Drawing Conclusions

Use the space below to address questions on datasets `clean_08.csv` and `clean_18.csv`

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
% matplotlib inline
```

In [2]:
```
# load datasets
df_08 = pd.read_csv('clean_08.csv')
df_18 = pd.read_csv('clean_18.csv')
```

In [3]:
```
df_08.head(1)
```

Out[3]:

	model	displ	cyl	trans	drive	fuel	veh_class	air_pollution_score	city_mpg	hwy_mpg
0	ACURA MDX	3.7	6	Auto-S5	4WD	Gasoline	SUV	7.0	15.0	20.0

Q1: Are more unique models using alternative sources of fuel? By how much?

Let's first look at what the sources of fuel are and which ones are alternative sources.

In [4]:
```
df_08.fuel.value_counts()
```

Out[4]:
```
Gasoline    984
gas           1
ethanol       1
CNG           1
Name: fuel, dtype: int64
```

In [5]:
```
df_18.fuel.value_counts()
```

Out[5]:
```
Gasoline       749
Gas             26
Ethanol         26
Diesel          19
Electricity     12
Name: fuel, dtype: int64
```

Looks like the alternative sources of fuel available in 2008 are CNG and ethanol, and those in 2018 ethanol and electricity. (You can use Google if you weren't sure which ones are alternative sources of fuel!)

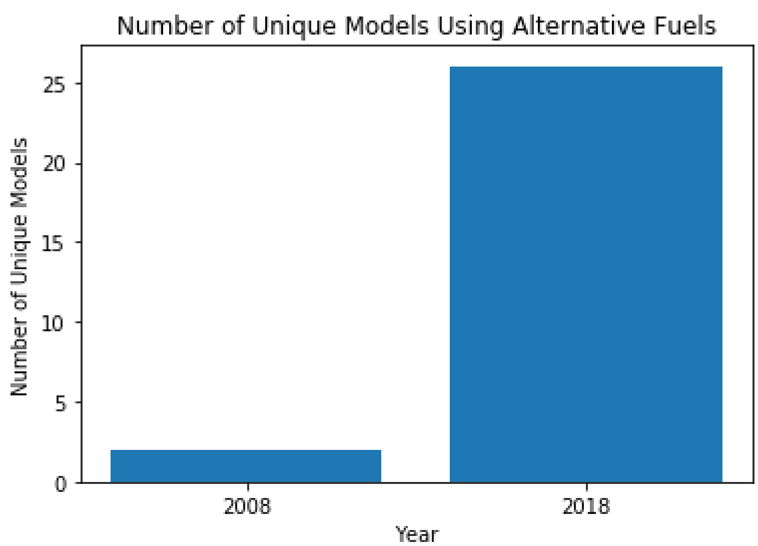
In [6]:
```python
# how many unique models used alternative sources of fuel in 2008
alt_08 = df_08.query('fuel in ["CNG", "ethanol"]').model.nunique()
alt_08
```

Out[6]:
```
2
```

In [7]:
```python
# how many unique models used alternative sources of fuel in 2018
alt_18 = df_18.query('fuel in ["Ethanol", "Electricity"]').model.nunique
()
alt_18
```

Out[7]:
```
26
```

In [8]:
```python
plt.bar(["2008", "2018"], [alt_08, alt_18])
plt.title("Number of Unique Models Using Alternative Fuels")
plt.xlabel("Year")
plt.ylabel("Number of Unique Models");
```



Since 2008, the number of unique models using alternative sources of fuel increased by 24. We can also look at proportions.

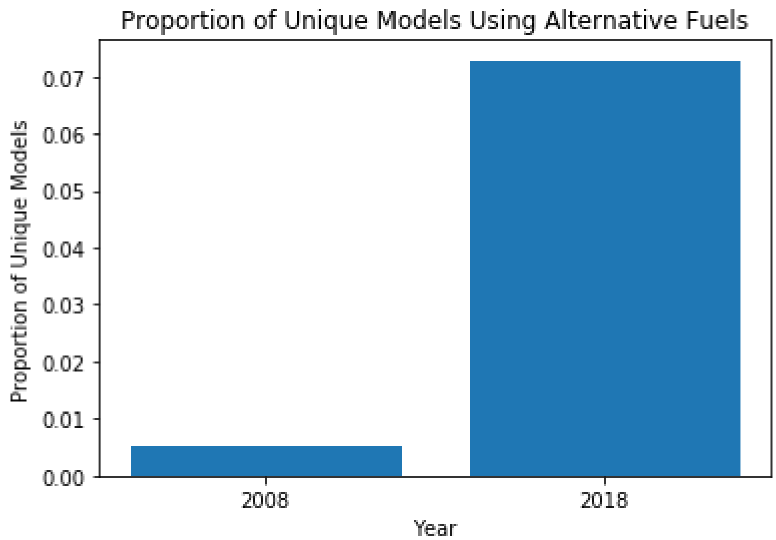
In [9]:
```python
# total unique models each year
total_08 = df_08.model.nunique()
total_18 = df_18.model.nunique()
total_08, total_18
```

Out[9]:
```
(377, 357)
```

In [10]:
```python
prop_08 = alt_08/total_08
prop_18 = alt_18/total_18
prop_08, prop_18
```

Out[10]:
```
(0.005305039787798408, 0.07282913165266107)
```

In [11]:
```
plt.bar(["2008", "2018"], [prop_08, prop_18])
plt.title("Proportion of Unique Models Using Alternative Fuels")
plt.xlabel("Year")
plt.ylabel("Proportion of Unique Models");
```



Q2: How much have vehicle classes improved in fuel economy?

Let's look at the average fuel economy for each vehicle class for both years.

In [12]:
```
veh_08 = df_08.groupby('veh_class').cmb_mpg.mean()
veh_08
```

Out[12]:
```
veh_class
SUV              18.471429
large car        18.509091
midsize car      21.601449
minivan          19.117647
pickup           16.277108
small car        21.105105
station wagon    22.366667
van              14.952381
Name: cmb_mpg, dtype: float64
```

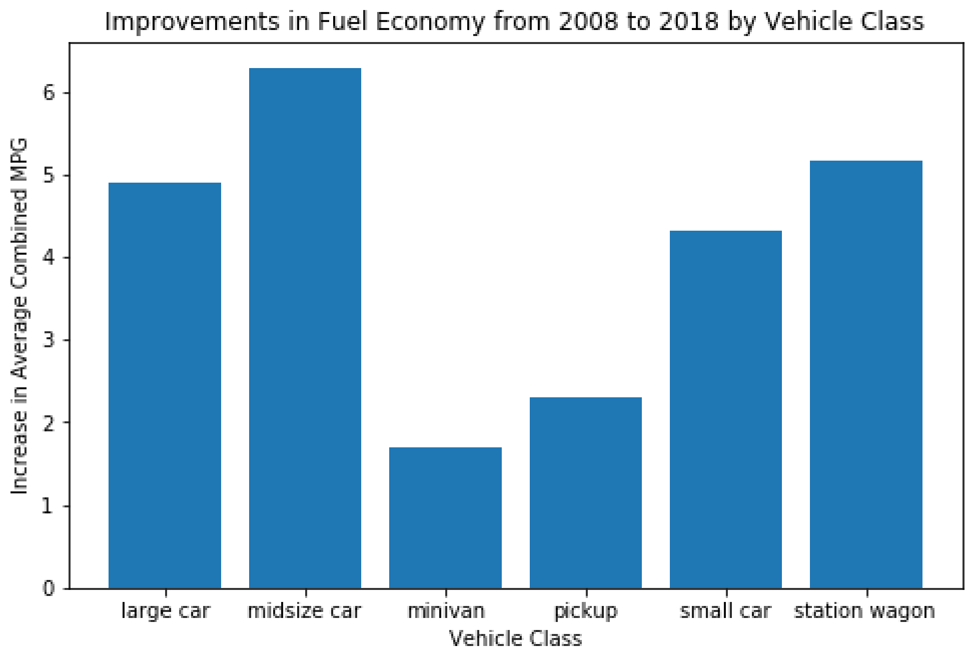
In [13]:
```
veh_18 = df_18.groupby('veh_class').cmb_mpg.mean()
veh_18
```

Out[13]:
```
veh_class
large car          23.409091
midsize car        27.884058
minivan            20.800000
pickup             18.589744
small SUV          24.074074
small car          25.421053
special purpose    18.500000
standard SUV       18.197674
station wagon      27.529412
Name: cmb_mpg, dtype: float64
```

In [14]:
```
# how much they've increased by for each vehicle class
inc = veh_18 - veh_08
inc
```

Out[14]:
```
veh_class
SUV                     NaN
large car          4.900000
midsize car        6.282609
minivan            1.682353
pickup             2.312635
small SUV               NaN
small car          4.315948
special purpose         NaN
standard SUV            NaN
station wagon      5.162745
van                     NaN
Name: cmb_mpg, dtype: float64
```

In [15]:
```
# only plot the classes that exist in both years
inc.dropna(inplace=True)
plt.subplots(figsize=(8, 5))
plt.bar(inc.index, inc)
plt.title('Improvements in Fuel Economy from 2008 to 2018 by Vehicle Cla
ss')
plt.xlabel('Vehicle Class')
plt.ylabel('Increase in Average Combined MPG');
```



Q3: What are the characteristics of SmartWay vehicles? Have they changed over time?

We can analyze this by filtering each dataframe by SmartWay classification and exploring these datasets.

In [16]:
```
# smartway labels for 2008
df_08.smartway.unique()
```

Out[16]:
```
array(['no', 'yes'], dtype=object)
```

In [17]:
```
# get all smartway vehicles in 2008
smart_08 = df_08.query('smartway == "yes"')
```

In [18]:
```
# explore smartway vehicles in 2008
smart_08.describe()
```

Out[18]:

	displ	cyl	air_pollution_score	city_mpg	hwy_mpg	cmb_mpg	greenhou
count	380.000000	380.000000	380.000000	380.000000	380.000000	380.000000	
mean	2.602895	4.826316	7.365789	20.984211	28.413158	23.736842	
std	0.623436	1.002025	1.148195	3.442672	3.075194	3.060379	
min	1.300000	4.000000	6.000000	17.000000	22.000000	20.000000	
25%	2.275000	4.000000	7.000000	19.000000	26.000000	22.000000	
50%	2.400000	4.000000	7.000000	20.000000	28.000000	23.000000	
75%	3.000000	6.000000	7.000000	22.000000	30.000000	25.000000	
max	5.000000	8.000000	9.500000	48.000000	45.000000	46.000000	

Use what you've learned so for to further explore this dataset on 2008 smartway vehicles.

In [19]:
```
# smartway labels for 2018
df_18.smartway.unique()
```

Out[19]: `array(['No', 'Yes', 'Elite'], dtype=object)`

In [20]:
```
# get all smartway vehicles in 2018
smart_18 = df_18.query('smartway in ["Yes", "Elite"]')
```

In [21]:
```
smart_18.describe()
```

Out[21]:

	displ	cyl	air_pollution_score	city_mpg	hwy_mpg	cmb_mpg	greenhou
count	108.000000	108.000000	108.000000	108.000000	108.000000	108.000000	
mean	1.787963	3.935185	5.212963	34.907407	41.472222	37.361111	
std	0.408031	0.416329	1.798498	16.431982	13.095236	14.848429	
min	1.200000	3.000000	3.000000	25.000000	27.000000	26.000000	
25%	1.500000	4.000000	3.000000	28.000000	36.000000	31.000000	
50%	1.700000	4.000000	5.500000	28.500000	37.000000	32.000000	
75%	2.000000	4.000000	7.000000	31.250000	40.250000	35.000000	
max	3.500000	6.000000	7.000000	113.000000	99.000000	106.000000	

Use what you've learned so for to further explore this dataset on 2018 smartway vehicles.

Q4: What features are associated with better fuel economy?

You can explore trends between cmb_mpg and the other features in this dataset, or filter this dataset like in the previous question and explore the properties of that dataset. For example, you can select all vehicles that have the top 50% fuel economy ratings like this.

In [22]:
```
top_08 = df_08.query('cmb_mpg > cmb_mpg.mean()')
top_08.describe()
```

Out[22]:

	displ	cyl	air_pollution_score	city_mpg	hwy_mpg	cmb_mpg	greenhou
count	519.000000	519.000000	519.000000	519.000000	519.000000	519.000000	
mean	2.667823	4.890173	6.998073	20.317919	27.603083	22.992293	
std	0.665551	1.034856	1.159565	3.198257	3.051120	2.926371	
min	1.300000	4.000000	4.000000	17.000000	20.000000	20.000000	
25%	2.300000	4.000000	6.000000	18.000000	25.000000	21.000000	
50%	2.500000	4.000000	7.000000	20.000000	27.000000	22.000000	
75%	3.000000	6.000000	7.000000	21.000000	29.000000	24.000000	
max	6.000000	8.000000	9.500000	48.000000	45.000000	46.000000	

In [23]:
```
top_18 = df_18.query('cmb_mpg > cmb_mpg.mean()')
top_18.describe()
```

Out[23]:

	displ	cyl	air_pollution_score	city_mpg	hwy_mpg	cmb_mpg	greenhou
count	328.000000	328.000000	328.000000	328.000000	328.000000	328.000000	
mean	1.964329	4.021341	4.856707	27.472561	35.304878	30.411585	
std	0.398593	0.465477	1.860802	11.033692	9.024857	10.081539	
min	1.200000	3.000000	1.000000	21.000000	27.000000	25.000000	
25%	1.600000	4.000000	3.000000	23.000000	31.000000	26.000000	
50%	2.000000	4.000000	5.000000	25.000000	33.000000	28.000000	
75%	2.000000	4.000000	7.000000	28.000000	36.000000	31.000000	
max	3.500000	6.000000	7.000000	113.000000	99.000000	106.000000	

In [ ]:
```
```