Grad_505_HW_2

February 2, 2025

[1]:
```
from sklearn import datasets
import pandas as pd
import numpy as np

import seaborn as sns
import matplotlib.pyplot as plt
```

```
Matplotlib is building the font cache; this may take a moment.
```

[3]:
```
from sklearn import datasets
iris = datasets.load_iris()
```

[4]:
```
# Reuse IRIS procesing code to dataframe from last homework:

# Create a DataFrame with the feature data
df = pd.DataFrame(iris.data, columns=iris.feature_names)

# Add the target variable as a column
df['target'] = iris.target

# Optionally map the target numbers to target names
df['class'] = df['target'].map({i: name for i, name in enumerate(iris.
 ↪target_names)})

df.head()

# Note I used AI to help me manipulate the iris dictionary data into a␣
 ↪dataframe.
# I was having a hard time processing the data as I did not know I needed to␣
 ↪select the
# data, feature_names and target separately. I was trying to use pd.
 ↪DataFrame(iris)
```

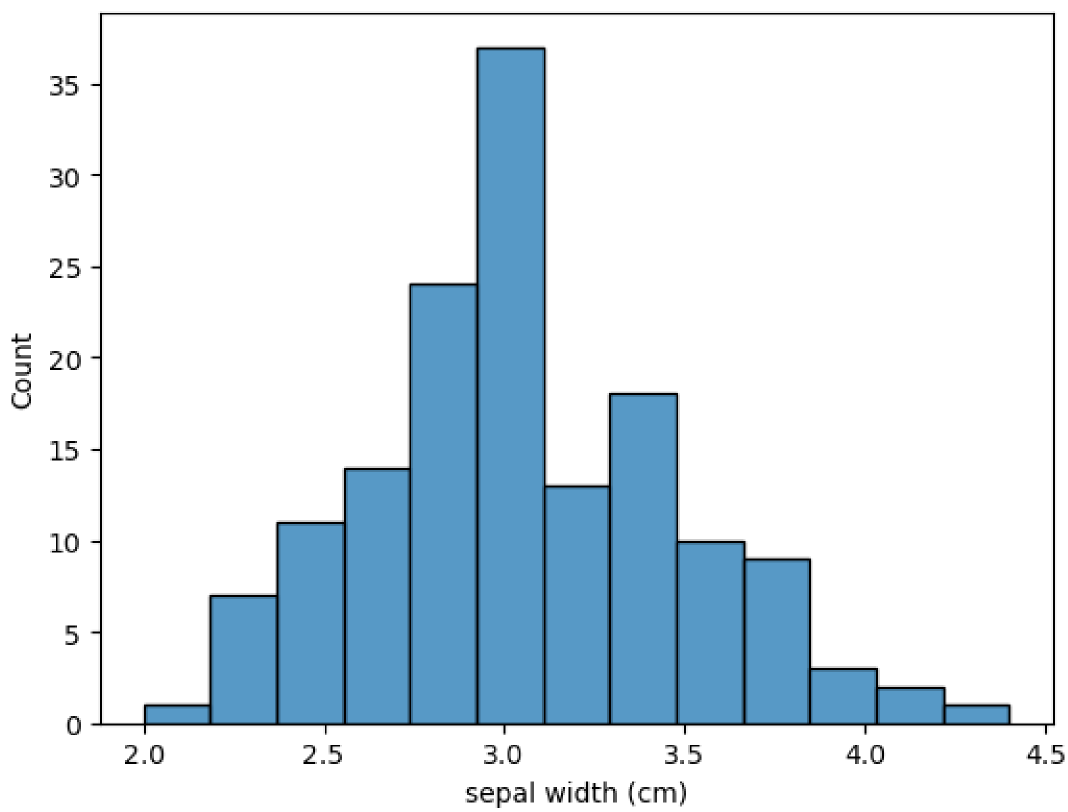
[4]:
```
   sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)  \
0                5.1               3.5                1.4               0.2
1                4.9               3.0                1.4               0.2
2                4.7               3.2                1.3               0.2
3                4.6               3.1                1.5               0.2
```

```
4                 5.0              3.6               1.4              0.2

   target   class
0       0  setosa
1       0  setosa
2       0  setosa
3       0  setosa
4       0  setosa
```

[5]:
```
sns.histplot(df['sepal width (cm)'])
```

[5]: <Axes: xlabel='sepal width (cm)', ylabel='Count'>



[ ]:
```
"""
I would expect the mean to be higher than the median because the
dataset appears to be slightly right skewed
"""
```

[6]:
```
df['sepal width (cm)'].mean()
```

[6]: 3.0573333333333337

[7]:
```
df['sepal width (cm)'].median()
```

[7]: 3.0

[20]:
```
np.percentile(df['sepal width (cm)'], [73])[0]

#To find the threshold where only 27% of the flowers have a hgiher sepal width
#we want to find the 73rd quantile
```

[20]: 3.3

[12]:
```
df.describe()
```

[12]:
```
       sepal length (cm)  sepal width (cm)  petal length (cm)  \
count         150.000000        150.000000         150.000000
mean            5.843333          3.057333           3.758000
std             0.828066          0.435866           1.765298
min             4.300000          2.000000           1.000000
25%             5.100000          2.800000           1.600000
50%             5.800000          3.000000           4.350000
75%             6.400000          3.300000           5.100000
max             7.900000          4.400000           6.900000

       petal width (cm)      target
count        150.000000  150.000000
mean           1.199333    1.000000
std            0.762238    0.819232
min            0.100000    0.000000
25%            0.300000    0.000000
50%            1.300000    1.000000
75%            1.800000    2.000000
max            2.500000    2.000000
```

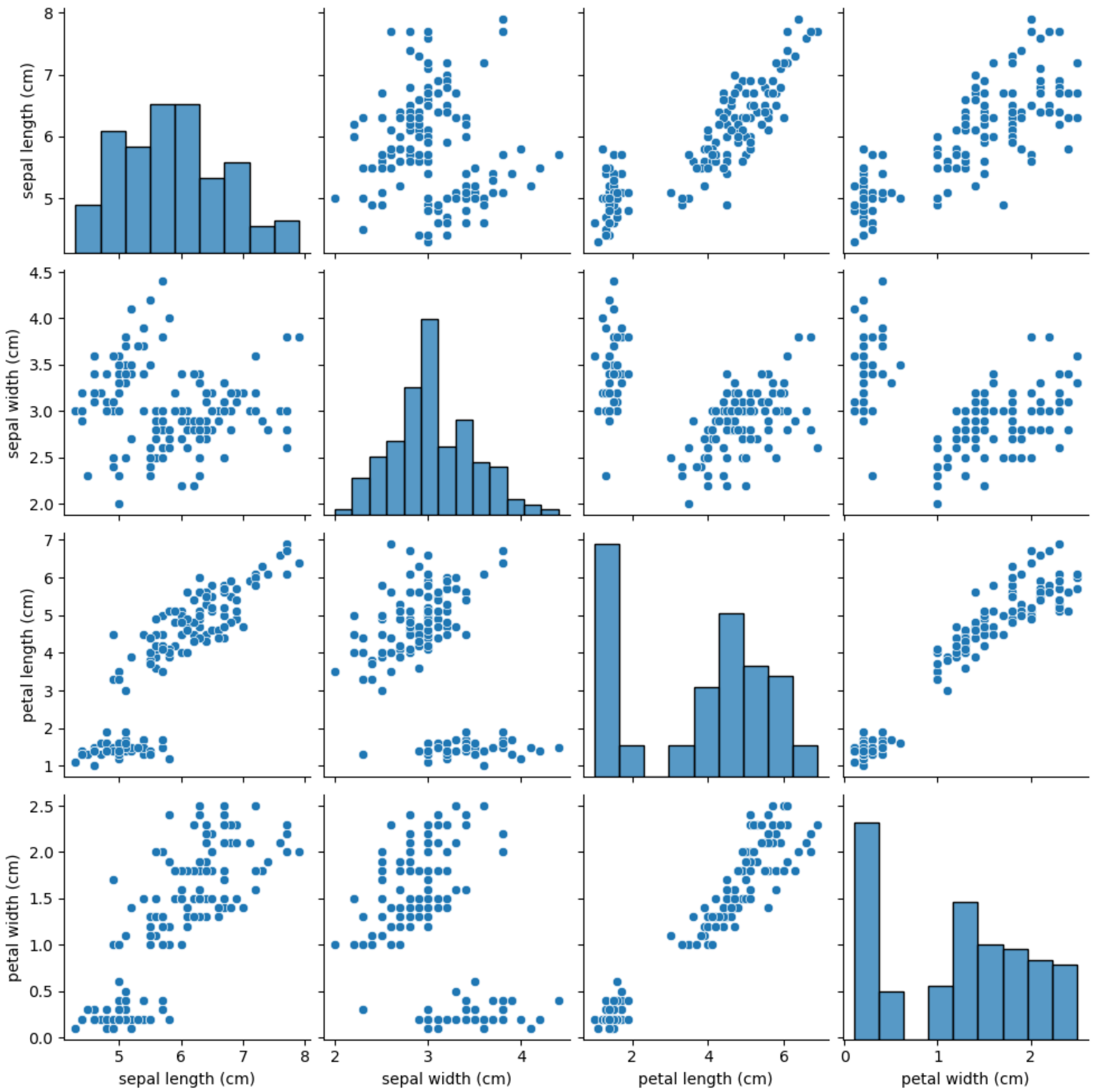
[16]:
```
plot_df = df.drop(['target','class'], axis =1)
```

[17]:
```
plot_df.columns
```

[17]:
```
Index(['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)',
       'petal width (cm)'],
      dtype='object')
```

[18]:
```
sns.pairplot(plot_df, markers='o')
```

[18]:
```
<seaborn.axisgrid.PairGrid at 0x1689a1910>
```



[19]:
```
"""
In the scatteplot matrix we see the 6 scatteplots to the left of the
histograms in the diagonal. Mirrored across the diagonal line we see
the same relationships but with x and y axis reversed.
"""
```

[19]:
```
'\nIn the scatteplot matrix we see the 6 scatteplots to the left of the
\nhistograms in the diagonal. Mirrored across the diagonal line we see\nthe same
relationships but with x and y axis reversed. \n'
```

[ ]:
```
"""
For Many of the realtionships there are signs that behavior is different or␣
↪clustered
```

```
amoung groups of the dataset likely the different classes. Just loooking at it␣
 ↪visually
without running the R^2 it looks like petal length and petal width have the␣
 ↪clearest
or strongest linear relationship. To me sepal length and sepal width appear to␣
 ↪have the most
scattered or weakest relationship.
"""
```

[23]:
```
data = { "weight": [4.17, 5.58, 5.18, 6.11, 4.50, 4.61, 5.17, 4.53, 5.33, 5.14,␣
 ↪4.81, 4.17,
                    4.41, 3.59, 5.87, 3.83, 6.03, 4.89, 4.32, 4.69, 6.31, 5.12,␣
 ↪5.54, 5.50,
                    5.37, 5.29, 4.92, 6.15, 5.80, 5.26], "group": ["ctrl"] * 10␣
 ↪+ ["trt1"] * 10 + ["trt2"] * 10}
PG = pd.DataFrame(data)
```

[24]:
```
PG.head()
```

[24]:

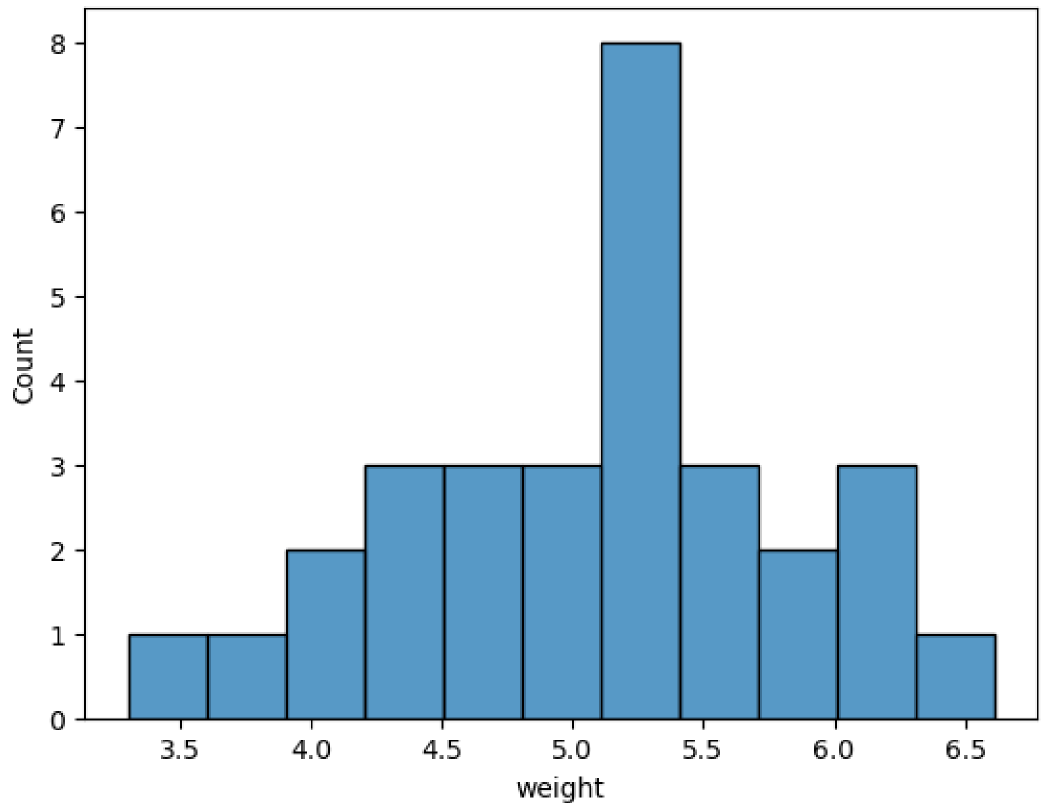
	weight	group
0	4.17	ctrl
1	5.58	ctrl
2	5.18	ctrl
3	6.11	ctrl
4	4.50	ctrl

[31]:
```
PG.group.value_counts()
```

[31]:
```
group
ctrl    10
trt1    10
trt2    10
Name: count, dtype: int64
```

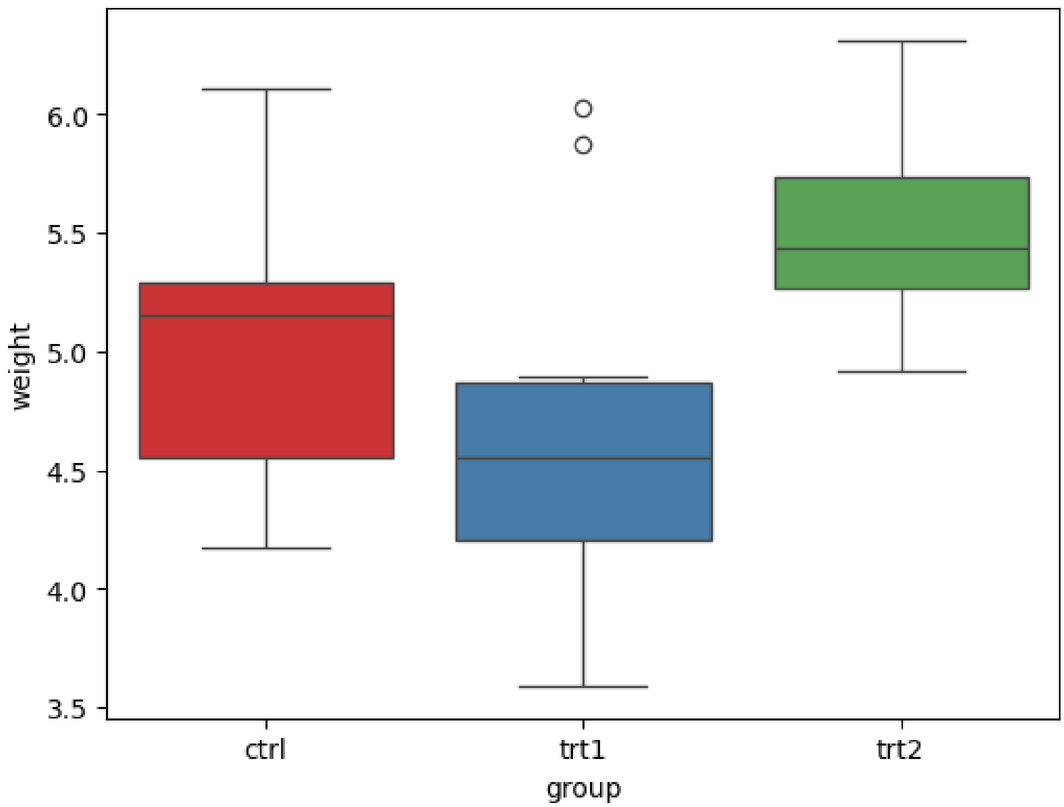
[30]:
```
sns.histplot(PG.weight, binwidth=.3, binrange=[3.3,PG.weight.max()+.3])
```

[30]:
```
<Axes: xlabel='weight', ylabel='Count'>
```



[44]:
```
sns.boxplot(x="group", y="weight", data=PG, hue="group", palette="Set1")
```

[44]: <Axes: xlabel='group', ylabel='weight'>



[ ]:
```
"""
It looks like nearly 100% of the trt1 weights are below the minimum trt2 weight
other than the two outlier values
"""
```

[49]:
```
PG.groupby("group").agg({"weight":["min","max"]
                        })
# checking the min and max for each group to see
#The max trt1 is above the min trt2
```

[49]:

	weight	
	min	max
group		
ctrl	4.17	6.11
trt1	3.59	6.03
trt2	4.92	6.31

[59]:
```
trt2_min = PG[PG["group"] == "trt2"].weight.min()
```

[60]:
```
# need to store the trt2_min in a variable for comparing
# to the trt1 weights
```

```
trt2_min
```

[60]: 4.92

[66]:
```
#create a separate series for the trt1 weights
#sum the count that are less than tt2_min
#divide by length to get the result as a percentage
#Looks like exactly 80% are less than the trt2 min


(PG[PG["group"] == "trt1"]["weight"] < trt2_min).sum() / len(PG[PG["group"] ==␣
↪"trt1"]["weight"])
```

[66]: 0.8

[67]:
```
above_df = PG[PG.weight > 5.5]
```

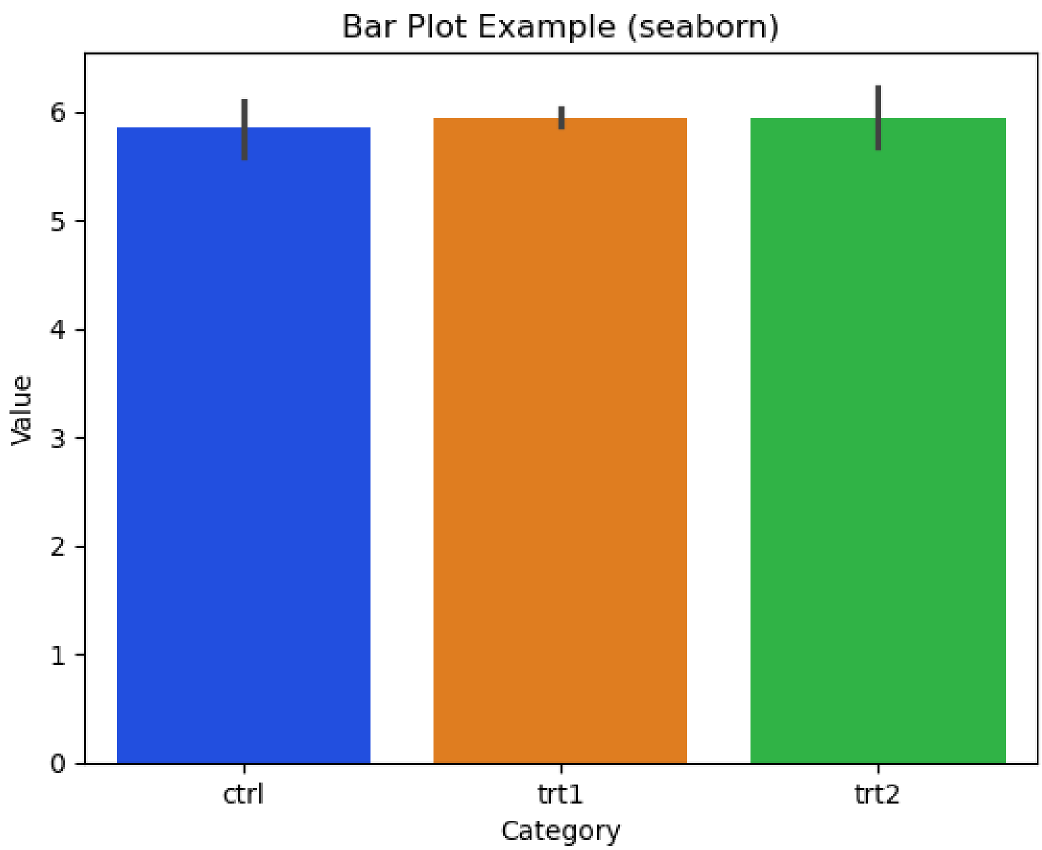
[68]:
```
above_df
```

[68]:

	weight	group
1	5.58	ctrl
3	6.11	ctrl
14	5.87	trt1
16	6.03	trt1
20	6.31	trt2
22	5.54	trt2
27	6.15	trt2
28	5.80	trt2

[81]:
```
#Reuse the code given in the lectures to create the Barplot for values
#using above_df we have already filtered for weights above 5.5
#with the basic bar plot we can see the maximum value for is group is about the␣
↪same

sns.barplot(x=above_df.group, y=above_df.weight, hue=above_df.group,␣
↪palette="bright")
plt.title("Bar Plot Example (seaborn)")
plt.xlabel("Category")
plt.ylabel("Value")
plt.show()
```

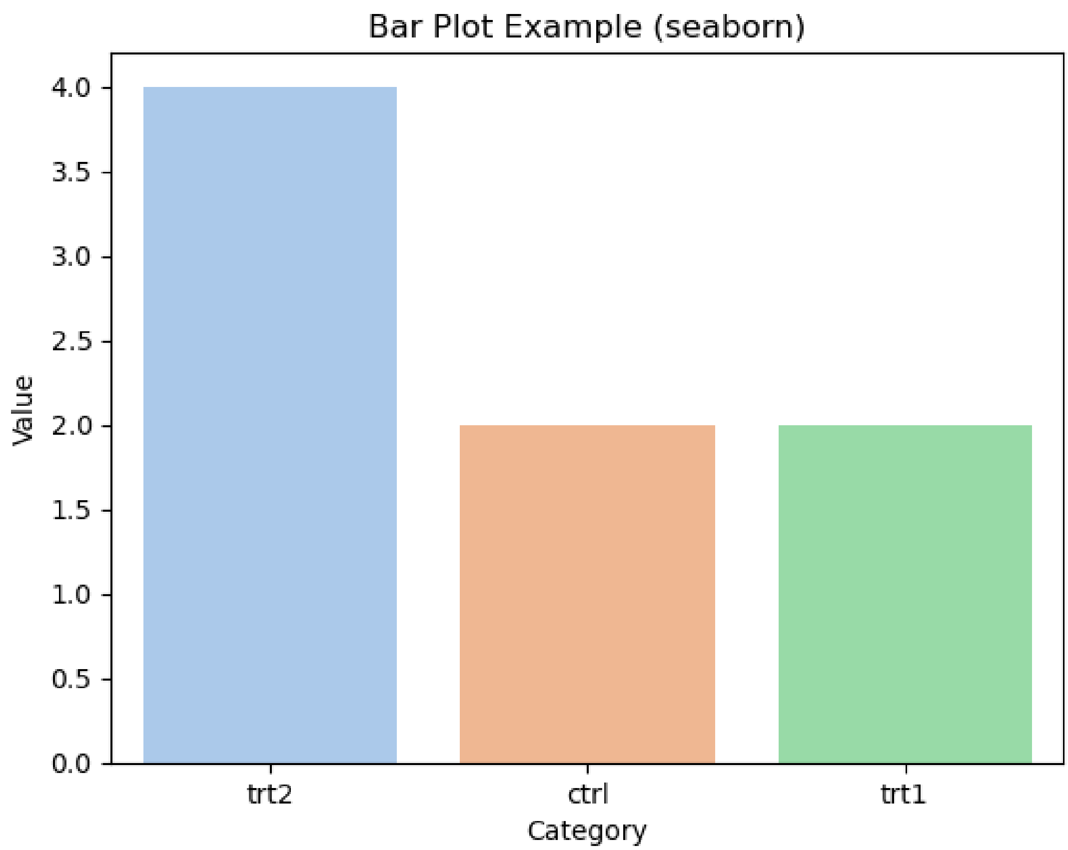


[79]:
```
#Reuse the code given in the lectures to create the Barplot for frequency␣
↪counts
#using above_df we have already filtered for weights above 5.5

# Data for the bar plot
frequency_table = above_df['group'].value_counts() # create frequency table␣
↪(equivlanet to table(cyl_cat))

labels_int = frequency_table.index.tolist() # returns the names, which are␣
↪integers (cylinders) in this case
labels = list(map(str, labels_int)) # convert those integers to strings
values = frequency_table.values

# Create the bar plot
sns.barplot(x=labels, y=values, hue=labels, palette="pastel")
plt.title("Bar Plot Example (seaborn)")
plt.xlabel("Category")
plt.ylabel("Value")
plt.show()
```


Bar Plot Example (seaborn)
Value
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
trt2
ctrl
trt1
Category

[ ]:

[ ]:

[ ]:

[ ]: