

Matplotlib Project

November 19, 2021

0.1 # Pymaceuticals Inc.

0.1.1 Background

Pymaceuticals Inc. is a burgeoning feaux pharmaceutical company based out of San Diego. Pymaceuticals specializes in anti-cancer pharmaceuticals. In its most recent efforts, it began screening for potential treatments for squamous cell carcinoma (SCC), a commonly occurring form of skin cancer.

I have been given access to the complete data from their most recent animal study. In this study, 250 mice identified with SCC tumor growth were treated through a variety of drug regimens. Over the course of 45 days, tumor development was observed and measured. The purpose of this study was to compare the performance of Pymaceuticals' drug of interest, Capomulin, versus the other treatment regimens. I have been tasked by the executive team to generate all of the tables and figures needed for the technical report of the study. The executive team also has asked for a top-level summary of the study results.

```
[1]: import matplotlib.pyplot as plt
import pandas as pd
import scipy.stats as st

mouse_metadata_path = "Mouse_metadata.csv"
study_results_path = "Study_results.csv"

mouse_metadata = pd.read_csv(mouse_metadata_path)
study_results = pd.read_csv(study_results_path)

study_data_complete = pd.merge(study_results, mouse_metadata, how="left", on="Mouse ID")

#pd.set_option("display.max_rows", None, "display.max_columns", None)
display(study_data_complete)
```

	Mouse ID	Timepoint	Tumor Volume (mm3)	Metastatic Sites	Drug Regimen	\
0	b128	0	45.000000	0	Capomulin	
1	f932	0	45.000000	0	Ketapril	
2	g107	0	45.000000	0	Ketapril	
3	a457	0	45.000000	0	Ketapril	
4	c819	0	45.000000	0	Ketapril	
...	

1888	r944	45	41.581521	2	Capomulin
1889	u364	45	31.023923	3	Capomulin
1890	p438	45	61.433892	1	Ceftamin
1891	x773	45	58.634971	4	Placebo
1892	b879	45	72.555239	2	Stelasyn

	Sex	Age_months	Weight (g)	
0	Female	9	22	
1	Male	15	29	
2	Female	2	29	
3	Female	11	30	
4	Male	21	25	
...	
1888	Male	12	25	
1889	Male	18	17	
1890	Female	11	26	
1891	Female	21	30	
1892	Female	4	26	

[1893 rows x 8 columns]

0.2 Summary Statistics

```
[2]: means = study_data_complete.groupby('Drug Regimen').mean()['Tumor Volume (mm3)']
medians = study_data_complete.groupby('Drug Regimen').median()['Tumor Volume\u2192(mm3)']
variances = study_data_complete.groupby('Drug Regimen').var()['Tumor Volume\u2192(mm3)']
sds = study_data_complete.groupby('Drug Regimen').std()['Tumor Volume (mm3)']
sems = study_data_complete.groupby('Drug Regimen').sem()['Tumor Volume (mm3)']
summary_table = pd.DataFrame({'Mean Tumor Volume':means,
                               'Median Tumor Volume':medians,
                               'Tumor Volume Variance':variances,
                               'Tumor Volume Std. Dev.':sds,
                               'Tumor Volume Std. Err.':sems})
summary_table
```

Drug Regimen	Mean Tumor Volume	Median Tumor Volume	Tumor Volume Variance	\
Capomulin	40.675741	41.557809	24.947764	
Ceftamin	52.591172	51.776157	39.290177	
Infubinol	52.884795	51.820584	43.128684	
Ketapril	55.235638	53.698743	68.553577	
Naftisol	54.331565	52.509285	66.173479	
Placebo	54.033581	52.288934	61.168083	
Propriova	52.322552	50.854632	42.351070	
Ramicane	40.216745	40.673236	23.486704	

Stelasyn	54.233149	52.431737	59.450562
Zoniferol	53.236507	51.818479	48.533355

Drug Regimen	Tumor Volume	Std. Dev.	Tumor Volume	Std. Err.
Capomulin	4.994774		0.329346	
Ceftamin	6.268188		0.469821	
Infubinol	6.567243		0.492236	
Ketapril	8.279709		0.603860	
Naftisol	8.134708		0.596466	
Placebo	7.821003		0.581331	
Propriova	6.507770		0.512884	
Ramicane	4.846308		0.320955	
Stelasyn	7.710419		0.573111	
Zoniferol	6.966589		0.516398	

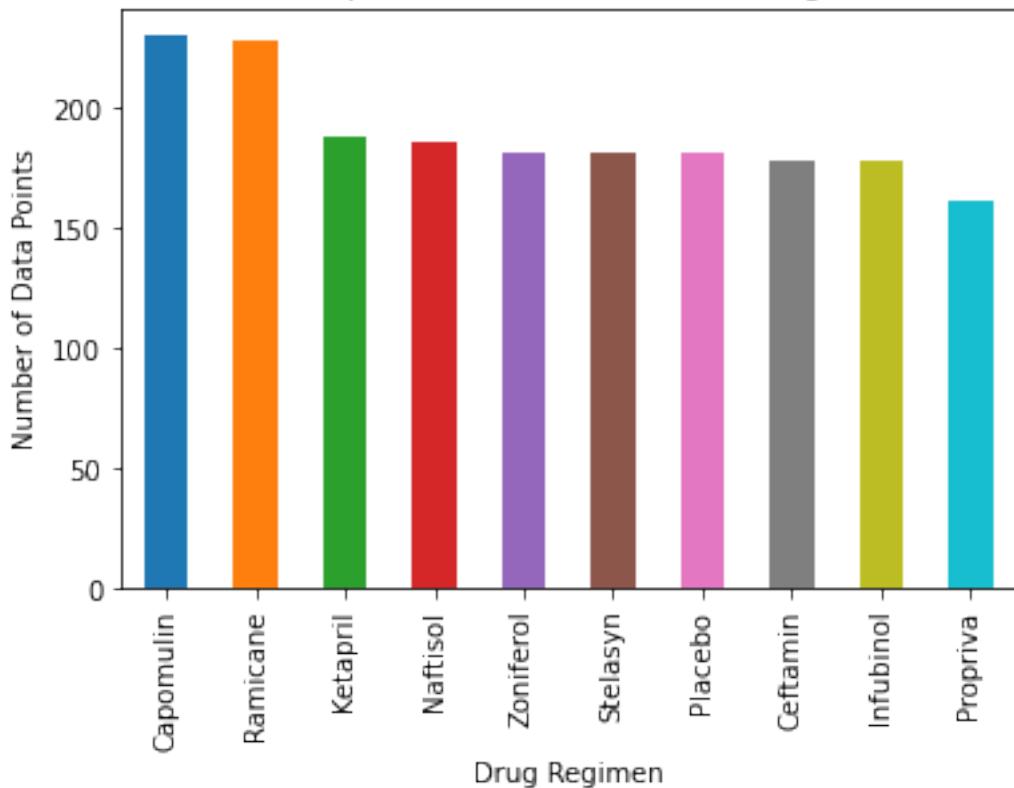
```
[3]: # Alternate method
summary_table = study_data_complete.groupby("Drug Regimen").agg({"Tumor Volume": ("mm3"):[ "mean", "median", "var", "std", "sem"]})
summary_table
```

Drug Regimen	Tumor Volume (mm3)	mean	median	var	std	sem
Capomulin	40.675741	41.557809	24.947764	4.994774	0.329346	
Ceftamin	52.591172	51.776157	39.290177	6.268188	0.469821	
Infubinol	52.884795	51.820584	43.128684	6.567243	0.492236	
Ketapril	55.235638	53.698743	68.553577	8.279709	0.603860	
Naftisol	54.331565	52.509285	66.173479	8.134708	0.596466	
Placebo	54.033581	52.288934	61.168083	7.821003	0.581331	
Propriova	52.322552	50.854632	42.351070	6.507770	0.512884	
Ramicane	40.216745	40.673236	23.486704	4.846308	0.320955	
Stelasyn	54.233149	52.431737	59.450562	7.710419	0.573111	
Zoniferol	53.236507	51.818479	48.533355	6.966589	0.516398	

0.3 Bar and Pie Charts

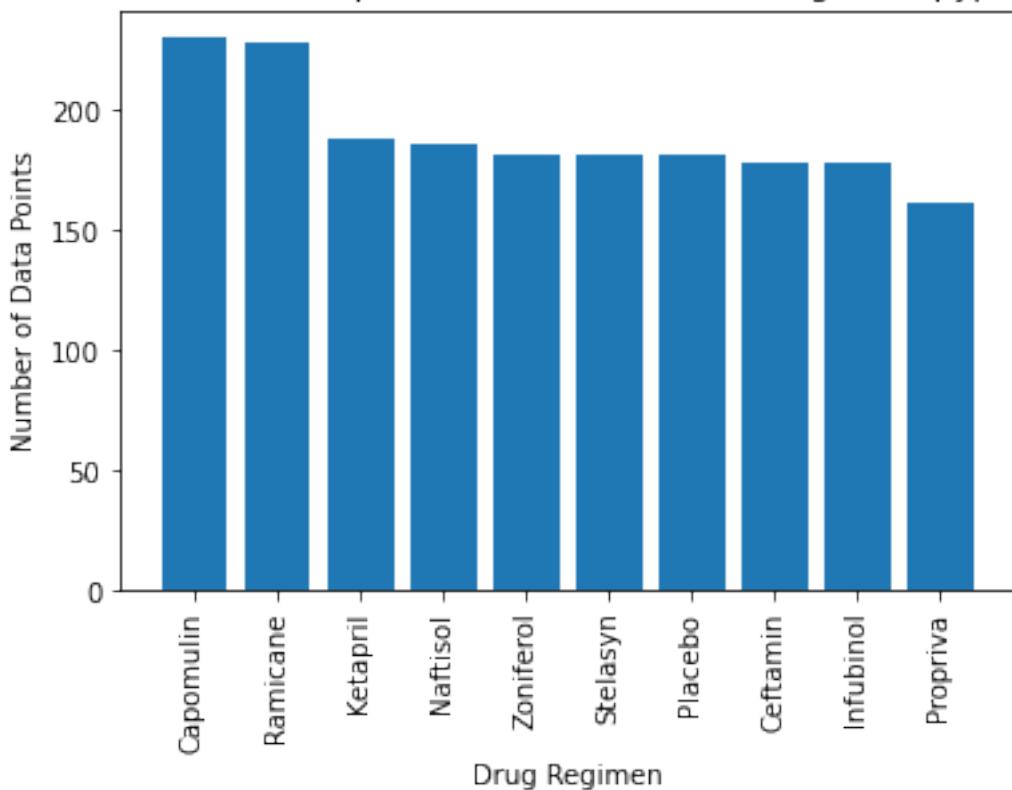
```
[4]: counts = study_data_complete['Drug Regimen'].value_counts()
tableau_colors = ['tab:blue','tab:orange','tab:green','tab:red','tab:purple','tab:brown','tab:pink','tab:gray','tab:olive','tab:cyan']
counts.plot(kind="bar", color=tableau_colors)
plt.title("Number of data points for each treatment regimen (Pandas)")
plt.xlabel("Drug Regimen")
plt.xticks(rotation=90)
plt.ylabel("Number of Data Points")
plt.show()
```

Number of data points for each treatment regimen (Pandas)



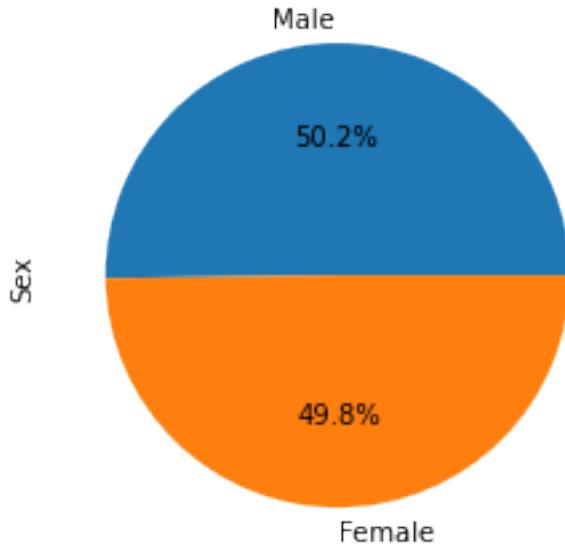
```
[5]: counts = study_data_complete['Drug Regimen'].value_counts()
plt.bar(counts.index.values,counts.values)
plt.title("Number of data points for each treatment regimen (pyplot)")
plt.xlabel("Drug Regimen")
plt.xticks(rotation=90)
plt.ylabel("Number of Data Points")
plt.show()
```

Number of data points for each treatment regimen (pyplot)



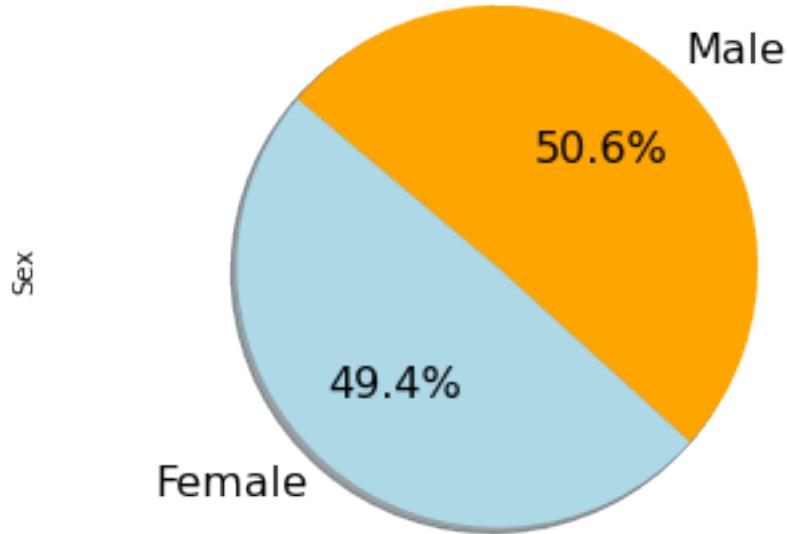
```
[6]: counts = mouse_metadata.Sex.value_counts()
counts.plot(kind="pie", autopct='%.1f%%')
# plt.pie(counts.values, labels=counts.index.values, autopct='%.1f%%')
plt.title("Distribution of female versus male mice (pandas)")
plt.show()
```

Distribution of female versus male mice (pandas)



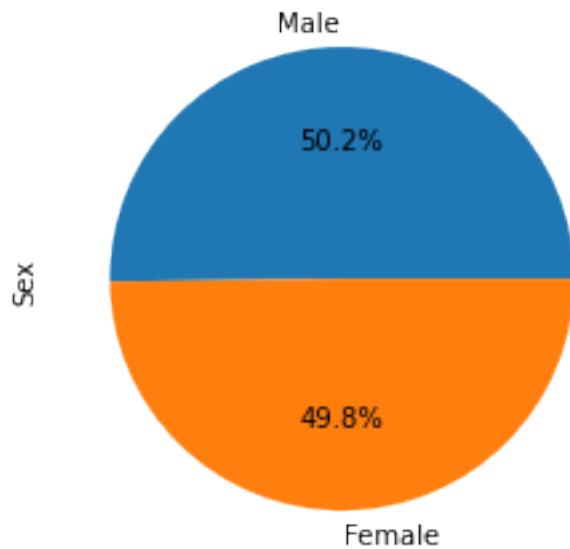
```
[7]: # Another way
gendergroup = study_data_complete.groupby('Sex')
gendercount = pd.DataFrame(gendergroup['Sex'].count())
gendercount.plot(kind='pie', y='Sex', title="Distribution of Female vs Male Mice", startangle=140, autopct='%1.1f%%', shadow=True, fontsize=16, colors=["lightblue", "orange"], legend=False)
plt.axis("equal")
plt.title("Distribution of female versus male mice (pandas)")
plt.show()
```

Distribution of female versus male mice (pandas)



```
[8]: counts = mouse_metadata.Sex.value_counts()
plt.pie(counts.values,labels=counts.index.values,autopct='%.1f%%')
plt.ylabel("Sex")
plt.title("Distribution of female versus male mice (pyplot)")
plt.show()
```

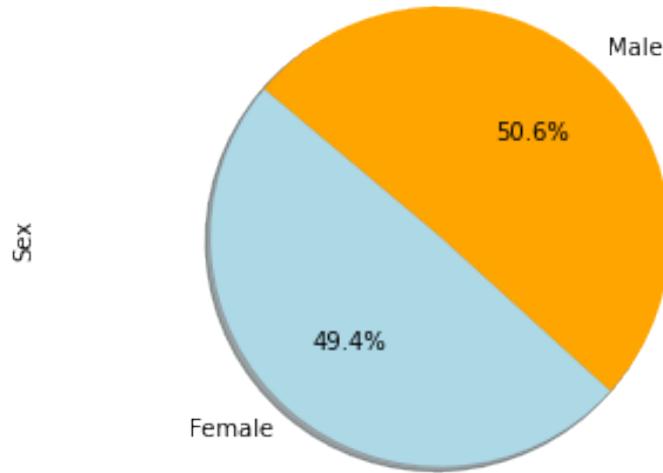
Distribution of female versus male mice (pyplot)



```
[9]: # Another way
genders = list(gendercount.index.values)
gendercounts = gendercount['Sex']
colors = ["lightblue", "orange"]
plt.pie(gendercounts, labels=genders, colors=colors, autopct="%1.1f%%",  

    shadow=True, startangle=140)
plt.rcParams['font.size'] = 16
plt.title("Distribution of female versus male mice (pyplot)")
plt.ylabel("Sex")
plt.axis("equal")
plt.show()
```

Distribution of female versus male mice (pyplot)



0.4 Quartiles, Outliers and Boxplots

```
[10]: # IQR and quantitative determination of any potential outliers

# Create a list of the four drugs to examine
druglist = ['Capomulin', 'Ramicane', 'Infubinol', 'Ceftamin']

# Slice the original combined_data dataframe using the list of four drugs
drugs = study_data_complete[study_data_complete['Drug Regimen'].isin(druglist)]

# Groupby 'Mouse ID'
finaltumor = drugs.groupby(['Drug Regimen', 'Mouse ID']).  

    agg(finaltumorsize=('Tumor Volume (mm3)', lambda x: x.iloc[-1])).round(3)
```

```

# Reshape dataframe of the final tumor volume of each mouse across four of the most promising treatment regimens
finaltumornew = finaltumor.stack(level=0).unstack(level=0)

counter = 0
# Quartile calculations for each drug
for drug in druglist:
    quartiles = finaltumornew[drug].quantile([.25,.5,.75]).round(2)
    lowerq = quartiles[0.25].round(2)
    upperq = quartiles[0.75].round(2)
    iqr = round(upperq-lowerq,2)
    lower_bound = round(lowerq - (1.5*iqr),2)
    upper_bound = round(upperq + (1.5*iqr),2)

    if counter == 0:
        print(f"-----")
    print(f"{drug} IQR data is:")
    print(f"The lower quartile of {drug} is: {lowerq}")
    print(f"The upper quartile of {drug} is: {upperq}")
    print(f"The interquartile range of {drug} is: {iqr}")
    print(f"The the median of {drug} is: {quartiles[0.5]} ")
    print(f"Values below {lower_bound} for {drug} could be outliers.")
    print(f"Values above {upper_bound} for {drug} could be outliers.")
    print(f"-----")
    counter += 1

```

Capomulin IQR data is:

The lower quartile of Capomulin is: 32.38
 The upper quartile of Capomulin is: 40.16
 The interquartile range of Capomulin is: 7.78
 The the median of Capomulin is: 38.12
 Values below 20.71 for Capomulin could be outliers.
 Values above 51.83 for Capomulin could be outliers.

Ramicane IQR data is:

The lower quartile of Ramicane is: 31.56
 The upper quartile of Ramicane is: 40.66
 The interquartile range of Ramicane is: 9.1
 The the median of Ramicane is: 36.56
 Values below 17.91 for Ramicane could be outliers.
 Values above 54.31 for Ramicane could be outliers.

Infubinol IQR data is:

The lower quartile of Infubinol is: 54.05
 The upper quartile of Infubinol is: 65.53
 The interquartile range of Infubinol is: 11.48

```
The the median of Infubinol is: 60.16
Values below 36.83 for Infubinol could be outliers.
Values above 82.75 for Infubinol could be outliers.
```

```
Ceftamin IQR data is:
The lower quartile of Ceftamin is: 48.72
The upper quartile of Ceftamin is: 64.3
The interquartile range of Ceftamin is: 15.58
The the median of Ceftamin is: 59.85
Values below 25.35 for Ceftamin could be outliers.
Values above 87.67 for Ceftamin could be outliers.
```

```
[11]: # Another way
```

```
# Start by getting the last (greatest) timepoint for each mouse
max_tumor = study_data_complete.groupby(["Mouse ID"]).max()
max_tumor = max_tumor.reset_index()

# Merge this group df with the original dataframe to get the tumor volume at
# the last timepoint
merged_data = max_tumor[['Mouse ID','Timepoint']].
    merge(study_data_complete, on=['Mouse ID', 'Timepoint'], how="left")

capomulin = merged_data.loc[merged_data["Drug Regimen"] == "Capomulin"]['Tumor
    Volume (mm3)']
ramicane = merged_data.loc[merged_data["Drug Regimen"] == "Ramicane"]['Tumor
    Volume (mm3)']
infubinol = merged_data.loc[merged_data["Drug Regimen"] == "Infubinol"]['Tumor
    Volume (mm3)']
ceftamin = merged_data.loc[merged_data["Drug Regimen"] == "Ceftamin"]['Tumor
    Volume (mm3)']
```

```
[12]: # Quantitatively determine capomulin outliers
```

```
cap_quartiles = capomulin.quantile([.25,.5,.75])
cap_lowerq = cap_quartiles[0.25]
cap_upperq = cap_quartiles[0.75]
cap_iqr = cap_upperq-cap_lowerq
cap_lower_bound = cap_lowerq - (1.5*cap_iqr)
cap_upper_bound = cap_upperq + (1.5*cap_iqr)
print(f"Capomulin potential outliers: {capomulin.loc[(capomulin <
    cap_lower_bound) | (capomulin > cap_upper_bound)]}")
```

```
Capomulin potential outliers: Series([], Name: Tumor Volume (mm3), dtype:
float64)
```

```
[13]: # Quantitatively determine ramicane outliers
ram_quartiles = ramicane.quantile([.25,.5,.75])
ram_lowerq = ram_quartiles[0.25]
ram_upperq = ram_quartiles[0.75]
ram_iqr = ram_upperq-ram_lowerq
ram_lower_bound = ram_lowerq - (1.5*ram_iqr)
ram_upper_bound = ram_upperq + (1.5*ram_iqr)
print(f"Ramicane potential outliers: {ramicane.loc[(ramicane < ram_lower_bound) | (ramicane > ram_upper_bound)]}")
```

Ramicane potential outliers: Series([], Name: Tumor Volume (mm3), dtype: float64)

```
[14]: # Quantitatively determine infubinol outliers
# The only one with outliers
inf_quartiles = infubinol.quantile([.25,.5,.75])
inf_lowerq = inf_quartiles[0.25]
inf_upperq = inf_quartiles[0.75]
inf_iqr = inf_upperq-inf_lowerq
inf_lower_bound = inf_lowerq - (1.5*inf_iqr)
inf_upper_bound = inf_upperq + (1.5*inf_iqr)
print(f"Infubinol potential outliers: {infubinol.loc[(infubinol < inf_lower_bound) | (infubinol > inf_upper_bound)]}")
```

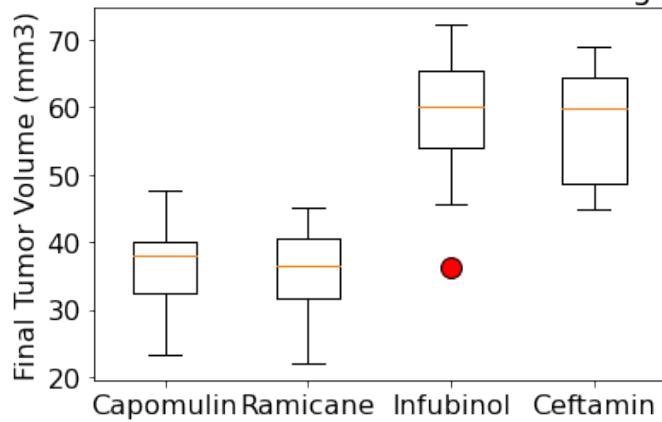
Infubinol potential outliers: 31 36.321346
Name: Tumor Volume (mm3), dtype: float64

```
[15]: # Quantitatively determine ceftamin outliers
cef_quartiles = ceftamin.quantile([.25,.5,.75])
cef_lowerq = cef_quartiles[0.25]
cef_upperq = cef_quartiles[0.75]
cef_iqr = cef_upperq-cef_lowerq
cef_lower_bound = cef_lowerq - (1.5*cef_iqr)
cef_upper_bound = cef_upperq + (1.5*cef_iqr)
print(f"Ceftamin potential outliers: {ceftamin.loc[(ceftamin < cef_lower_bound) | (ceftamin > cef_upper_bound)]}")
```

Ceftamin potential outliers: Series([], Name: Tumor Volume (mm3), dtype: float64)

```
[16]: orange_out = dict(markerfacecolor='red',markersize=12)
plt.boxplot([capomulin,ramicane,infubinol,ceftamin],labels=['Capomulin','Ramicane','Infubinol',
plt.ylabel('Final Tumor Volume (mm3)')
plt.title('Final tumor volume of each mouse across four regimens of interest')
plt.show()
```

Final tumor volume of each mouse across four regimens of interest

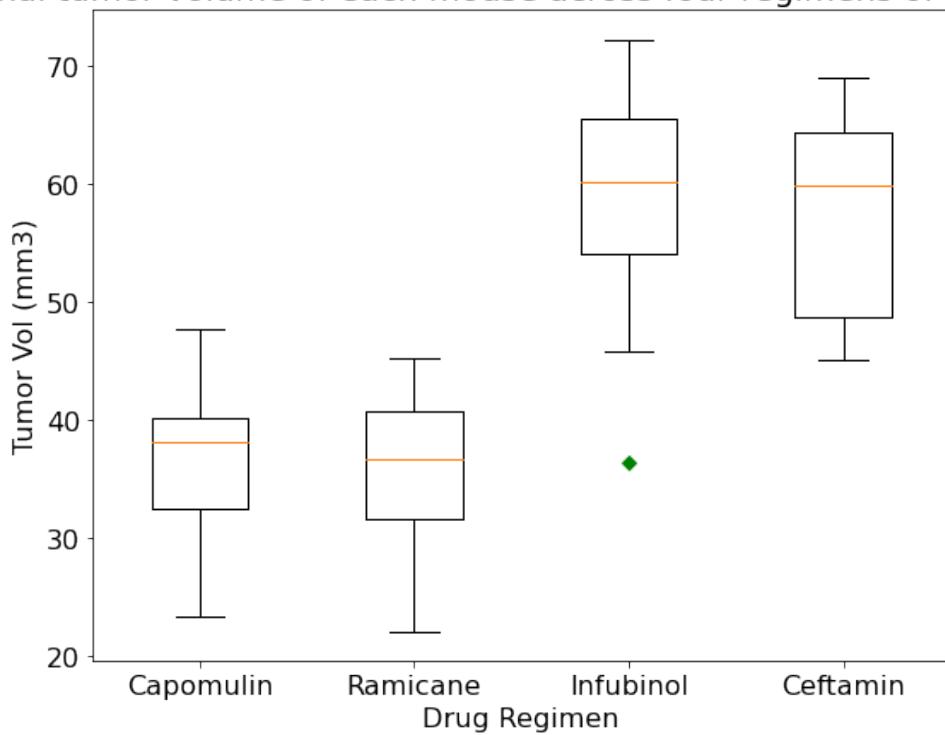


```
[17]: # Another way
boxplotlist = []

for drug in druglist:
    boxplotlist.append(list(finaltumornew[drug].dropna()))

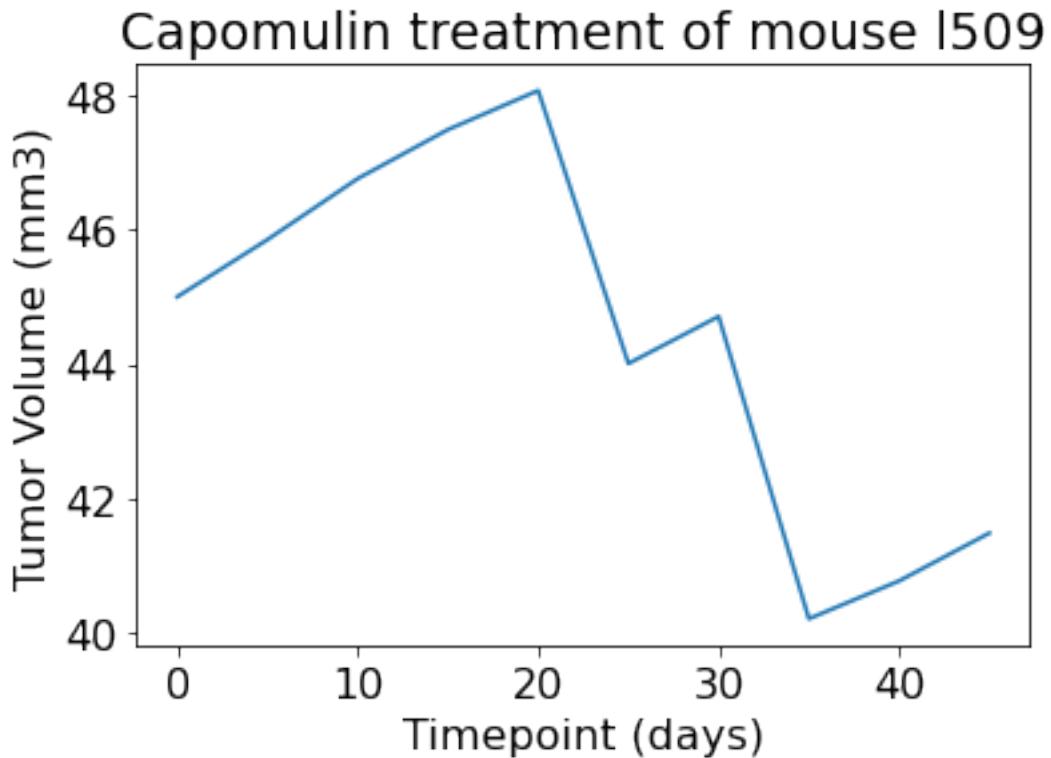
fig, ax = plt.subplots(figsize=(9,7))
ax.set_title('Final tumor volume of each mouse across four regimens of interest')
ax.set_xlabel('Drug Regimen')
ax.set_ylabel('Tumor Vol (mm3)')
ax.boxplot(boxplotlist,notch=0,sym='gD')
plt.xticks([1,2,3,4],druglist)
plt.show()
```

Final tumor volume of each mouse across four regimens of interest

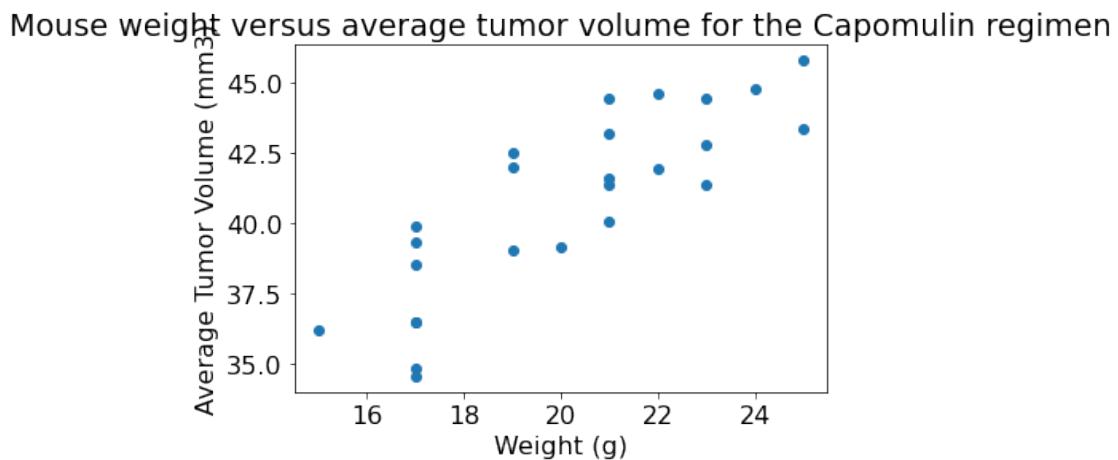


0.5 Line and Scatter Plots

```
[18]: capomulin_table = study_data_complete.loc[study_data_complete['Drug Regimen']  
    ↪== "Capomulin"]  
mousedata = capomulin_table.loc[capomulin_table['Mouse ID']== '1509']  
plt.plot(mousedata['Timepoint'],mousedata['Tumor Volume (mm3)'])  
plt.xlabel('Timepoint (days)')  
plt.ylabel('Tumor Volume (mm3)')  
plt.title('Capomulin treatment of mouse 1509')  
plt.show()
```



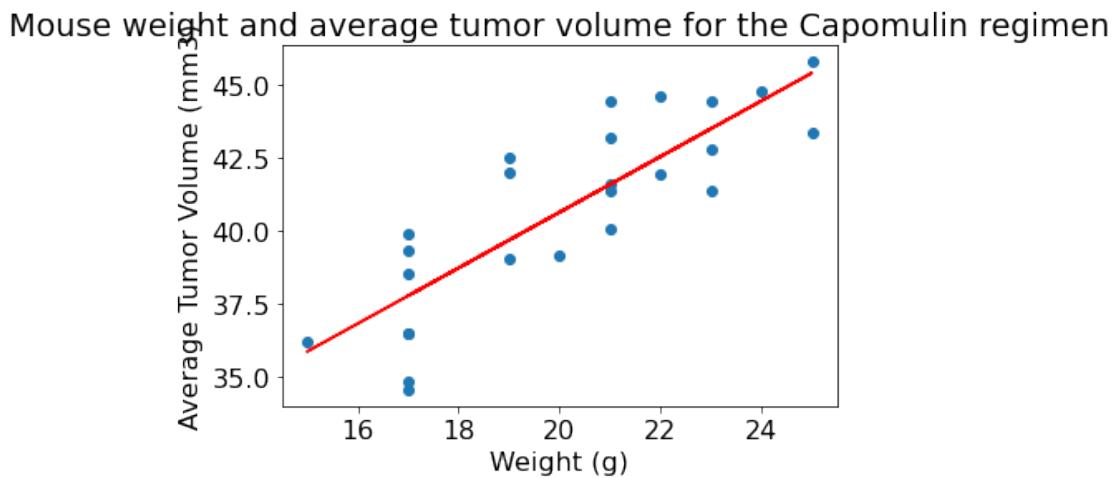
```
[19]: capomulin_average = capomulin_table.groupby(['Mouse ID']).mean()
plt.title('Mouse weight versus average tumor volume for the Capomulin regimen')
plt.scatter(capomulin_average['Weight (g)'],capomulin_average['Tumor Volume ↗(mm3)'])
plt.xlabel('Weight (g)')
plt.ylabel('Average Tumor Volume (mm3)')
plt.show()
```



0.6 Correlation and Regression

```
[20]: corr=round(st.pearsonr(capomulin_average['Weight (g)'],capomulin_average['Tumor Volume (mm3)'])[0],2)
print(f"The correlation between mouse weight and the average tumor volume is {corr}")
model = st.linregress(capomulin_average['Weight (g)'],capomulin_average['Tumor Volume (mm3)'])
y_values = capomulin_average['Weight (g)']*model[0]+model[1]
plt.scatter(capomulin_average['Weight (g)'],capomulin_average['Tumor Volume (mm3)'])
plt.plot(capomulin_average['Weight (g)'],y_values,color="red")
plt.title('Mouse weight and average tumor volume for the Capomulin regimen')
plt.xlabel('Weight (g)')
plt.ylabel('Average Tumor Volume (mm3)')
plt.show()
```

The correlation between mouse weight and the average tumor volume is 0.84



```
[21]: # Another way
# Groupby Mouse ID and get weight and mean of tumor volume
capmouse = capomulin_table.groupby(['Mouse ID']).agg(MouseWeight=('Weight (g)', np.mean), TumorMean=('Tumor Volume (mm3)', np.mean)).round(3)
correlation = st.pearsonr(capmouse['MouseWeight'],capmouse['TumorMean'])
print(f"The correlation between both factors is {round(correlation[0],2)}")

# Print out the r-squared value
from scipy.stats import linregress
x_values = capmouse['MouseWeight']
```

```

y_values = capmouse['TumorMean']
(slope, intercept, rvalue, pvalue, stderr) = linregress(x_values, y_values)
regress_values = x_values * slope + intercept
line_eq = f'y = {str(round(slope,2))}x + {str(round(intercept,2))}'

plt.scatter(x_values,y_values)
plt.plot(x_values,regress_values,"r-")
plt.annotate(line_eq,(17,37),fontsize=15,color="black")
plt.title("Mouse Weight vs. Avg. Tumor Volume")
plt.xlabel("Mouse weight (g)")
plt.ylabel("Tumor Volume (mm3)")

print(f"The r-squared is: {rvalue}")
print(f"The equation of the regression line is: {line_eq}")

plt.show()

```

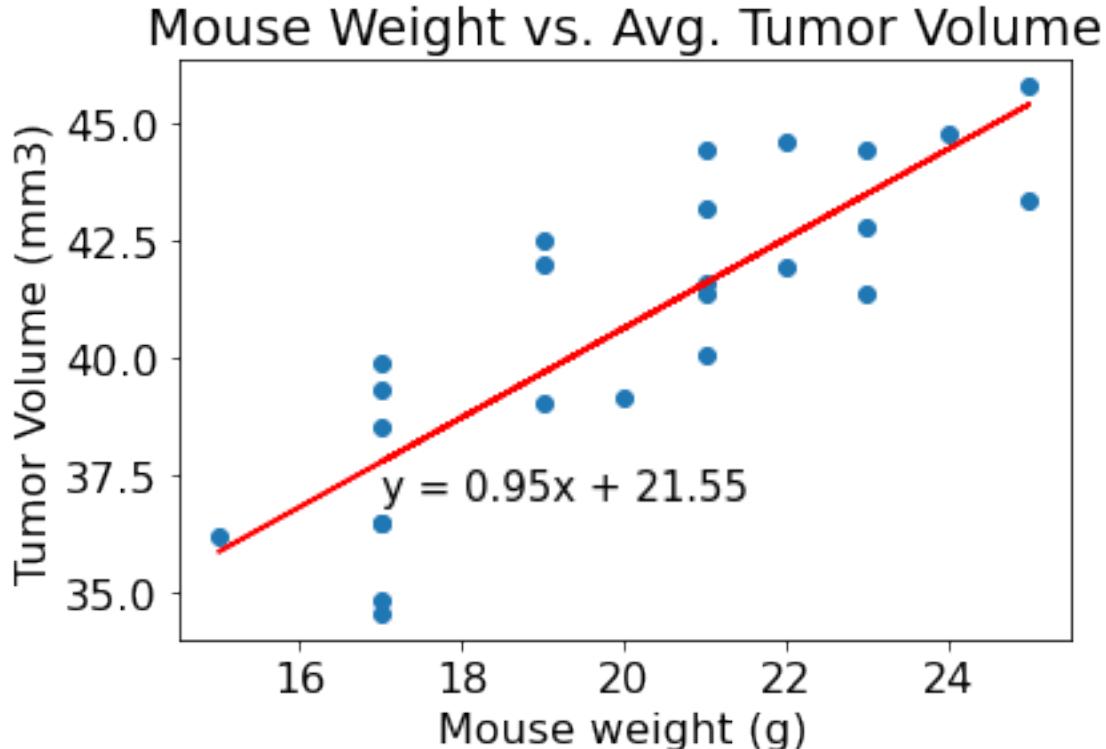
<IPython.core.display.Javascript object>

<IPython.core.display.Javascript object>

The correlation between both factors is 0.84

The r-squared is: 0.8419461020261079

The equation of the regression line is: $y = 0.95x + 21.55$

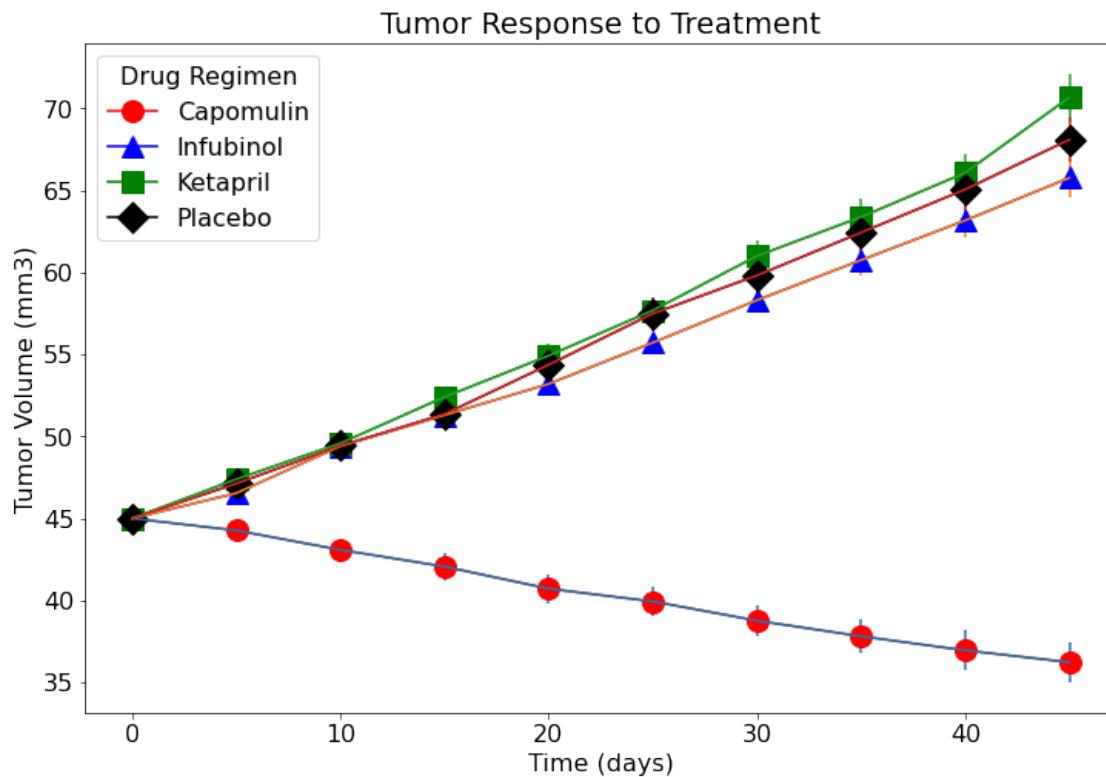


```
[22]: druglist2 = ['Capomulin', 'Infubinol', 'Ketapril', 'Placebo']
drugs2 = study_data_complete[study_data_complete['Drug Regimen'].
    ↪isin(druglist2)]
tumor_means = drugs2.groupby(['Timepoint', 'Drug Regimen'], ↴
    ↪as_index=False)['Tumor Volume (mm3)'].mean()
tumor_means = tumor_means.pivot(index='Timepoint', columns='Drug Regimen', ↴
    ↪values='Tumor Volume (mm3)')

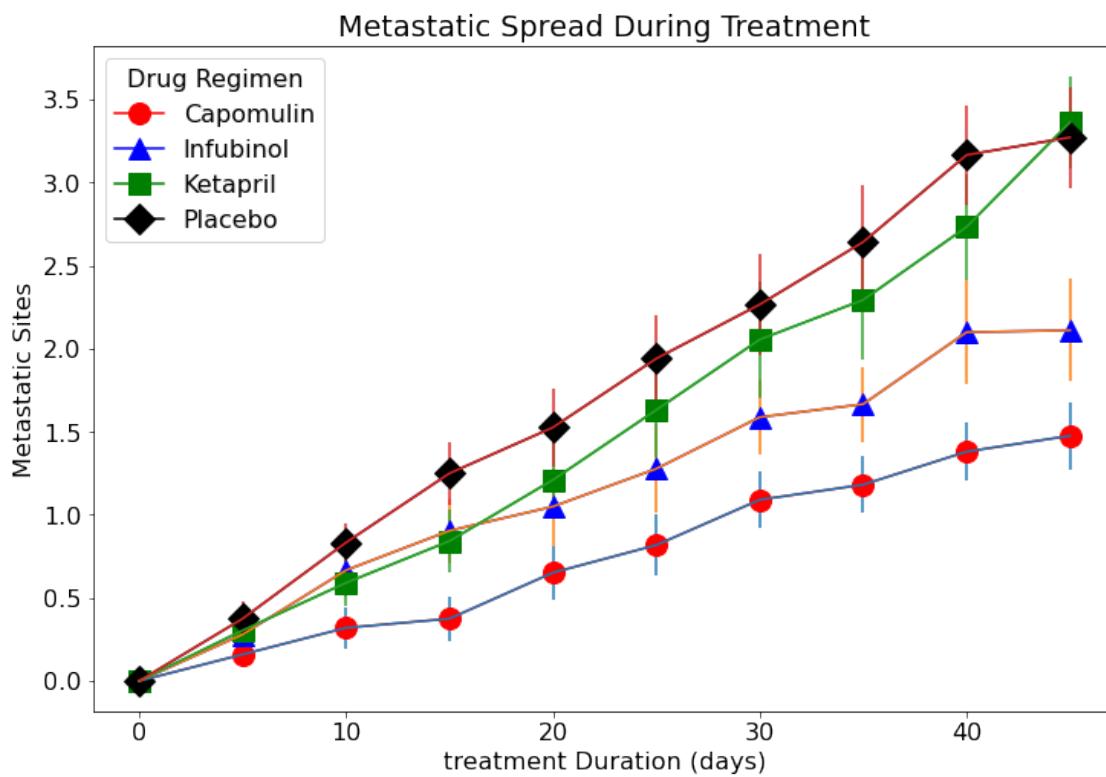
tumor_errs = drugs2.groupby(['Timepoint', 'Drug Regimen'], ↴
    ↪as_index=False)['Tumor Volume (mm3)'].sem()
tumor_errs = tumor_errs.pivot(index='Timepoint', columns='Drug Regimen', ↴
    ↪values='Tumor Volume (mm3)')

ax = tumor_means.plot(figsize=(12,8), yerr = tumor_errs, legend = False)
ax.set_prop_cycle(None)

tumor_means.plot(figsize=(12,8), style=['ro-', 'b^-', 'gs-', 'kD-'], ↴
    ↪markersize=14, ax = ax)
plt.title('Tumor Response to Treatment')
plt.xlabel('Time (days)')
plt.ylabel('Tumor Volume (mm3)')
plt.show()
```



```
[23]: met_means = drugs2.groupby(['Timepoint', 'Drug Regimen'],  
    ↪as_index=False)[['Metastatic Sites']].mean()  
met_means = met_means.pivot(index='Timepoint', columns='Drug Regimen',  
    ↪values='Metastatic Sites')  
  
met_errs = drugs2.groupby(['Timepoint', 'Drug Regimen'],  
    ↪as_index=False)[['Metastatic Sites']].sem()  
met_errs = met_errs.pivot(index='Timepoint', columns='Drug Regimen',  
    ↪values='Metastatic Sites')  
ax = met_means.plot(figsize=(12,8), yerr = met_errs, legend = False)  
ax.set_prop_cycle(None)  
  
met_means.plot(figsize=(12,8), style=['ro-', 'b^-', 'gs-', 'kD-'],  
    ↪markersize=14, ax = ax)  
plt.title('Metastatic Spread During Treatment')  
plt.xlabel('treatment Duration (days)')  
plt.ylabel('Metastatic Sites')  
plt.show()
```



```
[24]: # Dropping duplicate mice  
drop_dup_mouse_id = study_results.loc[study_results.duplicated(subset=['Mouse_ID',  
    ↪'Timepoint',]), 'Mouse ID'].unique()
```

```

clean_clinical_trial_df = study_results[study_results['Mouse ID'].
    ↪isin(drop_dup_mouse_id)==False]
clean_mouse_df = mouse_metadata[mouse_metadata['Mouse ID'].
    ↪isin(drop_dup_mouse_id)==False]
combined_data = pd.merge(clean_clinical_trial_df, clean_mouse_df, on = "MouseID")

# Sorting by Timepoint
sort_by_time = combined_data.sort_values("Timepoint", ascending= True)
all_sort_by_time = sort_by_time.reset_index(drop=True)
all_sort_by_time.head()

```

[24]:

	Mouse ID	Timepoint	Tumor Volume (mm3)	Metastatic Sites	Drug Regimen	\
0	b128	0	45.0	0	Capomulin	
1	v409	0	45.0	0	Placebo	
2	u946	0	45.0	0	Propriova	
3	w140	0	45.0	0	Zoniferol	
4	a577	0	45.0	0	Infubinol	

	Sex	Age_months	Weight (g)
0	Female	9	22
1	Female	16	25
2	Male	5	30
3	Female	19	30
4	Female	6	25

[25]:

```

metastatic_response = all_sort_by_time.drop('Tumor Volume (mm3)', axis = 1)
metastatic_sem = metastatic_response.pivot_table(metastatic_response, index = [
    ↪['Drug Regimen', 'Timepoint'],], aggfunc='sem')
metastatic_sem_table = metastatic_sem.pivot_table('Metastatic Sites', [
    ↪['Timepoint'], 'Drug Regimen'])

mouse_survive = metastatic_response.drop('Metastatic Sites', axis = 1)

mouse_survival = mouse_survive.pivot_table(mouse_survive, index=[ 'DrugRegimen', 'Timepoint'], aggfunc='count')
mouse_survival_rename = mouse_survival.rename(columns={"Mouse ID": "MouseCount"})
mouse_survival_tbl = mouse_survival_rename.pivot_table('MouseCount', [
    ↪['Timepoint'], 'Drug Regimen'])

# Survival rate
percent_surviving = (1-(mouse_survival_tbl.iloc[0]- mouse_survival_tbl)/
    ↪mouse_survival_tbl.iloc[0])*100

```

```

x_axis = np.arange(0,50,5)
count = np.arange(0,len(druglist2))
colors = ['red','blue','green','black']
markers = ['o', '^', 's', 'D']

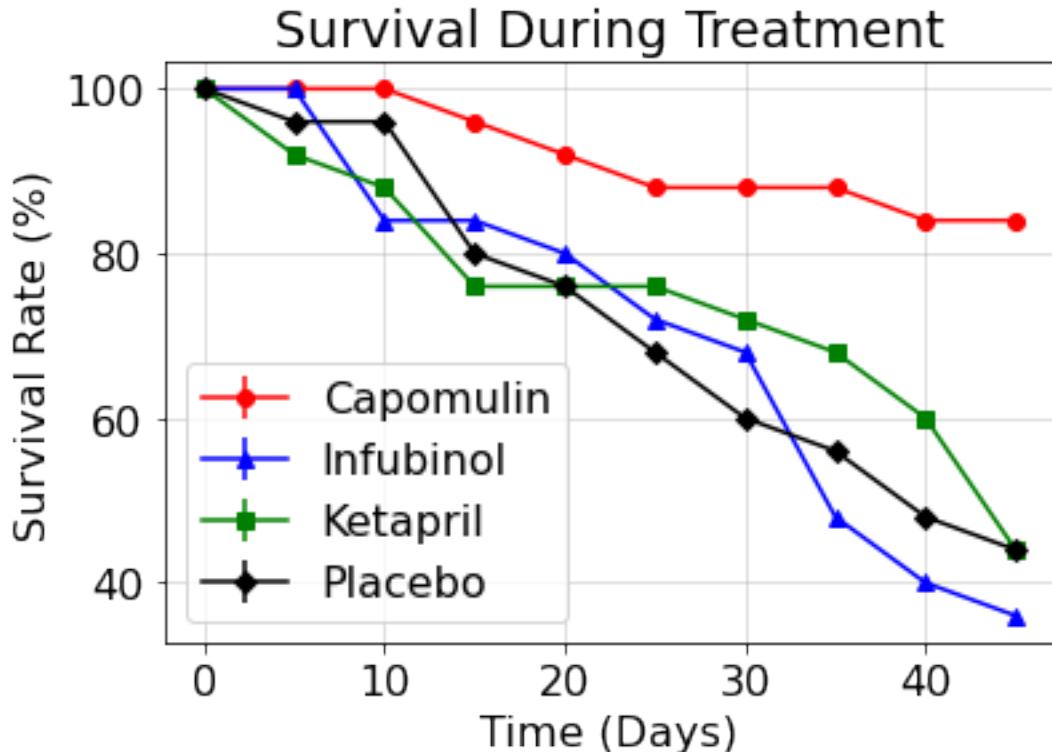
plt.title("Survival During Treatment")
plt.xlabel("Time (Days)")
plt.ylabel("Survival Rate (%)")
plt.grid(alpha = 0.5)

from scipy import stats
for i in count:
    graph_data = stats.sem(metastatic_sem_table[druglist2[i]])
    plt.errorbar(x_axis, percent_surviving[druglist2[i]], yerr = graph_data,marker= markers[i], color= colors[i], label = druglist2[i])
plt.legend(loc='best')
plt.show()

```

<IPython.core.display.Javascript object>

<IPython.core.display.Javascript object>



```
[26]: tumor_volume = all_sort_by_time.drop('Metastatic Sites', axis=1)

drug_groups = tumor_volume.pivot_table(tumor_volume, index=['Drug ↳ Regimen', 'Timepoint'], aggfunc='mean')

sem_tumor_volume = tumor_volume.pivot_table(tumor_volume, index=['Drug ↳ Regimen', 'Timepoint'], aggfunc='sem')

sem_table = sem_tumor_volume.pivot_table('Tumor Volume (mm3)', ['Timepoint'], ↳ 'Drug Regimen')
tumor_vol_table = drug_groups.pivot_table('Tumor Volume (mm3)', ['Timepoint'], ↳ 'Drug Regimen')

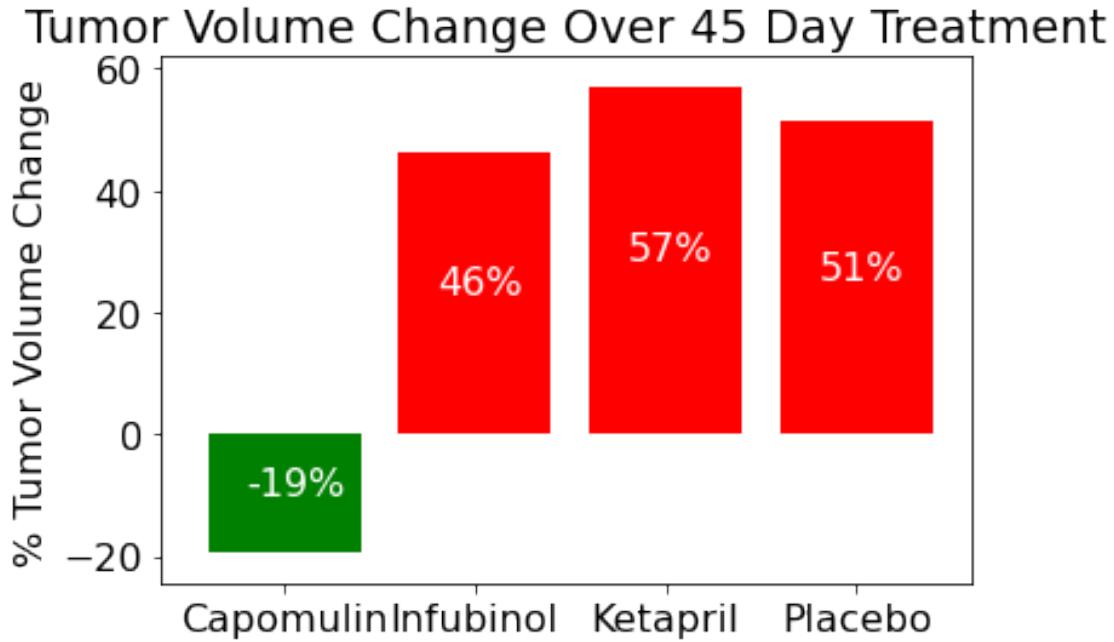
# Tumor volume change
summ_tumor_vol = tumor_vol_table.iloc[[0,-1]]
percent_change_tumor_vol= (((summ_tumor_vol -tumor_vol_table.iloc[0])/ ↳ tumor_vol_table.iloc[0]))*100
percent_changes = percent_change_tumor_vol.iloc[1:]
percent_changes.sum()

# Bar graph indicating tumor growth as red and tumor reduction as green
performance = {}
for x in count:
    performance[druglist2[x]] = float(percent_changes[druglist2[x]])
x_axis = np.arange(0, len(druglist2))
tick_locations = []
for x in x_axis:
    tick_locations.append(x + 0.4)
plt.xlim(-0.25, len(druglist2))
plt.ylim(min(performance.values()) - 5, max(performance.values()) + 5)
plt.title("Tumor Volume Change Over 45 Day Treatment")
plt.ylabel("% Tumor Volume Change")
bar_colors = pd.Series(list(performance.values()))
bar_colors = bar_colors > 0
bar_colors = bar_colors.map({True: "Red", False: "Green"})
plt.xticks(tick_locations, performance)
plt.bar(x_axis, performance.values(), color=bar_colors, align="edge")

for index,data in enumerate(list(performance.values())):
    plt.text(x = index+0.2, y = data/2, s = str(int(data))+'%', color = 'white')

plt.show()
```

<IPython.core.display.Javascript object>



0.6.1 Analysis

- Overall, it is clear that Capomulin is a viable drug regimen to reduce tumor growth.
- Capomulin had the most number of mice complete the study, with the exception of Remicane, all other regimens observed a number of mice deaths across the duration of the study.
- There is a strong correlation between mouse weight and tumor volume, indicating that mouse weight may be contributing to the effectiveness of any drug regimen. I.e. Mouse weight correlated strongly (R-squared of 0.84) with average tumor volume so one would want to factor in mouse weight whenever considering how effective a drug was in reducing a tumor.
- There was one potential outlier within the Infubinol regimen. While most mice showed tumor volume increase, there was one mouse that had a reduction in tumor growth in the study.
- When sample sizes are 30 or larger then the data can be seen as statistically significant and as shown in the bar plot, for each Drug Regimen there were at least 100 data points. Therefore, the next two observations are said to be statistically significant.
- The ratio of male to female mice is almost identical. Further analysis into specific sexes would be interesting.