Appendix

Table 1: Property ranges for each crude oil fraction of the PRELIM's crude assay inventory

Description	*Range*	*Whole Crude*	*LSR*	*Naphtha*	*Kerosene*	*Diesel*	*AGO*	*LVGO*	*HVGO*	*VR*	*AR*
Sulphur (wt%)	Min	0.0900	0.000	0.000	0.0100	0.0500	0.0900	0.180	0.310	0.100	0.220
	Max	5.14	0.310	0.980	2.17	2.98	3.54	4.18	4.90	8.55	7.47
Nitrogen (ppm)[a]	Min	350	0.00	0.00	0.00	35.0	194	514	1002	321	872
	Max	4600	0.00	9.00	152	733	1390	2203	3116	7077	5709
API gravity	Min	7	35	35	28	22	17	12	7	-1	1
	Max	39	105	76	41	33	29	25	22	14	40
Density (kg/m3)	Min	828	598	682	819	860	882	901	921	969	824
	Max	1019	848	848	887	924	953	988	1022	1111	1111
Hydrogen (wt%)	Min	10.1	12.2	12.2	12.0	11.6	11.1	10.3	9.6	8.0	8.7
	Max	13.2	18.9	15.5	13.3	13.4	12.9	12.6	12.2	13.8	12.8
MCR (wt%)	Min	0.02								1.72	
	Max	14.7								32.0	
Approximated Kw	Min	11.0	10.7	10.9	11.1	11.1	11.0	10.9	10.9	10.6	10.6
	Max	12.2	13.9	12.4	11.8	11.8	11.9	11.0	12.0	11.8	12.0
Tb(50%) weight basis (^oC)	Min	296	26	111	221	302	360	404	452	534	203
	Max	467	214	214	276	326	377	431	493	687	700
Mass fraction yield(%)	Min	100	0.00	0.00	1.70	4.80	6.00	7.00	5.00	1.00	19.0
	Max	100	8.00	21.0	26.4	20.0	26.0	26.0	15.9	59.3	83.7
Volume fraction yield(%)	Min	100	0.00	0.00	2.00	5.00	6.00	6.76	4.48	0.881	17.3
	Max	100	12.2	22.0	28.8	19.5	25.6	25.0	16.4	56.7	82.0

Table 1: An example of crude oil assay in PRELIM format

Belridge_Knovel		BRG					Crude specific destillation curve				
Assay #	**26**	**Cutoff Temp [°C]**	**80**	**175**	**295**	**340**	**400**	**455**	**530**	**530.00 +**	**397.00 +**
Property	**Units**	**Full Crude**	**LSR**	**Naphtha**	**Kerosene**	**Diesel**	**AGO**	**LVGO**	**HVGO**	**VR**	**AR**
Vol Flow	bpd	99,407.1	1,257.6	2,291.1	8,746.2	5,346.0	11,547.1	2,073.0	7,130.8	61,015.3	69,205.9
Vol Flow	m^3/d	15,805.7	200.0	364.3	1,390.6	850.0	1,836.0	329.6	1,133.8	9,701.4	11,003.7
Mass Flow	kg/d	15,359,400.0	153,594.0	307,188.0	1,228,752.0	767,970.0	1,689,534.0	307,188.0	1,075,158.0	9,830,016.0	11,212,362.0
Sulphur	wt%	0.2	0.0	0.0	0.0	0.1	0.2	0.4	0.6	0.1	0.3
Nitrogen	mass ppm	8,382.9	0.0	0.0	50.0	1,000.0	1,390.2	2,203.4	3,116.3	8,000.0	11,200.0
API gravity	oAPI	15.0	52.5	36.1	28.5	25.0	22.1	20.2	17.6	8.0	7.2
Density	kg/m^3	966.0	768.1	843.3	883.6	903.5	920.2	932.0	948.3	1,013.3	1,019.0
Hydrogen	wt%	10.6	11.7	11.9	11.8	12.2	11.9	11.8	11.5	9.9	10.1
MCR	wt%	5.9								9.2	8.1
Characterization Factor	Kw (Approximate)	12.0	10.7	10.9	11.1	11.2	11.4	11.6	11.8	11.9	11.9
Tb(50%) weight basis	[°C]	600.0	40.0	160.0	250.0	310.0	375.0	430.0	510.0	700.0	710.0

Table-3 Available Crude Assays in PRELIM Library

AVAILABLE CRUDES

Current Selection	**1**
Total assays	**53**

Crude	**#**
Access Western Blend_Crude Monitor	1
Alaskan North Slope_Exxon	2
Albian Heavy Synthetic_Crude Monitor_New	3

Crude Blender Dropdown Options

#	**Option**
1	Access Western Blend_Crude Monitor
1	Alaskan North Slope_Exxon
1	Albian Heavy Synthetic_Crude Monitor_New

Albian Heavy Synthetic_Crude Monitor_Old	4	1	Albian Heavy Synthetic_Crude Monitor_Old
Albian Residual Blend_Crude Monitor	5	1	Albian Residual Blend_Crude Monitor
Algerian Condensate_BP	6	1	Algerian Condensate_BP
Angola Cabinda_Stratiev	7	1	Angola Cabinda_Stratiev
Angola Girassol_Exxon	8	1	Angola Girassol_Exxon
Angola Girassol_Statoil	9	1	Angola Girassol_Statoil
Angola Kuito_Chevron	10	1	Angola Kuito_Chevron
Arab Heavy_Stratiev	11		Arab Heavy_Stratiev
Arab Light_Stratiev	12		Arab Light_Stratiev
Arab Medium_Stratiev	13		Arab Medium_Stratiev
Athabasca Mining_Alberta.ca	14		Athabasca Mining_Alberta.ca
Athabasca Thermal_Alberta.ca	15		Athabasca Thermal_Alberta.ca
Azeri Light_Chevron	16		Azeri Light_Chevron
Azeri light_Exxon	17		Azeri light_Exxon
Azeri Light_Statoil	18		Azeri Light_Statoil
Bakken_PNAS Laurenzi et al Bakken LCA	19		Bakken_PNAS Laurenzi et al Bakken LCA
Bakken_Various Sources	20		Bakken_Various Sources
Basrah Heavy_O&G	21		Basrah Heavy_O&G
Basrah Medium_COA	22		Basrah Medium_COA
Belridge_Knovel	23		Belridge_Knovel
Bonny Light_Chevron	24		Bonny Light_Chevron
Borealis Heavy Blend_Crude Monitor	25		Borealis Heavy Blend_Crude Monitor
Bow River North_Crude Monitor_New	26		Bow River North_Crude Monitor_New

Bow River North_Crude Monitor_Old
Bow River South_Crude Monitor
Brazil Frade_Chevron
Brazil Lula_BG Group
Brazil Polvo_BP
Brent_BP
Brent_Chevron
Brent_Exxon
Burgan (Wafra)_O&G
Canada Hibernia_Chevron
Canada Hibernia_Exxon
Canada Hibernia_Statoil
China Bozhong_Chevron
Christina Dilbit Blend_Crude Monitor
Christina Lake_Crude Monitor
CNRL Light Sweet Synthetic_Crude Monitor
ColdLake Thermal_Alberta.ca
Cold Lake_Crude Monitor_New
Cold Lake_Crude Monitor_Old
Colombia Cano Limon_Stratiev
Congo Emeraude_Stratiev
Cossack_Chevron
Cusiana_COA

Dukhan_Qatar_COA	50	Dukhan_Qatar_COA
Eagle Ford Ultralight_Platts	51	Eagle Ford Ultralight_Platts
Eagle Ford_PNAS Laurenzi et al Bakken LCA	52	Eagle Ford_PNAS Laurenzi et al Bakken LCA
East Texas Sweet_COA	53	East Texas Sweet_COA
Ecuador Oriente_Stratiev	54	Ecuador Oriente_Stratiev
Ekofisk_BP	55	Ekofisk_BP
Ekofisk_Chevron	56	Ekofisk_Chevron
Ekofisk_Statoil	57	Ekofisk_Statoil
Fateh_COA	58	Fateh_COA
Forties Blend_BP	59	Forties Blend_BP
Forties_Chevron	60	Forties_Chevron
Forties_Statoil	61	Forties_Statoil
Fosterton_Crude Monitor	62	Fosterton_Crude Monitor
Hamaca Venezuela_Knovel	63	Hamaca Venezuela_Knovel
High Sour Edmonton_Crude Monitor	64	High Sour Edmonton_Crude Monitor
Husky Synthetic Blend_Crude Monitor_New	65	Husky Synthetic Blend_Crude Monitor_New
Husky Synthetic Blend_Crude Monitor_Old	66	Husky Synthetic Blend_Crude Monitor_Old
India Bombay_COA	67	India Bombay_COA
Indonesia Duri_Chevron	68	Indonesia Duri_Chevron
Indonesia Tangguh_BP	69	Indonesia Tangguh_BP
Iran Ardeshir_COA	70	Iran Ardeshir_COA
Iranian Heavy_COA	71	Iranian Heavy_COA
Iraq Basra_BP	72	Iraq Basra_BP

Isthmus_Stratiev
Kearl Lake_Crude Monitor
Kirkuk_O&G
Kuwait Eocene_Chevron
Kuwait Export_Stratiev
Kuwait Ratawi_Chevron
Libya Es Sider_COA
Light Sour Blend_Crude Monitor_New
Light Sour Blend_Crude Monitor_Old
Lloyd Blend_Crude Monitor_New
Lloyd Blend_Crude Monitor_Old
Lloyd Kerrobert_Crude Monitor_New
Lloyd Kerrobert_Crude Monitor_New
Long Lake Light Synthetic_Crude Monitor
Louisiana light sweet_Stratiev
Margham Light_Ceric Emir
Marine Qatar_O&G
Mars USA-Gulf of Mexico_BP
MAYA_Stratiev
Medium Sour Blend_Crude Monitor
Merey_O&G
Midale_Crude Monitor
Midway-Sunset_Knovel

Mixed Sweet Blend_Crude Monitor
Nanhai Light_Chevron
Nigera Bonga_Exxon
Nigera Erha_Exxon
Nigera Quaib_Exxon
Nigeria Agbami_Chevron
Nigeria Agbami_Statoil
Nigeria Escravos_Chevron
Nigeria Pennington_Chevron
North Sea Dansk Blend_Statoil
Norway North Sea Skarv_BP
Norway Oseberg_Statoil
Olmeca_COA
Peace River Insitu_Alberta.ca
Premium Albian Synthetic_Crude Monitor
Premium Conventional Heavy_Crude Monitor
Premium Synthetic_Crude Monitor
Qin Huang Dao_Chevron
Russia Sokol_Exxon
Russian Export Blend_Stratiev
Seal Heavy_Crude Monitor_New
Seal Heavy_Crude Monitor_New

Shell Synthetic Light_Crude Monitor
Siberian Light_COA
Smiley Coleville_Crude Monitor_New
Smiley-Coleville_Crude Monitor_Old
Snohvit Condensate_Statoil
Sumatran Light (Minas)_Chevron
Suncor Synthetic A_Crude Monitor_New
Suncor Synthetic A_Crude Monitor_Old
Suncor Synthetic H_Crude Monitor_New
Suncor Synthetic H_Crude Monitor_Old
Synbit Blend_Crude Monitor_New
Synbit Blend_Crude Monitor_Old
Syncrude Sweet Premium_Crude Monitor_New
Syncrude Sweet Premium_Crude Monitor_Old
Syncrude Synthetic_Crude Monitor
Synthetic Sweet Blend_Crude Monitor
Tengiz_Chevron
Thunderhorse_BP
Thunderhorse_Exxon
UAE DAS Blend_BP
UAE Murban_BP
Venezuela Leona_COA
Venezuela Tia Juana_Stratiev

Wabasca Heavy_Crude Monitor_New
Wabasca Heavy_Crude Monitor_Old
Wabasca Primary_Alberta.ca
West texas intermediate_Stratiev
West texas sour_Stratiev
Western Canadian Blend_Crude Monitor
Western Canadian Select_Crude Monitor
Wilmington CA_Knovel
Wyoming Sweet_COA

Crude Oil Classification Algorithms in Python

In [8]:
```
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.markers
import pandas as pd
from sklearn import datasets, linear_model, neighbors
from sklearn.metrics import mean_squared_error, r2_score, explained_variance_score
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import NearestNeighbors
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report
from sklearn.svm import SVC
import time
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
from sklearn import datasets
from IPython.display import Image
from sklearn.cluster import KMeans
from sklearn import metrics
from sklearn.cluster import MeanShift, estimate_bandwidth
from sklearn.cluster import DBSCAN
from sklearn.preprocessing import scale
from mpl_toolkits.mplot3d import Axes3D

from collections import Counter

import graphviz
import pydotplus
import openpyxl
import matplotlib.pyplot as plt
```

In [9]:
```
path="C:\Project_619\PRELIM v1.3.xlsm"

wb= openpyxl.load_workbook('PRELIM v1.3.xlsm')

# Get workbook active sheet object
sheet= wb['Assay Inventory']

Properties= ['Sulfur','Nitrogen','API','Density','Hydrogen','MCR','Characterization
Factor', 'Tb(50%) weight basis']

Location_dictionary = dict()

Location_dictionary['crude_name'] = []

for i in range (25,2185,15):
    cell= sheet.cell(row = i, column = 3)
    Location_dictionary['crude_name'].append(cell.value)

# print(Location_dictionary)
Location_dictionary['crude_name']
```

```
Out[9]: ['Access Western Blend_Crude Monitor',
 'Alaskan North Slope_Exxon',
 'Albian Heavy Synthetic_Crude Monitor_New',
 'Albian Heavy Synthetic_Crude Monitor_Old',
 'Albian Residual Blend_Crude Monitor',
 'Algerian Condensate_BP',
 'Angola Cabinda_Stratiev',
 'Angola Girassol_Exxon',
 'Angola Girassol_Statoil',
 'Angola Kuito_Chevron',
 'Arab Heavy_Stratiev',
 'Arab Light_Stratiev',
 'Arab Medium_Stratiev',
 'Azeri Light_Chevron',
 'Azeri light_Exxon ',
 'Azeri Light_Statoil',
 'Bakken_PNAS Laurenzi et al Bakken LCA',
 'Bakken_Various Sources',
 'Basrah Heavy_O&G',
 'Basrah Medium_COA',
 'Belridge_Knovel',
 'Bonny Light_Chevron',
 'Borealis Heavy Blend_Crude Monitor',
 'Bow River North_Crude Monitor_New',
 'Bow River North_Crude Monitor_Old',
 'Bow River South_Crude Monitor',
 'Brazil Frade_Chevron',
 'Brazil Lula_BG Group',
 'Brazil Polvo_BP',
 'Brent_BP',
 'Brent_Chevron',
 'Brent_Exxon',
 'Burgan (Wafra)_O&G',
 'Canada Hibernia_Chevron',
 'Canada Hibernia_Exxon',
 'Canada Hibernia_Statoil ',
 'China Bozhong_Chevron',
 'Christina Dilbit Blend_Crude Monitor',
 'Christina Lake_Crude Monitor',
 'CNRL Light Sweet Synthetic_Crude Monitor',
 'Cold Lake_Crude Monitor_New',
 'Cold Lake_Crude Monitor_Old',
 'Colombia Cano Limon_Stratiev',
 'Congo Emeraude_Stratiev',
 'Cossack_Chevron',
 'Cusiana_COA',
 'Dukhan_Qatar_COA',
 'Eagle Ford Ultralight_Platts',
 'Eagle Ford_PNAS Laurenzi et al Bakken LCA',
 'East Texas Sweet_COA',
 'Ecuador Oriente_Stratiev',
 'Ekofisk_BP',
 'Ekofisk_Chevron ',
 'Ekofisk_Statoil',
 'Fateh_COA',
 'Forties Blend_BP',
 'Forties_Chevron ',
 'Forties_Statoil ',
 'Fosterton_Crude Monitor ',
 'Hamaca Venezuela_Knovel',
 'High Sour Edmonton_Crude Monitor',
 'Husky Synthetic Blend_Crude Monitor_New',
 'Husky Synthetic Blend_Crude Monitor_Old',
 'India Bombay_COA',
```

In [10]:
```
wbo=pd.read_csv('Crude oils_updated.csv')
# Gewbo=pd.read_csvt workbook active sheet object

country=wbo.iloc[:,3]
len(country)

c = Counter(country)
c
```

Out[10]:
```
Counter({'Canada': 53,
         'USA': 15,
         'Alegria': 1,
         'Angola': 4,
         'Saudi Arabia': 3,
         'Azerbaijan': 3,
         'Iraq': 4,
         'Nigeria': 8,
         'Brazil': 3,
         'UK': 6,
         'Kuwait': 4,
         'China': 3,
         'Colombia': 2,
         'Congo': 1,
         'Australia': 1,
         'Qatar': 2,
         'Ecuador': 1,
         'Norway': 6,
         'UAE': 4,
         'Venezuela': 4,
         'India': 1,
         'Indonesia': 3,
         'Iran': 2,
         'Mexico': 3,
         'Libya': 1,
         'Louisiana': 1,
         'Denmark': 1,
         'Russia': 3,
         'Kazakhstan': 1})
```

In [11]:
```
len(Location_dictionary['crude_name'])
```

Out[11]:
```
144
```

In [12]:
```
Location_dictionary['crude_name'][0]
```

Out[12]:
```
'Access Western Blend_Crude Monitor'
```

In [13]:
```
Location_dictionary['Sulfur']=[]

for j in range(31,2185,15):
      cell= sheet.cell(row = j, column = 5)
      Location_dictionary['Sulfur'].append(cell.value)

sul=Location_dictionary['Sulfur']
print(np.transpose(Location_dictionary['Sulfur']))
len(Location_dictionary['Sulfur'])
```

```
[4.19645003e+00 8.46315860e-01 2.58481761e+00 2.24227432e+00
 3.24210978e+00 5.88533578e-04 3.13651330e-01 3.12777273e-01
 3.52958165e-01 8.71157225e-01 2.32817701e+00 1.62805609e+00
 2.40164450e+00 1.48091217e-01 1.93083878e-01 1.50482547e-01
 9.70000000e-02 7.28706151e-02 8.13338624e+00 2.67509229e+00
 2.47007298e-01 1.69800000e-01 4.36334774e+00 3.11786788e+00
 2.69602215e+00 2.69329209e+00 8.00391225e-01 2.67902593e-01
 9.57060173e-01 3.36059135e-01 3.73902018e-01 5.61287040e-01
 3.43391348e+00 5.61733626e-01 6.19730984e-01 4.77897028e-01
 2.82134007e-01 4.02448963e+00 3.52032490e+00 5.23975010e-02
 4.01078133e+00 3.88522089e+00 6.41170872e-01 7.74717639e-01
 5.90152967e-02 9.74021341e-01 1.63861204e+00 1.06827727e-01
 2.40000000e-01 2.89286448e-01 9.49088287e-01 2.07880805e-01
 3.25222894e-01 2.42978962e-01 1.93079543e+00 7.47188191e-01
 8.49166504e-01 8.48801084e-01 3.10466366e+00 1.63046707e+00
 1.34798709e+00 5.89544360e-02 9.36766838e-02 1.45007658e-01
 2.38557678e-01 1.43761031e-01 2.54744873e+00 1.46999954e+00
 2.65868146e+00 1.33166929e+00 4.16791499e+00 1.97373797e+00
 5.26366193e+00 2.32144205e+00 5.01704906e+00 1.93060772e-01
 9.44321338e-01 1.06600000e+00 3.50984511e+00 3.68909240e+00
 3.21731028e+00 3.21731028e+00 4.35713297e-02 3.03696033e-01
 4.00000000e-02 2.09980017e+00 1.55547260e+00 3.27464765e+00
 1.61767863e+00 2.12298901e+00 2.34272187e+00 1.18550000e+00
 3.40075893e-01 4.71762448e-02 1.84951730e-01 1.78275352e-01
 1.16144943e-01 8.16720240e-02 7.27675133e-02 2.35383021e-01
 1.46370090e-01 3.21494635e-01 3.71328902e-01 2.03947850e-01
 8.31709891e-01 7.07345802e-03 2.91299561e+00 5.40258900e-02
 2.86620493e-01 3.72809699e-01 1.33173117e+00 4.62654382e+00
 4.62654382e+00 1.13707711e-01 4.73468397e-01 2.99416849e+00
 2.98766016e+00 1.64556992e-02 8.76563463e-02 1.44987262e-01
 2.11322737e-01 2.95580254e+00 3.06257120e+00 2.98147036e+00
 2.98429636e+00 1.11322026e-01 2.02367399e-01 1.67054359e-01
 1.03580857e-01 7.05955021e-01 6.72700405e-01 7.57965298e-01
 1.19279061e+00 8.78084593e-01 1.28900782e+00 2.49217735e+00
 4.01109338e+00 4.00227287e+00 3.08339455e-01 1.31331005e+00
 3.29811933e+00 3.37980903e+00 1.56000000e+00 3.04716405e-01]
```

Out[13]: 144

In [14]:
```
Location_dictionary['Nitrogen']=[]
for j in range(32,2185,15):
      cell= sheet.cell(row = j, column = 5)
      Location_dictionary['Nitrogen'].append(cell.value)

N=Location_dictionary['Nitrogen']

print(np.transpose(Location_dictionary['Nitrogen']))
len(Location_dictionary['Nitrogen'])
```

```
[4.06208136e+03 9.08136080e+02 4.50937588e+03 2.58132987e+03
 2.23926255e+03 2.32470190e+00 1.57082293e+03 1.40911982e+03
 1.37828226e+03 5.00317053e+03 1.84954244e+03 1.40247320e+03
 1.65269673e+03 9.09646455e+02 1.04103756e+03 9.69178292e+02
 4.45000000e+02 0.00000000e+00 3.59009440e+01 1.98197284e+03
 8.38292467e+03 1.04000000e+03 4.15517383e+03 4.18125976e+03
 1.59610723e+03 1.63649289e+03 5.90567004e+03 1.11963024e+03
 3.13473974e+03 5.18555290e+02 7.56865414e+02 1.32897342e+03
 1.71955239e+02 1.05026215e+03 1.63780878e+03 8.64460404e+02
 4.25027426e+03 3.15612118e+03 2.33936577e+03 1.73902627e+02
 4.00030373e+03 2.20095192e+03 1.60632961e+03 2.18342328e+03
 1.53431229e+02 1.49786446e+03 1.76760174e+03 8.82048292e+02
 2.68000000e+02 1.77668476e+03 1.59413768e+03 1.03473795e+03
 1.73167068e+03 1.04814755e+03 1.73309450e+03 6.82703348e+02
 1.30312021e+03 8.70480585e+02 2.05061996e+03 2.90454233e+03
 7.93570284e+02 2.96856177e+02 3.49738544e+02 1.61552275e+03
 3.80686834e+03 5.52586109e+02 2.16738550e+03 1.91168561e+03
 7.98477915e+02 1.41098290e+03 4.18401808e+03 5.83233106e+02
 2.03667709e+03 1.55933958e+03 2.29101072e+03 1.79587930e+03
 7.57439681e+02 8.57180000e+02 2.57853454e+03 2.17497241e+03
 2.15275524e+03 2.15275524e+03 7.25558754e+01 9.71259050e+02
 2.32470190e+00 1.59481872e+02 1.17797424e+03 2.48143292e+03
 1.02232079e+03 1.71456508e+02 1.03366025e+03 1.23953517e+03
 5.14114125e+02 4.00444583e+02 1.39140554e+03 1.39314907e+03
 1.16231126e+03 8.94581948e+02 7.10419594e+02 2.15322884e+03
 1.03472991e+03 1.80800797e+03 6.97962461e+02 5.61212139e+02
 1.68697038e+03 2.78284730e+01 3.38042677e+03 1.67308537e+02
 4.11687224e+03 1.86268623e+03 1.49145124e+03 2.30615824e+03
 2.30615824e+03 3.55795543e+02 1.82498433e+03 2.24791080e+03
 1.79748485e+03 3.90622356e+00 8.60265005e+02 5.25115067e+02
 6.82417798e+02 1.16680637e+03 1.15835068e+03 2.33016816e+03
 1.20176710e+03 4.16374542e+02 7.40914804e+02 6.68461395e+02
 3.87265644e+02 3.12275924e+02 9.22312822e+02 8.32082597e+02
 3.85996551e+02 4.08591785e+02 1.36897713e+03 2.33785200e+03
 2.21364339e+03 1.82512476e+03 1.08482975e+03 9.57000000e+02
 1.35373546e+03 1.99850119e+03 0.00000000e+00 1.76422986e+03]
```

Out[14]: 144

In [15]:
```
Location_dictionary['API']=[]
for j in range(33,2185,15):
      cell= sheet.cell(row = j, column = 5)
      Location_dictionary['API'].append(cell.value)
api=Location_dictionary['API']
print(np.transpose(Location_dictionary['API']))
len(Location_dictionary['API'])
```

```
[22.64       31.4        19.4        19.48134328 20.         68.43403691
 31.7        29.9        29.8057656  22.05000003 27.4        33.4
 28.5        36.08011113 36.1        34.8        42.4        38.4
 24.7        29.6        15.         32.710282   21.85       20.31
 21.09459459 22.77       19.8115606  29.3        20.26957327 37.42502987
 38.2        38.5        23.3        33.53068494 34.6        35.
 16.89682534 22.24       22.24       34.99       20.44       20.73007812
 29.3        23.6        47.3        36.35       41.8        43.10008939
 44.6        37.         29.2        38.41990084 38.40361189 38.41752081
 31.1        38.62437726 40.30925211 38.70396958 21.92       26.
 34.94130435 32.14       32.62820513 37.9        20.29067576 44.11907764
 26.9        31.         30.16192967 33.3        22.01       39.28929642
 18.29413086 31.4        24.20006729 35.7        37.86       37.1349283
 21.37       20.87276786 19.29       19.29       39.93       36.1
 50.33       32.64915675 28.75091533 22.2        34.79       14.7
 29.60335196 22.6        39.95       39.50230507 30.6        34.8
 36.         47.87619626 48.03285662 33.50722565 35.4159067  33.49672163
 35.98413399 39.7        38.6        31.33       23.06       32.5
 16.483952   36.4        31.8        21.57       21.57       30.83
 36.2        20.47       19.91575342 61.25011072 33.94000177 33.5
 33.5        19.1        19.90588235 19.76       19.76       32.65
 32.65       33.61       33.61       46.42406131 33.4630776  32.9
 39.26997345 40.06960862 24.1        12.1        20.6        20.94333333
 40.8        34.1        20.64340659 20.53959732 19.4        37.2       ]
```

Out[15]: 144

In [16]:
```
API_class=np.zeros(len(Location_dictionary['API']))
j=0
k=0
l=0
b=0
v=0
s=0

for i in range (0,144):
    if (Location_dictionary['API'][i]>32):
        if (Location_dictionary['Sulfur'][i]<=0.5):
            API_class[i]=1
            j+=1
        if (Location_dictionary['Sulfur'][i]>0.5):
            API_class[i]=2
            b+=1
    if (Location_dictionary['API'][i]>22 and Location_dictionary['API'][i]<=32):
        if (Location_dictionary['Sulfur'][i]<=0.5):
            API_class[i]=3
            k+=1
        if (Location_dictionary['Sulfur'][i]>0.5):
            API_class[i]=4
            v+=1
    if (Location_dictionary['API'][i]<=22):
        if (Location_dictionary['Sulfur'][i]<=0.5):
            API_class[i]=5
            l+=1
        if (Location_dictionary['Sulfur'][i]>0.5):
            API_class[i]=6
            s+=1
# print(API_class)
sum=j+b+k+v+l+s

print("Light and sweet,%d,\n Light and sour, %d \n Medium and sweet,%d,\n Medium an
d sour,%d,\n Heavy and sweet,%d,\n heavy and sour,%d",j,b,k,v,l,s)

print("sum",sum)
```

```
Light and sweet,%d,
 Light and sour, %d
 Medium and sweet,%d,
 Medium and sour,%d,
 Heavy and sweet,%d,
 heavy and sour,%d 50 23 7 29 4 31
sum 144
```

In [17]:
```
Location_dictionary['Density']=[]
for j in range(34,2185,15):
      cell= sheet.cell(row = j, column = 5)
      Location_dictionary['Density'].append(cell.value)

print(np.transpose(Location_dictionary['Density']))
len(Location_dictionary['Density'])
```

```
[917.09239977 868.6        936.7834493  936.27874428 933.07341584
 707.1        867.         876.7        876.7        920.6162323
 890.         858.         884.         843.54057022 843.44046838
 850.52004373 813.68602645 832.09745438 905.07911332 878.3
 966.         860.8383     921.81690577 931.16805546 926.38027497
 916.31958579 934.2354407  880.2        931.5        836.9
 830.         831.53307353 913.26458333 856.57174938 851.05732992
 849.42052107 952.58521993 919.47848641 919.6        849.06374257
 930.37134724 928.59850196 880.         912.         790.67873322
 843.1        816.5        809.61298754 803.52072686 839.8
 881.         832.         832.00481099 832.40042846 870.5
 831.         822.77654297 831.00090077 921.39631404 898.4
 849.31215274 863.85127414 861.28171809 835.3        931.28660105
 805.         893.3        870.8        874.5        859.
 920.85611687 857.         943.69934047 869.         907.90341302
 846.3        834.67538085 838.26       924.7113397  927.72891435
 937.46682472 937.46682472 824.59675961 844.         777.43289061
 861.6        882.2        921.         850.08492693 966.98602941
 877.45301873 918.         824.50056868 826.65916368 872.0581277
 850.03380938 843.94401493 788.06790115 787.86424419 856.69352931
 846.89725081 856.74806808 844.1        826.         831.9
 868.14851379 914.60030085 861.95501524 955.24292055 841.93342764
 867.         923.50311949 923.50311949 870.82253742 843.8
 930.18768507 933.5925708  733.90038689 854.45249632 856.73104545
 856.73104545 938.64955179 933.65343739 934.55389726 934.55389726
 861.16736217 861.16736217 856.16027194 856.16027194 794.49975152
 857.         859.85780109 828.6        824.         909.4
 985.         929.39265286 927.29947193 821.         854.
 929.12749665 929.76188438 937.16049    838.8       ]
```

Out[17]: 144

In [18]:
```
Location_dictionary['Hydrogen']=[]
for j in range(35,2185,15):
      cell= sheet.cell(row = j, column = 5)
      Location_dictionary['Hydrogen'].append(cell.value)

h=Location_dictionary['Hydrogen']
print(np.transpose(Location_dictionary['Hydrogen']))
len(Location_dictionary['Hydrogen'])
```

```
[11.74151585 12.81432004 11.39010061 10.71895231 11.12016655 15.42606854
 13.14206488 12.81102874 12.14071068  9.04411843 12.62276165 13.01188416
 12.66742343 12.72138306 13.34       12.62755927 13.6        13.31737603
 11.25974476 12.44459037 10.62207716 12.93164891 11.64986374 11.43029027
 11.64129054 11.83012004  7.95435464 12.74005473 11.10502668 13.07926381
 12.99665093 12.13569853 11.52731093 12.79208488 11.79116989 12.28751638
  9.57102389 11.74042655 12.09441938 12.63066409 12.81259672 11.1922951
 12.99506601 12.13568498 13.71818713 13.22949649 13.21425117 14.15475736
 14.         13.22763203 12.64327842 13.15698226 10.82023246 12.43929452
 12.62374557 12.94060841 10.61330351 12.26782971 11.78759692 13.82936855
 12.82090896 12.62697055 12.86516103 13.44136207  8.16529509 13.30881924
 12.15853624 12.85759909 12.52197133 13.14307215 11.77656728 12.33278382
  8.20932876 12.89959783  8.63444727 13.17216051 12.92745412 12.3165613
 11.74992316 11.20672442 11.37886335 11.37886335 13.10124073 13.2419885
 13.91365316 12.74528831 12.55690893 11.83210871 12.73817906 12.85033739
 12.09908852 11.94816962 13.07092187 13.73883101 12.28920814 12.12689936
 13.00968661 13.26876076 12.87278978 11.44743396 12.53710409 10.90753242
 12.97286548 13.10039567 13.28850966 12.39692329 11.66779535 12.48184684
  9.80367322 12.12378659 12.79904128 11.58033428 11.58033428 12.47130709
 13.09114617 11.55842862 11.24549096 14.74499425 12.14675799 12.66416044
 13.00969903 11.16586838 11.13247494 11.6124048  11.9112943  12.5843088
 12.57033146 12.9766476  12.65371357 12.86450124 12.85677925 12.53079914
 13.25528229 13.30702731 12.50429257 11.05327626 11.53356398 11.23930483
 13.45499708 12.95201389 11.54669203 11.20542568 11.55303231 13.02016701]
```

Out[18]: 144

In [19]:
```python
Location_dictionary['MCR']=[]
for j in range(36,2185,15):
      cell= sheet.cell(row = j, column = 5)
      Location_dictionary['MCR'].append(cell.value)

mcr=Location_dictionary['MCR']
print(np.transpose(Location_dictionary['MCR']))
len(Location_dictionary['MCR'])
```

```
[1.05500000e+01 4.86000000e+00 1.37000000e+01 1.09007826e+01
 8.14600000e+00 1.00000000e-03 3.60000000e+00 3.03000000e+00
 3.20000000e+00 6.14000000e+00 6.80000000e+00 3.60000000e+00
 5.90000000e+00 1.30000000e+00 1.40000000e+00 1.40000000e+00
 7.00000000e-01 7.50000000e-01 9.32000000e+00 6.40000000e+00
 5.90000000e+00 1.20000000e+00 1.02300000e+01 1.12400000e+01
 8.57258278e+00 8.45000000e+00 6.04000000e+00 3.24000000e+00
 8.60000000e+00 2.27000000e+00 2.04000000e+00 2.18000000e+00
 7.70000000e+00 2.61000000e+00 1.71000000e+00 2.20000000e+00
 8.00000000e+00 1.02200000e+01 1.05500000e+01 1.00000000e-02
 1.04500000e+01 1.06270053e+01 3.30000000e+00 7.57000000e+00
 2.33000000e+00 1.20000000e+00 1.70000000e+00 1.08240215e-02
 6.50000000e-01 2.11000000e+00 6.30000000e+00 1.71000000e+00
 1.83000000e+00 1.80000000e+00 4.62000000e+00 1.94000000e+00
 1.55000000e+00 1.80000000e+00 9.19000000e+00 7.10000000e+00
 3.79659091e+00 2.00000000e-02 6.04166667e-02 1.20000000e+00
 8.00000000e+00 2.74000000e-02 5.90000000e+00 5.00000000e+00
 6.33000000e+00 4.30000000e+00 8.42000000e+00 5.40000000e+00
 1.04400000e+01 5.70000000e+00 1.02100000e+01 1.80000000e+00
 2.87000000e+00 2.93000000e+00 9.25000000e+00 9.69226667e+00
 9.99000000e+00 9.99000000e+00 2.00000000e-02 1.10000000e+00
 0.00000000e+00 4.85000000e+00 5.78000000e+00 1.20000000e+01
 3.56000000e+00 1.12100000e+01 5.80000000e+00 4.30000000e+00
 1.77000000e+00 2.32000000e+00 1.19000000e+00 1.03000000e+00
 1.22000000e+00 6.80000000e-01 7.00000000e-01 3.90000000e-01
 1.39000000e+00 1.78000000e+00 1.43000000e+00 1.56820287e+00
 1.50000000e+00 2.00000000e-01 9.38000000e+00 1.30000000e-01
 7.11000000e+00 1.03000000e+00 3.90000000e+00 9.18000000e+00
 9.18000000e+00 1.40000000e-01 2.87000000e+00 9.61000000e+00
 9.38772727e+00 3.20414558e-04 3.52000000e+00 3.00000000e-02
 3.00000000e-02 1.40000000e-01 5.90967742e-01 8.97000000e+00
 8.97000000e+00 2.00000000e-02 2.00000000e-02 5.00000000e-02
 5.00000000e-02 3.90000000e-01 4.06000000e+00 3.90000000e-01
 1.60000000e+00 4.54000000e+00 6.00000000e+00 1.12000000e+01
 8.77000000e+00 8.52006173e+00 1.10000000e+00 3.30000000e+00
 8.67928000e+00 9.35852459e+00 4.90000000e+00 2.70000000e+00]
```

Out[19]: 144

In [20]:
```
Location_dictionary['CF']=[]
for j in range(37,2185,15):
      cell= sheet.cell(row = j, column = 5)
      Location_dictionary['CF'].append(cell.value)

print(np.transpose(Location_dictionary['CF']))
len(Location_dictionary['CF'])
```

```
[12.07865782 11.67046916 11.775354   11.63910626 11.48875019 14.79773985
 12.35643647 12.09971619 12.00077964 12.37116341 12.08928738 12.10837652
 11.99476202 12.17209444 12.50103736 12.17842901 11.8        11.98971186
 11.56084777 11.92351201 12.03746321 11.70015349 12.00932485 11.88205051
 11.64927344 11.77610362 12.1908176  11.77565475 11.87078944 12.13263576
 12.16218391 12.48286239 11.45722942 12.79273421 12.19649084 12.12696721
 11.75909745 11.98138501 11.85979659 11.62308408 11.99666362 11.78797253
 12.02436271 12.31636317 13.23354405 11.98611683 12.33920828 11.92109357
 12.4        12.03253313 11.86276177 12.47698082 12.83252922 12.16893958
 12.00301845 12.07746089 12.682839   12.0831113  11.79497104 11.47145547
 12.04532541 11.87728856 11.91310753 11.95442725 12.5666916  11.3345479
 11.93420579 11.99563652 12.05812544 12.03595384 12.08702003 12.64064697
 12.308132   12.21216708 12.59498327 12.07699389 11.94870583 11.98304915
 12.01398107 11.80787228 11.79887651 11.79887651 12.05502281 11.9682644
 12.03700862 12.14918958 12.04369009 12.07475235 12.03667422 10.82071667
 11.90157619 12.41547562 12.18984949 12.6564124  11.22861402 11.44567532
 11.60267025 12.88326576 12.23484245 12.49326777 12.93887153 13.29339893
 13.49380391 12.04493965 12.18200814 11.56550223 12.02650073 11.71880076
 10.95275251 11.95472054 12.08634085 11.86293904 11.86293904 11.92615543
 12.01012796 11.793067   11.67232305 14.26603513 12.24472904 11.7867182
 11.86561393 11.14424499 11.36529908 11.66804072 11.58061991 11.79288522
 11.85802235 11.88770653 11.78919796 12.47983968 12.047864   12.26235407
 12.22998946 13.82296102 11.83821974 11.45118263 11.74605448 11.69712967
 12.15907801 11.99494046 11.71464624 11.73918554 12.39899794 12.0817447 ]
```

Out[20]: 144

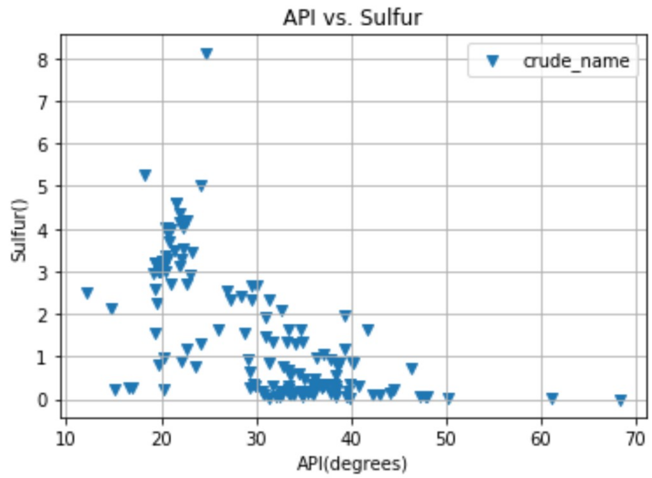
In [21]:
```
Location_dictionary['Tb']=[]
for j in range(38,2185,15):
      cell= sheet.cell(row = j, column = 5)
      Location_dictionary['Tb'].append(cell.value)

tb=Location_dictionary['Tb']
# Location_dictionary['Tb'] = Location_dictionary['Tb'][:-1]
print(np.transpose(Location_dictionary['Tb']))
len(Location_dictionary['Tb'])
```

```
[484.21771043 305.61       474.76287761 447.934      413.25
 365.         410.         390.         375.         550.
 420.         350.         390.         330.         380.
 345.         259.         280.         365.         365.
 600.         296.18836686 482.81423849 481.54219069 427.13670886
 426.94541226 550.         345.         480.         310.
 306.26       350.         365.         460.         350.
 335.         510.         471.85168711 449.4        262.39564543
 501.60055049 457.67391304 385.         515.         365.
 300.         295.         227.82       262.         300.
 360.         350.         405.         305.         360.
 290.         360.         290.         442.07307277 335.
 323.43055556 328.68899731 328.74722222 280.         620.
 150.         400.         360.         380.         340.
 495.17422204 365.         600.         390.         560.
 320.         279.59762764 291.6        490.84558338 459.31973684
 480.90176017 480.90176017 274.16890446 300.         183.47103319
 365.         395.         490.         323.77247807 365.
 361.44482759 550.         292.54113885 365.         250.
 240.         250.         310.         225.         410.
 460.         550.         550.         275.         305.
 290.86030054 468.37079292 301.11821809 365.         295.
 365.         459.51165742 459.51165742 351.01849499 305.
 462.38530193 447.88363636 365.         365.         300.60130065
 312.2        364.63433985 392.6        449.31753173 433.2
 310.47564691 320.2        314.3        299.81680678 270.
 340.         380.         305.         550.         420.
 525.         451.76185872 437.91518987 280.         325.
 445.3469697  451.35365854 600.         305.        ]
```

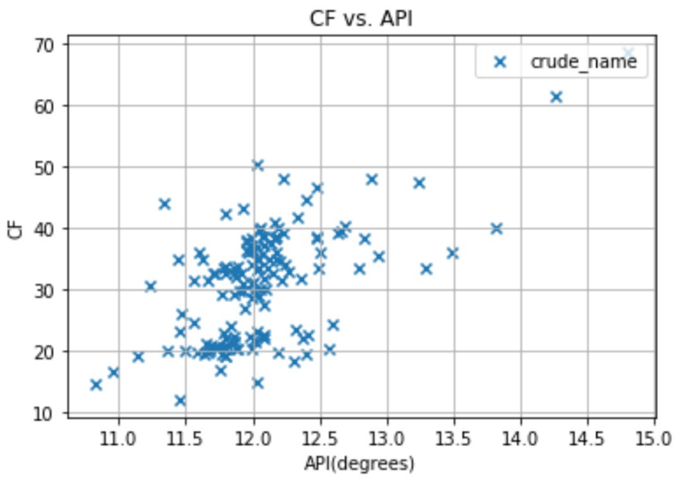
Out[21]: 144

In [22]:
```
# Location_dictionary['crude_name']=[s,N,a,h,mcr,cf,tb]
# Location_dictionary['crude_name'][0]
```

In [23]:
```
plt.scatter(api,sul,marker='v', label='crude_name')
plt.xlabel('API(degrees)')
plt.ylabel('Sulfur()')
plt.title("API vs. Sulfur")
plt.legend(loc='upper right')
plt.grid()
```



In [24]:
```
cf=Location_dictionary['CF']
plt.scatter(cf,api,marker='x', label='crude_name')
plt.xlabel('API(degrees)')
plt.ylabel('CF')
plt.title("CF vs. API")
plt.legend(loc='upper right')
plt.grid()
```



In [25]:
```
X_data=np.array([api,sul])
X_data=X_data.T
print(X_data.shape)

# for n in range (1,5):
#     start[n] = time.time()
cl=KMeans(n_clusters=3, n_init=10, tol=0.0001, random_state=10)
cl.fit(X_data)

# user_input=np.array([[20,0.7]])
# print(cl.predict(user_input))

# calcul=np.zeros(144)

# def apis(api,sul):
#     for i in range (0,144):
# #     if(cl.predict==1):
#         calcul[i]=((api[i]-user_input[0,0])**2 + (sul[i]-user_input[0,1])**2)**0.
5
#     return api and sul for (calcul.min())


# iner=cl.inertia_
# print(iner)
```

```
(144, 2)
```

Out[25]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
    n_clusters=3, n_init=10, n_jobs=1, precompute_distances='auto',
    random_state=10, tol=0.0001, verbose=0)
```

In [26]:
```
#DBSCAN

H_db=np.zeros(10)
C_db=np.zeros(10)
F_db=np.zeros(10)
Abs=np.zeros(10)

X_data=np.array([api,sul,cf])
X_data=X_data.T

# for n in range (10,95):
db = DBSCAN(eps=2.5, min_samples=3)
db.fit(X_data)
#     H_db[n]=metrics.homogeneity_score(X_target,db.labels_)  #Homogeneity
#     C_db[n]=metrics.completeness_score(X_target,db.labels_)
#     F_db[n]=metrics.fowlkes_mallows_score(X_target,db.labels_)

# Number of clusters in labels, ignoring noise if present.
labels = db.labels_
n_clusters_ = len(set(labels)) - (1 if -1 in labels else 0)
n_noise_ = list(labels).count(-1)

print('Estimated number of clusters for API,S,N: %d' % n_clusters_)
print('Estimated number of noise points for API, S, N: %d' % n_noise_)
```

```
Estimated number of clusters for API,S,N: 2
Estimated number of noise points for API, S, N: 4
```

iner

np.count(cl.labels_==0)

In [76]:
```
# #PCA
# print(__doc__)

# from time import time
# import numpy as np
# import matplotlib.pyplot as plt

# from sklearn import metrics
# from sklearn.cluster import KMeans
# from sklearn.datasets import load_digits
# from sklearn.decomposition import PCA
# from sklearn.preprocessing import scale

# # np.random.seed(42)
# data=np.array([a,tb,N,h,mcr,cf,tb])
# data=data.T


# # digits = load_digits()
# # data = scale(digits.data)

# n_samples, n_features = X_data.shape
# # n_digits = len(np.unique(digits.target))`
# # labels = digits.target

# sample_size = 144

# print("\t n_samples %d, \t n_features %d"
#       % (n_samples, n_features))


# print(82 * '_')
# print('init\t\ttime\tinertia\thomo\tcompl\tv-meas\tARI\tAMI\tsilhouette')


# def bench_k_means(estimator, name, data):
#     t0 = time()
#     estimator.fit(data)
#     print('%-9s\t%.2fs\t%i\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f'
#           % (name, (time() - t0), estimator.inertia_,
#              metrics.homogeneity_score(labels, estimator.labels_),
#              metrics.completeness_score(labels, estimator.labels_),
#              metrics.v_measure_score(labels, estimator.labels_),
#              metrics.adjusted_rand_score(labels, estimator.labels_),
#              metrics.adjusted_mutual_info_score(labels,  estimator.labels_,
#                                                 average_method='arithmetic'),
#              metrics.silhouette_score(data, estimator.labels_,
#                                       metric='euclidean',
#                                       sample_size=sample_size)))

# bench_k_means(KMeans(init='k-means++', n_clusters=3, n_init=10),
#               name="k-means++", data=data)

# bench_k_means(KMeans(init='random', n_clusters=3, n_init=10),
#               name="random", data=X_data)

# # in this case the seeding of the centers is deterministic, hence we run the
# # kmeans algorithm only once with n_init=1
# pca = PCA(n_components=7).fit(data)
# bench_k_means(KMeans(init=pca.components_, n_clusters=3, n_init=1),
#               name="PCA-based",
#               data=data)
# print(82 * '_')
```

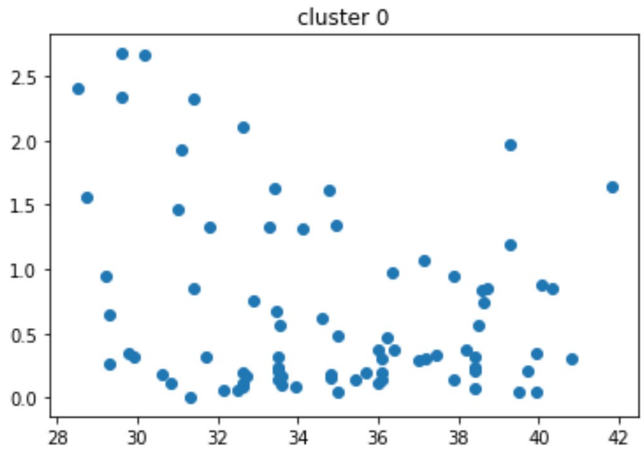
In [77]:
```
api=np.array(Location_dictionary['API'])
sulfur=np.array(Location_dictionary['Sulfur'])
```

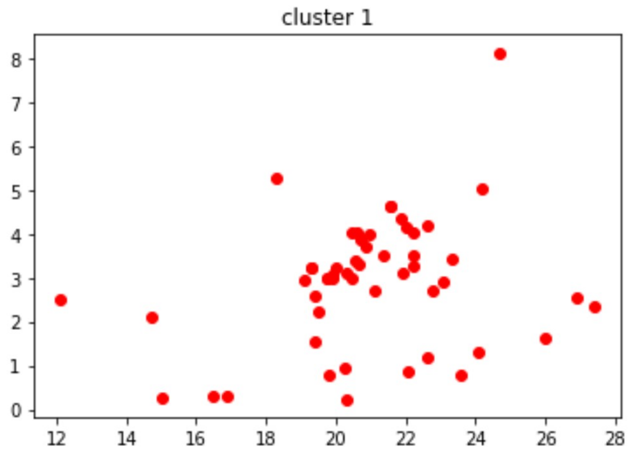
In [78]:
```
from plotly.subplots import make_subplots
import plotly.graph_objects as go
```

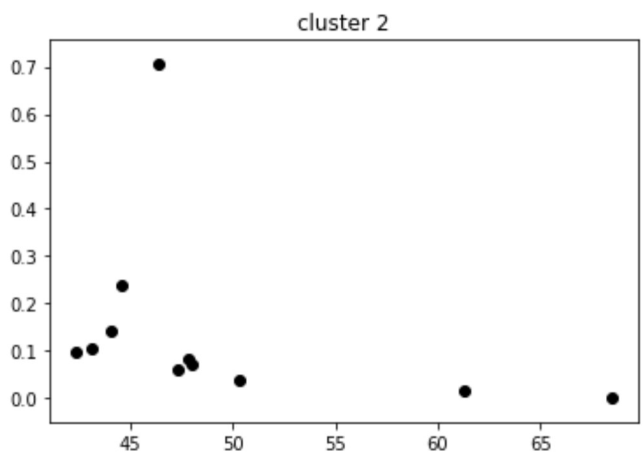
In [79]:
```
x0=api[cl.labels_==0]
x1=api[cl.labels_==1]
x2=api[cl.labels_==2]
print(len(x0),len(x1), len(x2))
x01=np.append(x0,x1)
print(np.shape(x01))

x012=np.append(x01,x2)
print(np.shape(x012))

y0=sulfur[cl.labels_==0]
y1=sulfur[cl.labels_==1]
y2=sulfur[cl.labels_==2]

y01=np.append(y0,y1)
y012=np.append(y01,y2)

# fig, axs = plt.subplots(2, 2)
# axs[0, 0].scatter(x0, y0)
# axs[0, 0].set_title('cluster0')
# axs[0, 1].scatter(x1, y1, 'tab:orange')
# axs[0, 1].set_title('Axis [0,1]')
# axs[1, 0].plot(x2, y2, 'tab:green')
# axs[1, 0].set_title('Axis [1,0]')

plt.figure(1)
plt.title("cluster 0")
plt.scatter(x0,y0)

plt.figure(2)
plt.title("cluster 1")
plt.scatter(x1,y1,color='red')

plt.figure(3)
plt.title("cluster 2")
plt.scatter(x2,y2,color='black')


# fig = make_subplots(rows=1, cols=3)

# fig.add_trace(go.Scatter(x0, y0,row=1, col=1)

# fig.add_trace(go.Scatter(x1, y1,row=1, col=2)

# fig.add_trace(go.Scatter(x2, y2,row=1, col=3)

# fig.update_layout(height=600, width=800, title_text="Subplots")
# fig.show()
```

```
81 52 11
(133,)
(144,)
```

Out[79]: <matplotlib.collections.PathCollection at 0x1ac3e7c49b0>







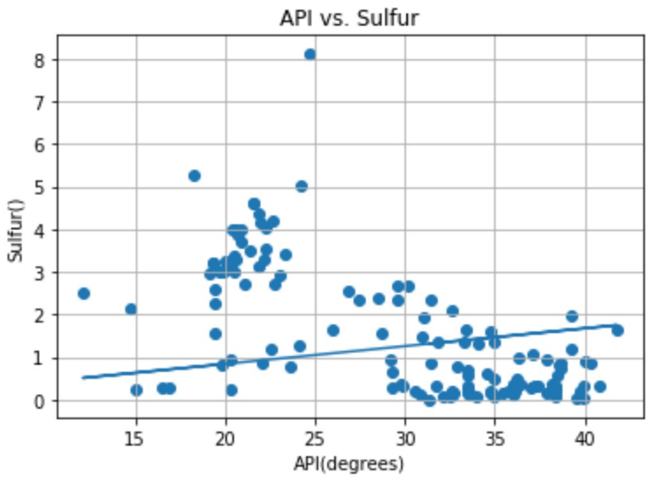
In [82]:
```
grid.cv_results_['mean_test_score']
```

Out[82]: array([-0.86751704, -4.7601552])

In [80]:
```
x_r=np.array([x01]).T
print(x_r.shape)
y_r=np.array([y01]).T
print(y_r.shape)

reg = LinearRegression(fit_intercept=False)
reg.fit(x_r,y_r)
ypred = reg.predict(x_r)
m=mean_squared_error(ypred,y_r)
print(m)

model = linear_model.LinearRegression()
parameters = {'fit_intercept':[True,False]}
grid = GridSearchCV(model,parameters, cv=5)
grid.fit(x_r, y_r)

print(grid.best_params_)

plt.scatter(x01,y01)
plt.xlabel('API(degrees)')
plt.ylabel('Sulfur()')
plt.title('API vs. Sulfur')

plt.plot(x01,ypred)
plt.grid()
# plt.scatter(x_r,ypred,color='b',label='Linear')

# x_2=x_r**2
# ones=np.ones(len(x_r))

# x2=(x_2,x_r,ones)

# reg_2=LinearRegression(fit_intercept=False)
# reg_2.fit(x2,y_r)
# ypred = reg_2.predict(x2)
# m=mean_squared_error(ypred,y_r)*144
# print(m_2)

# A=np.dot(np.linalg.inv(np.dot(x2,np.transpose(x2))),np.dot(x2,np.transpose(y_r)))

# Y_est=np.dot(A,x2)

# np.sum((y_r-Y_est)**2)
```

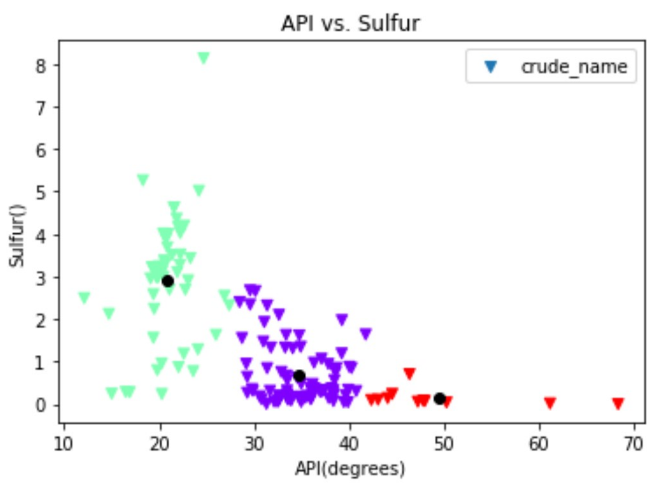
```
(133, 1)
(133, 1)
3.1295761511292404
{'fit_intercept': True}
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\model_selection\_search.py:84
1: DeprecationWarning:

The default of the `iid` parameter will change from True to False in version 0.2
2 and will be removed in 0.24. This will change numeric results when test-set si
zes are unequal.
```



In [81]:
```
x=Location_dictionary['API']
# print(np.shape(x))
y=Location_dictionary['Sulfur']
plt.figure(1)
plt.scatter(x,y,marker='v', label='crude_name',c=cl.labels_, cmap='rainbow')
plt.scatter(cl.cluster_centers_[:,0],cl.cluster_centers_[:,1], c='black')
plt.xlabel('API(degrees)')
plt.ylabel('Sulfur()')
plt.title('API vs. Sulfur')
plt.legend(loc='upper right')


# print(np.shape(x))plt.xlabel('API(degrees)')
plt.ylabel('Sulfur()')
plt.title('API vs. Sulfur')
# plt.figure(2)
# x=[]
# for i in range(0,145):
#     if (cl.labels_[i]==0):
# #       plt.figure(2)
#         plt.scatter (x[i],y[i])
#         a[j].append(x,y)
#         j+=1
# #     i=0
#     if (cl.labels_[i]==1):
#         plt.figure(3)
#         plt.scatter (x[i],y[i]
#         b=b+1
#     i=0
#     if (cl.labels_[i]==2):
#         plt.figure(3)
#         plt.scatter (x[i],y[i]
# a
```

Out[81]: Text(0.5, 1.0, 'API vs. Sulfur')



In [34]:
```
cl.cluster_centers_
```

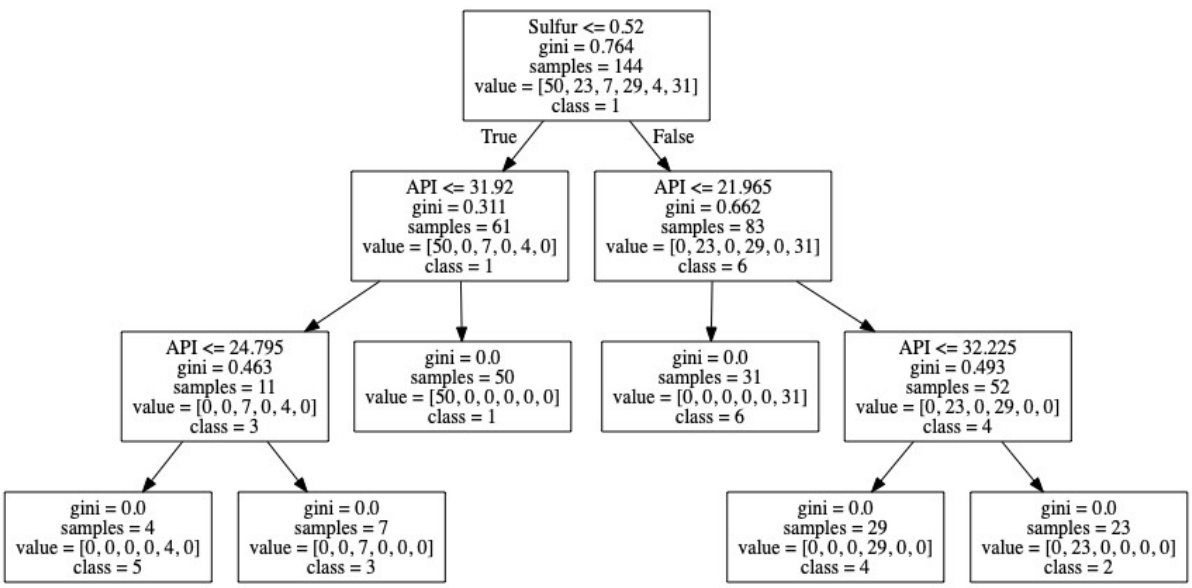
Out[34]:
```
array([[34.74973517,  0.68534936],
       [20.88622196,  2.90466448],
       [49.44240262,  0.14218571]])
```

In [35]:
```
X_all=np.array([N,h,api,sul,tb,cf,mcr])
X_all.shape
# API_class.shape,h,m,tb,cf
```

Out[35]: (7, 144)

In [36]:
```
#Decission Tree

X_all=np.array([sul,N,h,mcr,tb,cf,api]).T

# We Create an instance of Neighbors Classifier and fit the data

cltree=DecisionTreeClassifier(splitter='best', max_depth=3, min_impurity_decrease=
0.01)

#Train the model
model =cltree.fit(X_all,API_class)

feature_names=np.array(['Sulfur', 'N', 'hydrogen', 'MCR', 'Tb ', 'charac factor', '
API'])
class_names=np.array(['1','2','3','4','5','6'])

dot_data=tree.export_graphviz(cltree, out_file=None,feature_names=feature_names, cl
ass_names= class_names)

# Draw Graph
graph= pydotplus.graph_from_dot_data(dot_data)

# Show Graph
Image(graph.create_png())
```

Out[36]:



In [34]:
```
x=Location_dictionary['API']
y=Location_dictionary['Sulfur']
X_data=np.array([x,y,tb]).T
X=X_data
estimators = [('k_means_iris_4', KMeans(n_clusters=4)),
              ('k_means_iris_3', KMeans(n_clusters=3))]

fignum = 1
titles = ['4 clusters', '3 clusters']
for name, est in estimators:
    fig = plt.figure(fignum, figsize=(3, 3))
    ax = Axes3D(fig, rect=[0, 0, .95, 1], elev=48, azim=134)
    est.fit(X)
    labels = est.labels_

    ax.scatter(X[:, 0], X[:, 1], X[:, 2],c=labels.astype(np.float), edgecolor='k')

    ax.w_xaxis.set_ticklabels([])
    ax.w_yaxis.set_ticklabels([])
    ax.w_zaxis.set_ticklabels([])
    ax.set_xlabel('API')
    ax.set_ylabel('Sulfur')
    ax.set_zlabel('tb')
    ax.set_title(titles[fignum - 1])
    ax.dist = 12
    fignum = fignum + 1
```