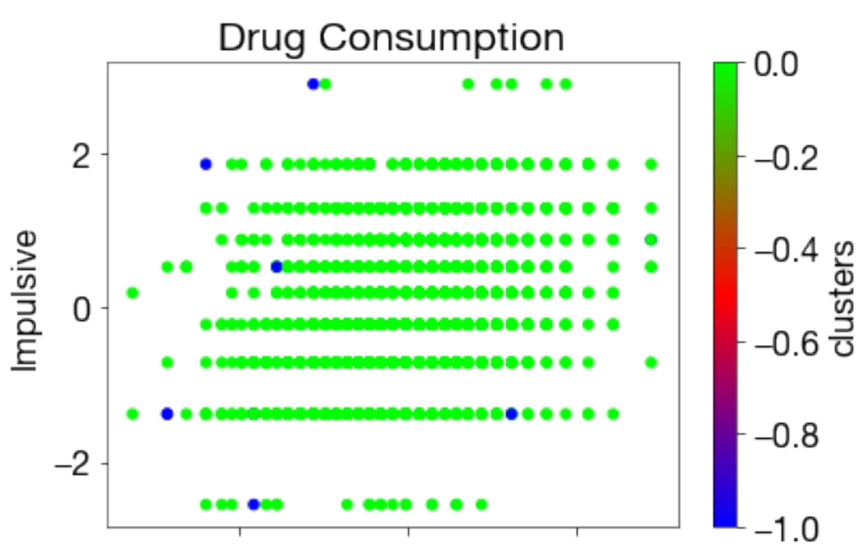
In [202]:
```
ax = data.plot(kind = 'scatter', x = 'Nicotine', y = 'Amyl', c = 'clusters', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Nicotine', ylabel = 'Amyl')
```

Out[202]:
```
[Text(0, 0.5, 'Amyl'),
 Text(0.5, 0, 'Nicotine'),
 Text(0.5, 1.0, 'Drug Consumption')]
```



In [203]:
```
ax = data.plot(kind = 'scatter', x = 'Oscore', y = 'Impulsive', c = 'clusters', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Oscore', ylabel = 'Impulsive')
```

Out[203]:
```
[Text(0, 0.5, 'Impulsive'),
 Text(0.5, 0, 'Oscore'),
 Text(0.5, 1.0, 'Drug Consumption')]
```



In [204]:
```
#Cluster7 with Hierarchial Clustering with Complete Linkage
```

In [205]:
```
clustering = linkage(x_scaled,method='complete',metric="euclidean")
clusters = fcluster(clustering, 2, criterion = 'maxclust')
clusters = clusters - 1
print(clusters)
```

```
[1 1 1 ... 1 1 1]
```

In [206]:
```
#Silhouette coefficient
cl_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(cl_sil)
```

```
0.2200681697633267
```

In [207]:
```
#Cluster7 with K-Means
```

In [208]:
```
clustering = KMeans(n_clusters = 2, init = 'random', n_init = 1, rando
m_state = 0).fit(x_scaled)
clusters = clustering.labels_
print(clusters)
data['clusters'] = clusters
```

```
[0 1 0 ... 1 1 1]
```

In [209]:
```
#Silhouette coefficient
km_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(km_sil)
```

```
0.1663782954936895
```

In [210]:
```
#Cluster7 with DBSCAN
```

In [211]:
```
clustering = DBSCAN(eps = 2, min_samples = 3, metric = "euclidean").fi
t(x_scaled)
clusters = clustering.labels_
data['clusters'] = clusters
```

In [212]:
```
#Silhouette coefficient
db_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(db_sil)
```

```
-0.211881563006982
```

In [213]:
```
cluster_tab = cluster_tab.append({'Type':'Personality Traits and Non-Illegal drugs','Single Linkage': sl_sil, 'Complete Linkage':cl_sil,'K-Means':km_sil,'DBSCAN':db_sil},ignore_index=True)
```

In [ ]:
```
```

In [214]:
```
#Cluster8: Using Personality traits and Illegal drugs
```

In [215]:
```
variables = illegal_drugs
var_indices = [data.columns.get_loc(variable) for variable in variables] + [6,7,8,9,10,11,12]
print(var_indices)
```

```
[14, 20, 21, 22, 23, 26, 28, 6, 7, 8, 9, 10, 11, 12]
```

In [216]:
```
#Standardizing the data
x = data.iloc[:,var_indices]
scaler = StandardScaler()
x_scaled = scaler.fit_transform(x)
```

In [217]:
```
#Cluster8 with Hierarchial Clustering with Single Linkage
```

In [218]:
```
clustering = linkage(x_scaled,method="single",metric="euclidean")
clusters = fcluster(clustering, 2, criterion = 'maxclust')
clusters = clusters - 1
print(clusters)
```

```
[0 0 0 ... 0 0 0]
```

In [219]:
```
#Silhouette coefficient
sl_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric = "euclidean")
print(sl_sil)
```

```
-0.2673306540216515
```

In [220]:
```
#Cluster8 with Hierarchial Clustering with Complete Linkage
```

In [221]:
```
clustering = linkage(x_scaled,method='complete',metric="euclidean")
clusters = fcluster(clustering, 2, criterion = 'maxclust')
clusters = clusters - 1
print(clusters)
```

```
[1 1 1 ... 1 1 1]
```

In [222]:
```
#Silhouette coefficient
cl_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(cl_sil)
```

```
-0.2673306540216515
```

In [223]:
```
#Cluster8 with K-Means
```

In [224]:
```
clustering = KMeans(n_clusters = 2, init = 'random', n_init = 1, rando
m_state = 0).fit(x_scaled)
clusters = clustering.labels_
print(clusters)
data['clusters'] = clusters
```

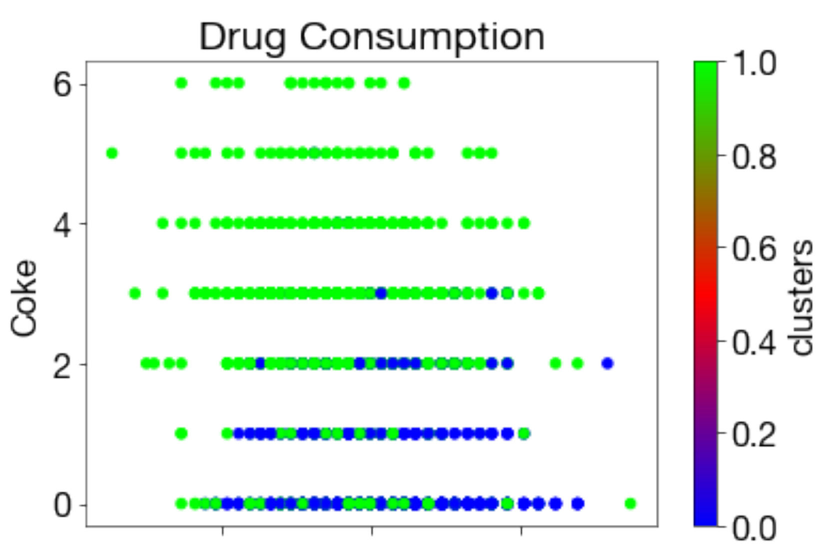
```
[0 1 0 ... 1 1 1]
```

In [225]:
```
#Silhouette coefficient
km_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(km_sil)
```

```
0.2401118477537548
```

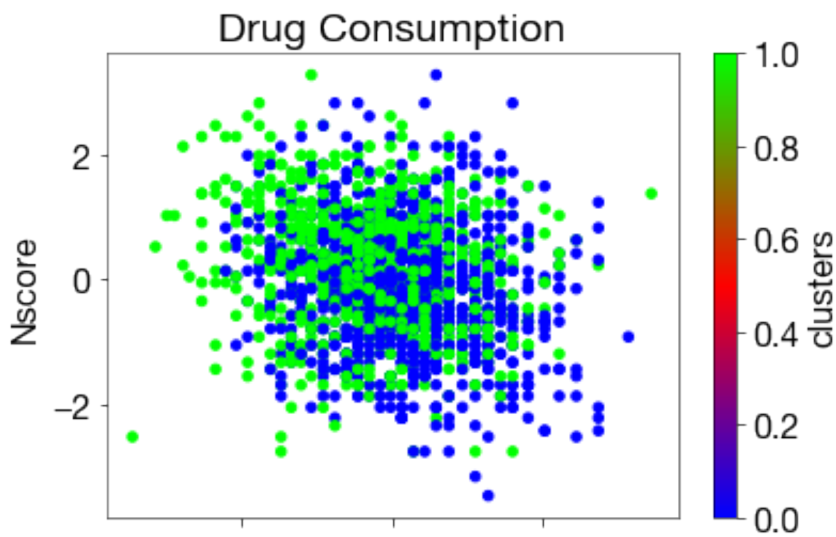
In [226]:
```
ax = data.plot(kind = 'scatter', x = 'Ascore', y = 'Coke', c = 'cluste
rs', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Ascore', ylabel = 'Coke')
```

Out[226]:
```
[Text(0, 0.5, 'Coke'),
 Text(0.5, 0, 'Ascore'),
 Text(0.5, 1.0, 'Drug Consumption')]
```



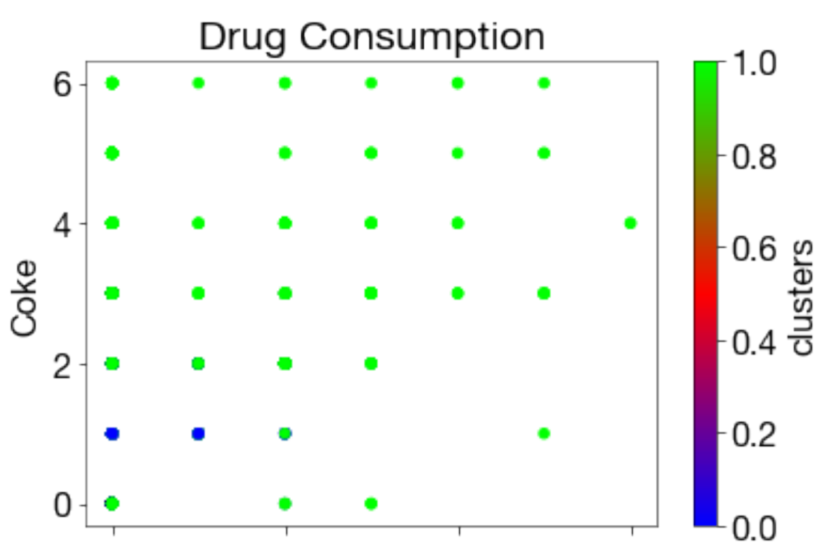
In [227]:
```
ax = data.plot(kind = 'scatter', x = 'Ascore', y = 'Nscore', c = 'clus
ters', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Ascore', ylabel = 'Nscore
')
```

Out[227]:
```
[Text(0, 0.5, 'Nscore'),
 Text(0.5, 0, 'Ascore'),
 Text(0.5, 1.0, 'Drug Consumption')]
```



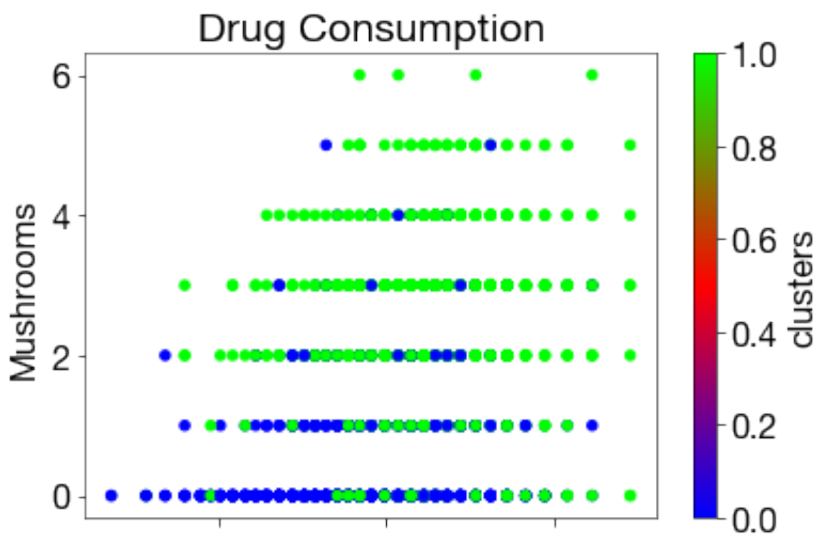
In [228]:
```
ax = data.plot(kind = 'scatter', x = 'Crack', y = 'Coke', c = 'cluster
s', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Crack', ylabel = 'Coke')
```

Out[228]:
```
[Text(0, 0.5, 'Coke'),
 Text(0.5, 0, 'Crack'),
 Text(0.5, 1.0, 'Drug Consumption')]
```



In [229]:
```
ax = data.plot(kind = 'scatter', x = 'Oscore', y = 'Mushrooms', c = 'c
lusters', colormap = plt.cm.brg)
ax.set(title = 'Drug Consumption', xlabel = 'Oscore', ylabel = 'Mushro
oms')
```

Out[229]:
```
[Text(0, 0.5, 'Mushrooms'),
 Text(0.5, 0, 'Oscore'),
 Text(0.5, 1.0, 'Drug Consumption')]
```



In [230]:
```
#Cluster8 with DBSCAN
```

In [231]:
```
clustering = DBSCAN(eps = 2, min_samples = 3, metric = "euclidean").fi
t(x_scaled)
clusters = clustering.labels_
data['clusters'] = clusters
```

In [232]:
```
#Silhouette coefficient
db_sil = metrics.silhouette_score(x_scaled, data['clusters'], metric =
"euclidean")
print(db_sil)
```

```
-0.11209916794288363
```

In [233]:
```
cluster_tab = cluster_tab.append({'Type':'Personality traits and Illeg
al Drugs','Single Linkage': sl_sil, 'Complete Linkage':cl_sil,'K-Means
':km_sil,'DBSCAN':db_sil},ignore_index=True)
```

In [234]:
```
cluster_tab
```

Out[234]:

	Type	Single Linkage	Complete Linkage	K-Means	DBSCAN
0	All Features	0.507951	0.662999	0.183011	-0.189872
1	Non_Illegal	0.823376	0.793181	0.225031	0.094018
2	Illegal	0.608208	0.541589	0.448770	0.516004
3	Only Drugs	0.779997	0.743257	0.268466	-0.066339
4	Not Using Drugs	-0.211147	-0.211147	0.158041	-0.115110
5	Personality Traits	-0.322901	-0.322901	0.189828	0.312260
6	Personality Traits and Non-Illegal drugs	0.220068	0.220068	0.166378	-0.211882
7	Personality traits and Illegal Drugs	-0.267331	-0.267331	0.240112	-0.112099

In [ ]: