## derek\_stage4

November 6, 2024

```
[22]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from numpy.polynomial.polynomial import polyfit, polyval
from sklearn.metrics import root_mean_squared_error
from seaborn import regplot
import scipy.stats as stats
```

### 0.0.1 Load Data

```
[23]: cases = pd.read_csv('./data/covid_cases_weekly', index_col=0)
deaths = pd.read_csv('./data/covid_deaths_weekly', index_col=0)
```

1 First task: create linear and non-linear models to predict the number of new cases and deaths in Florida

#### 1.0.1 Linear Model

```
[27]: x = np.arange(len(florida_new_cases)) * 7
cases_linear = LinearRegression()
deaths_linear = LinearRegression()
reshape = lambda a: a.copy().reshape(-1, 1)
```

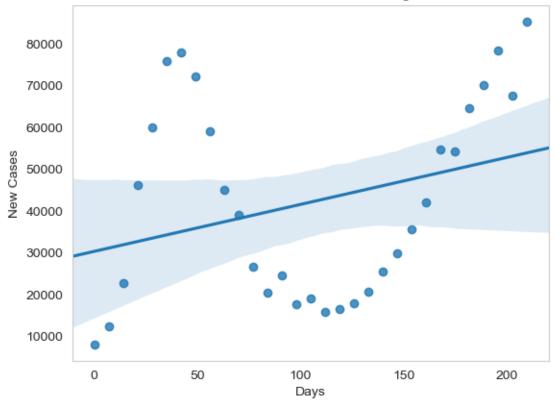
```
cases_linear.fit(reshape(x), florida_new_cases)
deaths_linear.fit(reshape(x), florida_new_deaths)
```

[27]: LinearRegression()

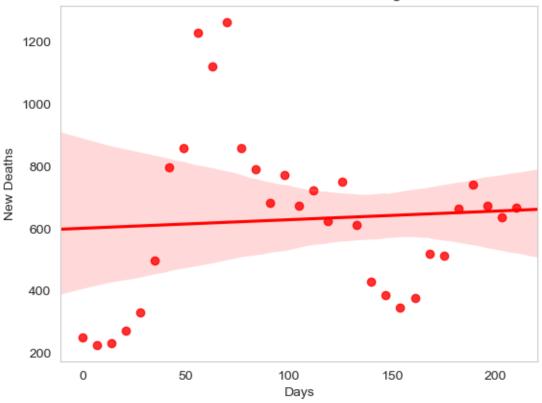
## 1.0.2 Get Predictions and plot with 1 week prediction into the future

```
[28]: x_ext = np.arange(len(florida_new_cases) + 1) * 7
    cases_pred_linear = cases_linear.predict(reshape(x))
    deaths_pred_linear = deaths_linear.predict(reshape(x))
[29]: ax = resploy(florida_new_cases__v=v__v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases'_v=v=florida_new_cases__label='Cases__label='Cases__label='Cases__label='Cases__label='Cases__label='Cases__label='Cases__label='Cases__label='Cases__label='Cases__label='Cases__label='Cases__label='Cases__label='Cases__label='Cases__label='Cases__label='Cases__label='Cases__label='Cases__label='Cases__label='Cases__label='Cases__label='Case
```

## Florida New Cases with Linear Regression



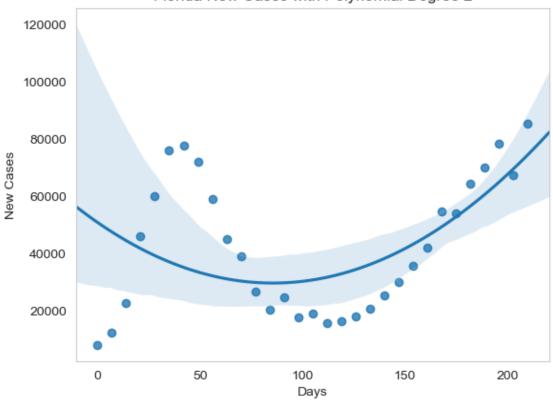
## Florida New Deaths with Linear Regression



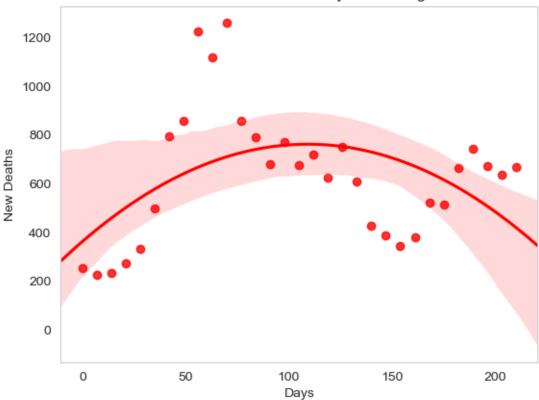
## 1.0.3 Non-Linear Model - Polynomial Degree 2

```
ax.set_ylabel('New Cases')
plt.grid()
plt.show()
```

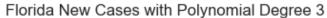


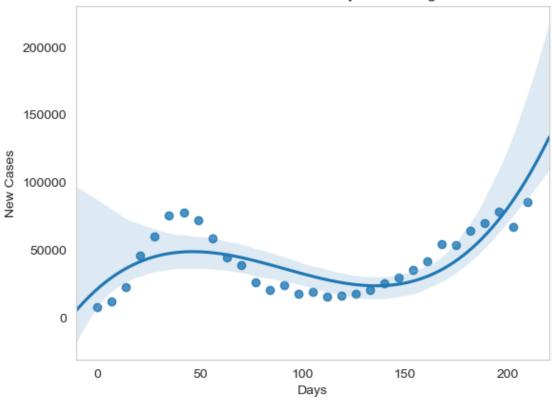




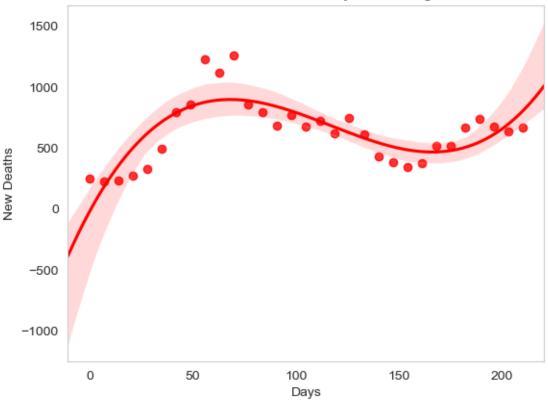


## 1.0.4 Non-Linear Model - Polynomial Degree 3









## 1.0.5 Root Mean Squared Error of Models

```
[39]: # Linear
      linear_cases_rmse = root_mean_squared_error(florida_new_cases,__
       ⇔cases_pred_linear)
      linear_deaths_rmse = root_mean_squared_error(florida_new_deaths,__

deaths_pred_linear)
      # Polynomial degree 2
      poly2_cases_rmse = root_mean_squared_error(florida_new_cases, cases_pred_poly2)
      poly2_deaths_rmse = root_mean_squared_error(florida_new_deaths,__
       →deaths_pred_poly2)
      # Polynomial degree 3
      poly3_cases_rmse = root_mean_squared_error(florida_new_cases, cases_pred_poly3)
      poly3_deaths_rmse = root_mean_squared_error(florida_new_deaths,__

deaths_pred_poly3)
      data = {
          'Model': ['Linear', 'Polynomial Degree 2', 'Polynomial Degree 3'],
          'Cases RMSE': [linear_cases_rmse, poly2_cases_rmse, poly3_cases_rmse],
          'Deaths RMSE': [linear_deaths_rmse, poly2_deaths_rmse, poly3_deaths_rmse]
```

```
rmse_df = pd.DataFrame(data).set_index('Model')
rmse_df
```

## [39]: Cases RMSE Deaths RMSE

Model
Linear 22187.631338 264.658561
Polynomial Degree 2 19740.446819 237.114555
Polynomial Degree 3 14433.191037 159.315881

# 2 Task 2: Find the top 5 counties in Florida with the highest risk of infection and analyze the trend of cases in those counties

I choose to define the risk of infection as the percentage of the population that has been infected. This is calculated by dividing the cumulative number of infected people by the population of the county.

	top_5_counties = top top_5_counties	5_5_counties	.nead(5)					
[40]:		population	2020-06-	01 00:00:00	2020-06-	08 00	0:00:00	\
	County Name							
	Miami-Dade County	2716940		18139			19756	
	Broward County	1952778		7196			7924	
	Palm Beach County	1496770		6135			7329	
	Hillsborough County	1471968		2251			2861	
	Orange County	1393452		2031			2378	
		2020-06-15	00:00:00	2020-06-22	00:00:00	\		
	County Name							
	Miami-Dade County		22197		26239			
	Broward County		9086		11327			
	Palm Beach County		9015		10943			
	Hillsborough County		3826		5973			
	Orange County		3282		5157			
		2020-06-29	00:00:00	2020-07-06	00:00:00	\		
	County Name							
	Miami-Dade County		35222		48992			
	Broward County		15045		21856			
	Palm Beach County		13711		17242			
	Hillsborough County		10323		14677			

Orange County		10014		14407		
County Name	2020-07-13	00:00:00	2020-07-20	00:00:00	\	
Miami-Dade County		67713		87035		
Broward County		31484		40976		
Palm Beach County		21806		26426		
Hillsborough County		19828		24135		
Orange County		18937		23584		
Q V	2020-07-27	00:00:00	2020-11-	-02 00:00:	00	\
County Name		107015	•••	1077	· <b>-</b> · <b>-</b> ·	
Miami-Dade County		107315	•••	1877		
Broward County		50784		874		
Palm Beach County		30958	•••	531		
Hillsborough County		27483	•••	489		
Orange County		27393	•••	469	186	
County Name	2020-11-09	00:00:00	2020-11-16	00:00:00	\	
Miami-Dade County		194879		203654		
Broward County		91441		95734		
Palm Beach County		55816		58754		
Hillsborough County		51055		53187		
Orange County		49029		51888		
County Name	2020-11-23	00:00:00	2020-11-30	00:00:00	\	
Miami-Dade County		216442		229618		
Broward County		101747		107524		
Palm Beach County		62278		65372		
Hillsborough County		55835		58293		
Orange County		55047		58325		
County Name	2020-12-07	00:00:00	2020-12-14	00:00:00	\	
Miami-Dade County		245064		260138		
Broward County		114426		120840		
Palm Beach County		69331		73079		
Hillsborough County		61599		66041		
Orange County		60291		64593		
County Name	2020-12-21	00:00:00	2020-12-28	00:00:00	\	
Miami-Dade County		276414		290363		
Broward County		128157		133480		
Palm Beach County		77241		80865		
				22300		

	Orange County		69491		73691	
		2021-01-03 00:00:00				
	County Name	2021 01 00	00.00.00			
	Miami-Dade County		305734			
	Broward County		141010			
	Palm Beach County		85479			
	Hillsborough County		80035			
	Orange County		79165			
			70100			
	[5 rows x 33 columns	]				
[41]:	# log normalize case top_5_counties_norma div(top_5_counties top_5_counties_norma top_5_counties_new = top_5_counties_new = top_5_counties_new	lized = top s['populatio lized = np.1 top_5_coun	_5_countie n'], axis= log1p(top_ ties_norma	s.copy()[top=0) * 100000 5_counties_1 lized.diff(a	p_5_counti normalized axis=1)	
[41]:		2020-06-08	00:00:00	2020-06-15	00:00:00	\
	County Name					
	Miami-Dade County		0.085271		0.116349	
	Broward County		0.096122		0.136524	
	Palm Beach County		0.177432		0.206670	
	Hillsborough County		0.238411		0.289357	
	Orange County		0.156737		0.320587	
	County Name	2020-06-22		2020-06-29		\
	Miami-Dade County		0.167101		0.294160	
	Broward County		0.220030		0.283431	
	Palm Beach County		0.193518		0.225223	
	Hillsborough County		0.444051		0.546089	
	Orange County		0.450364		0.662321	
	County Name	2020-07-06	00:00:00	2020-07-13	00:00:00	\
	Miami-Dade County		0.329769		0.323468	
	Broward County		0.373026		0.364731	
	Palm Beach County		0.228926		0.234655	
	Hillsborough County		0.351485		0.300553	
	Orange County		0.363306		0.273172	
	o					
	County Name	2020-07-20	00:00:00	2020-07-27	00:00:00	\

Hillsborough County

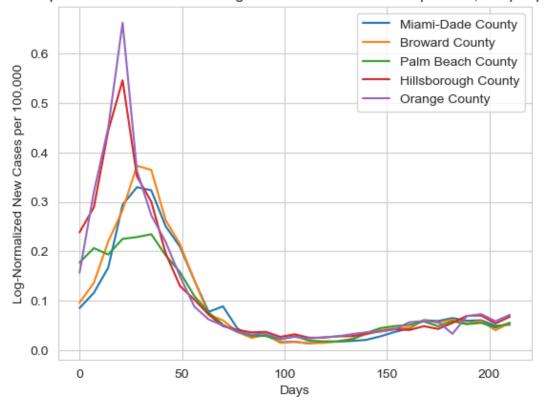
Miami-Dade County		0.250943		0.209399		
Broward County		0.263363		0.214503		
Palm Beach County		0.192043		0.158200		
Hillsborough County		0.196436		0.129830		
Orange County		0.219306		0.149637		
GJ						
	2020-08-03	00:00:00	2020-08-10	00:00:00		\
County Name						
Miami-Dade County		0.141605		0.077600		
Broward County		0.141924		0.071935		
Palm Beach County		0.109726		0.076473		
Hillsborough County		0.102466		0.072203	•••	
Orange County		0.088431		0.062280		
			0000 44 00		,	
County Name	2020-11-02	00:00:00	2020-11-09	00:00:00	\	
Miami-Dade County		0.028268		0.037225		
Broward County		0.040762		0.044548		
Palm Beach County		0.044913		0.048910		
Hillsborough County		0.038428		0.042602		
Orange County		0.037812		0.042550		
orange county		0.037012		0.042550		
	2020-11-16	00:00:00	2020-11-23	00:00:00	\	
County Name						
Miami-Dade County		0.044038		0.060892		
Broward County		0.045870		0.060904		
Palm Beach County		0.051285		0.058235		
Hillsborough County		0.040899		0.048574		
Orange County		0.056660		0.059084		
	2020-11-30	00:00:00	2020-12-07	00:00:00	\	
County Name						
Miami-Dade County		0.059087		0.065095		
Broward County		0.055214		0.062203		
Palm Beach County		0.048474		0.058785		
Hillsborough County		0.043070		0.055150		
Orange County		0.057829		0.033144		
	2020-12-14	00:00:00	2020-12-21	00:00:00	\	
County Name		0 050696		0 060601		
Miami-Dade County		0.059686		0.060681		
Broward County		0.054530		0.058779		
Palm Beach County		0.052638		0.055378		
Hillsborough County		0.069614		0.070260		
Orange County		0.068908		0.073076		
	2020-12-28	00:00:00	2021-01-03	00:00:00		

County Name		
Miami-Dade County	0.049227	0.051579
Broward County	0.040690	0.054871
Palm Beach County	0.045842	0.055480
Hillsborough County	0.054096	0.067794
Orange County	0.058672	0.071641

[5 rows x 31 columns]

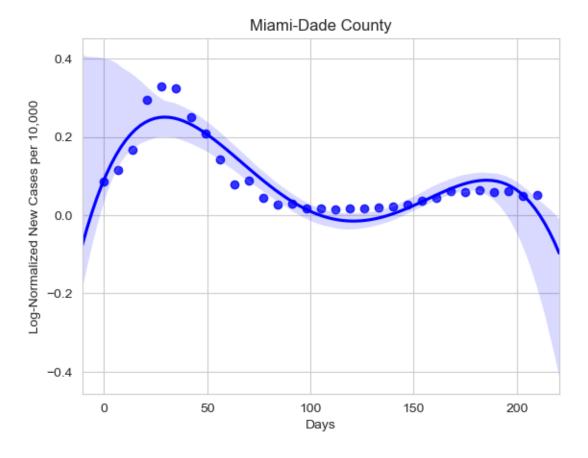
```
[42]: # first view the log-normalized cases per 100,000 people
plt.plot(x, top_5_counties_new.T)
plt.legend(top_5_counties.index)
plt.title('Top 5 Counties in Florida: Log-Normalized New Cases per 100,000
people')
plt.xlabel('Days')
plt.ylabel('Log-Normalized New Cases per 100,000')
plt.show()
```

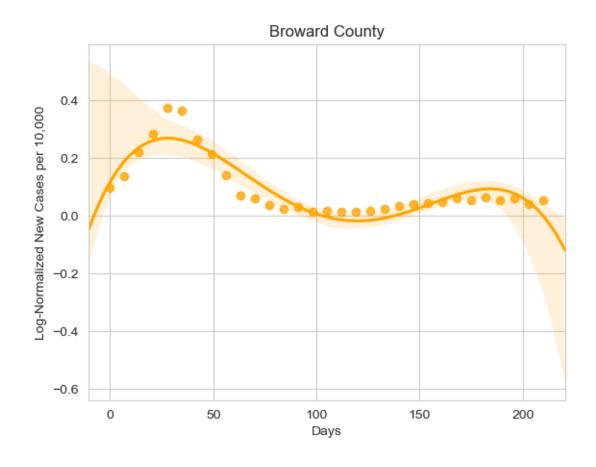
Top 5 Counties in Florida: Log-Normalized New Cases per 100,000 people

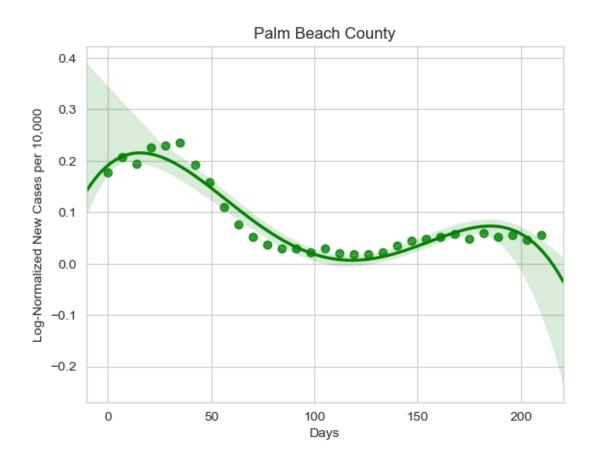


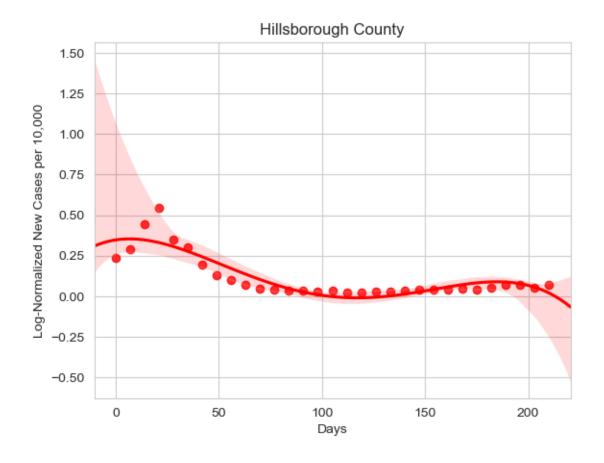
## 2.0.1 Polynomial Degree 3 Regression to Analyze Trends in Top 5 Counties

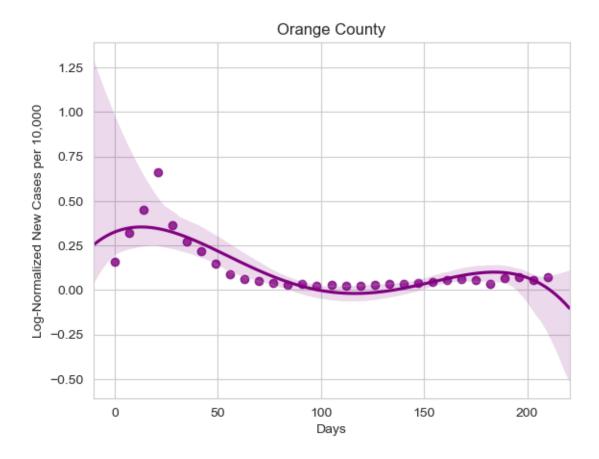
```
[43]: colors = ['blue', 'orange', 'green', 'red', 'purple']
    for county, color in zip(top_5_counties_new.index, colors):
        plt.figure()
        y = top_5_counties_new.loc[county]
        regplot(y=y, x=x, order=4, label='Trendline', truncate=False, color=color)
        plt.title(f'{county}')
        plt.xlabel('Days')
        plt.ylabel('Log-Normalized New Cases per 10,000')
        plt.show()
```











As we can see in the above diagrams, each county follows roughly the same trend. There is a spike at around 30 days, which would be around the 4th of July. After that, the number of new cases per 100,000 people decreases and levels off.

## 3 Task 3: Perform hypothesis testing between election result data and COVID-19 cases in Florida

```
vote_info['dem_prop'] = vote_info['dem_votes'] / vote_info['total_votes'] * 100
vote_info['rep_prop'] = vote_info['rep_votes'] / vote_info['total_votes'] * 100
vote_info['population'] = florida_cases.set_index('County Name')['population']
vote_info['turnout'] = vote_info['total_votes'] / vote_info['population'] * 100
```

## 3.0.1 Hypothesis 1: Counties with a higher proportion of votes for the Democratic candidate have a lower number of COVID-19 cases

## 3.0.2 First perform 2 sided 2 sample T-test

- Null Hypothesis: The number of COVID-19 cases in Dem-leaning counties is the same as the number of COVID-19 cases in Rep-leaning counties
- Alternative Hypothesis: The number of COVID-19 cases in counties in Dem-leaning counties is different from the number of COVID-19 cases in Rep-leaning counties

```
[47]: dem_cases_2_sided = hypothesis[hypothesis['dem_prop'] > 50].iloc[:, -1]
rep_cases_2_sided = hypothesis[hypothesis['rep_prop'] > 50].iloc[:, -1]
_, p_val = stats.ttest_ind(dem_cases_2_sided, rep_cases_2_sided,
equal_var=False, alternative='two-sided')
print(f'P-value: {p_val}')
print(f'Reject Null Hypothesis: {p_val < 0.05}')
```

P-value: 0.026620782044504937 Reject Null Hypothesis: True

We reject the Null Hypothesis that the number of COVID-19 cases in Dem-leaning counties is the same as the number of COVID-19 cases in Rep-leaning counties. This suggests that there is a significant difference in the number of COVID-19 cases between the two groups.

## 3.0.3 Next, perform 1 sided 2 sample T-test

- Null Hypothesis: The number of COVID-19 cases in counties in Dem-leaning counties is less than or equal to the number of COVID-19 cases in Rep-leaning counties
- Alternative Hypothesis: The number of COVID-19 cases in counties in Dem-leaning counties is greater than the number of COVID-19 cases in Rep-leaning counties

```
print(f'Reject Null Hypothesis: {p_val < 0.05}')</pre>
```

P-value: 0.013310391022252469 Reject Null Hypothesis: True

We reject the Null Hypothesis that the number of COVID-19 cases in Dem-leaning counties is less than or equal to the number of COVID-19 cases in Rep-leaning counties. This suggests that the number of COVID-19 cases is higher in Dem-leaning counties than in Rep-leaning counties.

## 3.0.4 Hypothesis 2: Counties with a higher voter turnout have a higher number of COVID-19 cases

## 3.0.5 First perform 2 sided 2 sample T-test

- Null Hypothesis: The number of COVID-19 cases in high-turnout counties is the same as the number of COVID-19 cases in low-turnout counties
- Alternative Hypothesis: The number of COVID-19 cases in high-turnout counties is different from the number of COVID-19 cases in low-turnout counties

P-value: 0.39884269097381786 Reject Null Hypothesis: False

We accept the Null Hypothesis that the number of COVID-19 cases in high-turnout counties is the same as the number of COVID-19 cases in low-turnout counties. This suggests that there is no significant difference in the number of COVID-19 cases between the two groups.

#### 3.0.6 Next, perform 1 sided 2 sample T-test

- Null Hypothesis: The number of COVID-19 cases in high-turnout counties is less than or equal to the number of COVID-19 cases in low-turnout counties
- Alternative Hypothesis: The number of COVID-19 cases in high-turnout counties is greater than the number of COVID-19 cases in low-turnout counties

P-value: 0.8005786545130911 Reject Null Hypothesis: False We accept the Null Hypothesis that the number of COVID-19 cases in high-turnout counties is less than or equal to the number of COVID-19 cases in low-turnout counties. This suggests that there is no significant difference in the number of COVID-19 cases between the two groups.

## 3.0.7 Hypothesis 3: Counties with a higher proportion of votes for the Democratic candidate have a lower infection rate

- Null Hypothesis: The infection rate in Dem-leaning counties is the same as the infection rate in Rep-leaning counties
- Alternative Hypothesis: The infection rate in counties in Dem-leaning counties is different from the infection rate in Rep-leaning counties

## 3.0.8 First perform 2 sided 2 sample T-test

P-value: 0.8373095955695355 Reject Null Hypothesis: False

We accept the Null Hypothesis that the infection rate in Dem-leaning counties is the same as the infection rate in Rep-leaning counties. This suggests that there is a no significant difference in the infection rate between the two groups.

## 3.0.9 Next, perform 1 sided 2 sample T-test

P-value: 0.4186547977847678 Reject Null Hypothesis: False

We accept the Null Hypothesis that the infection rate in Dem-leaning counties is less than or equal to the infection rate in Rep-leaning counties. This suggests that there is no significant difference in the infection rate between the two groups.

#### **3.0.10** Results

- Hypothesis 1: We find, based on our tests, that the number of cases in Democratic leaning counties is higher than in Republican leaning counties.
- Hypothesis 2: We find, based on our tests, that the number of cases in high-turnout counties is the same as in low-turnout counties.

• Hypothesis 3: We find, based on our tests, that the infection rate in Democratic leaning counties is the same as in Republican leaning counties.

These results suggest that the number of cases is related to the political leaning of the county, but not to the voter turnout or the infection rate. This implies that there is another variable which is causing the difference in the number of cases between Democratic and Republican leaning counties. My guess is that this variable is the population density of the county, which is likely to be higher in Democratic leaning counties due to cities often being left-leaning compared to rural areas. This would lead to a higher number of cases in these counties.