

# Problem Set #2

ECE 4424 / CS 4824 - Machine learning Virginia  
Tech

September 22, 2020

- Feel free to collaborate with other classmates in doing the homework. Please indicate your collaborators with their student ID. You should, however, write down your solution yourself. Please try to keep the answers brief and clear.
- Whenever you need clarification, please post the related questions on Piazza under the corresponding homework folder.
- Total: 100 points
- **Due date: 10/5/2020, 11:59PM ET**
- Late submission: each student will have a total of **four** free late (calendar) days to use for homeworks. Once these late days are exhausted, any assignments turned in late will be penalized 20% per late day. However, no assignment will be accepted more than three days after its due date. Each 24 hours or part thereof that a homework is late uses up one full late day.

## 1 Maximum likelihood estimation

**Question 1.1 (30 points):** Suppose we throw a coin  $n$  times. Let  $D = \{y_1, \dots, y_n\}$  denote the dataset we obtain, where  $y_i \in \{0, 1\}$  is the outcome of the  $i$ -th throw (i.e.,  $y_i = 1$  if the coin comes up to be a head and 0 if it comes up to be a tail). We are interested in finding the maximum likelihood estimation of the probability that the coin comes up with a head,  $\theta \in [0, 1]$ , given this dataset  $D$ .

- a) (10 pts) Write out  $P_\theta(D)$ , i.e., the probability of observing the dataset  $D$  under the probability distribution parameterized by  $\theta$ . Hint: this probability distribution is NOT binomial distribution, since we assume that you have already observed the outcome of every coin.
- b) (10 pts) Write out the log-likelihood,  $\log P_\theta(D)$

c) (10 pts) Obtain the maximum likelihood estimation of  $\theta$  given the dataset D

a.)

$$\begin{aligned}
 P_{\theta}(D) &= \text{probability of observing the dataset } \{y_1, y_2, \dots, y_n\} \\
 &= \theta^{y_1}(1-\theta)^{1-y_1} \theta^{y_2}(1-\theta)^{1-y_2} \dots \theta^{y_n}(1-\theta)^{1-y_n} \\
 &= \theta^{\sum_{i=1}^n y_i} (1-\theta)^{n - \sum_{i=1}^n y_i}
 \end{aligned}$$

b.)  $P_{\theta}(D) = \theta^{\sum_{i=1}^n y_i} (1-\theta)^{n - \sum_{i=1}^n y_i}$

$$\ln P_{\theta}(D) = \sum_{i=1}^n \ln \theta + \left( n - \sum_{i=1}^n y_i \right) \ln (1-\theta)$$

c.)

$$\frac{d \ln P_{\theta}(D)}{d(\theta)} = 0$$

$$\frac{\sum_{i=1}^n y_i}{\theta} - \frac{n \cdot \sum_{i=1}^n y_i}{1-\theta} = 0 \Rightarrow \frac{\sum_{i=1}^n y_i}{\theta} = \frac{n - \sum_{i=1}^n y_i}{1-\theta} = 0$$

$$\sum_{i=1}^n y_i - \theta \cdot \sum_{i=1}^n y_i = n\theta - \theta \sum_{i=1}^n y_i \Rightarrow \theta = \frac{1}{n} \sum_{i=1}^n y_i = \bar{y}$$



## 2 Gaussian discriminant analysis

**Question 2.1 (30 points):** Suppose we are given a dataset  $D = \{(x_1, y_1), \dots, (x_n, y_n)\}$ , where  $x_i \in \mathbb{R}^d$  and  $y_i \in \{0, 1\}$ . We will model the joint distribution of  $(x, y)$  according to:

$$p(y) = \phi^y(1 - \phi)^{1-y}$$

$$p(x|y=0) = \frac{1}{(2\pi)^{d/2}|\Gamma|^{1/2}} \exp\left(-\frac{1}{2}(x - \mu_0)^\top \Gamma^{-1}(x - \mu_0)\right)$$

$$p(x|y=1) = \frac{1}{(2\pi)^{d/2}|\Gamma|^{1/2}} \exp\left(-\frac{1}{2}(x - \mu_1)^\top \Gamma^{-1}(x - \mu_1)\right)$$

Here, the parameters of our model are  $\phi$ ,  $\Gamma$ ,  $\mu_0$  and  $\mu_1$ . Note that while there are two different mean vectors  $\mu_0$  and  $\mu_1$ , there is only one covariance matrix  $\Gamma$ .

- a) (5 pts) Suppose we have already fit  $\phi$ ,  $\Gamma$ ,  $\mu_0$  and  $\mu_1$ , and now want to make a prediction at some new query point  $x$ . Show that the posterior distribution of the label at  $x$  can be written as

$$p(y=1|x) = \frac{1}{1 + \exp(-\theta^\top x + \theta_0)},$$

where the vector  $\theta$  and scalar  $\theta_0$  are some appropriate functions of  $\phi$ ,  $\Gamma$ ,  $\mu_0$  and  $\mu_1$  that you need to specify.

- b) (25 pts) For this part of the problem only, you may assume  $d$  (the dimension of  $x$ ) is 1, so that  $\Gamma = \sigma^2$  is just a real number, and likewise the determinant of  $\Gamma$  is given by  $|\Gamma| = \sigma^2$ . Given the dataset, we claim that the maximum likelihood estimates of the parameters are given by

$$\phi = \frac{1}{n} \sum_{i=1}^n \mathbb{1}\{y_i = 1\}$$

$$\mu_0 = \frac{\sum_{i=1}^n \mathbb{1}\{y_i = 0\}x_i}{\sum_{i=1}^n \mathbb{1}\{y_i = 0\}}$$

$$\mu_1 = \frac{\sum_{i=1}^n \mathbb{1}\{y_i = 1\}x_i}{\sum_{i=1}^n \mathbb{1}\{y_i = 1\}}$$

$$\Gamma = \frac{1}{n} \sum_{i=1}^n (x_i - \mu_{y_i})(x_i - \mu_{y_i})^\top$$

where  $\mathbb{1}(\cdot)$  is the indicator function we have seen in class. The log-likelihood of the data is

$$\log P_\Theta(D) = \log \prod_{i=1}^n p(x_i, y_i) = \log \prod_{i=1}^n p(x_i|y_i)p(y_i).$$

By maximizing  $\log P_\Theta(D)$  with respect to the four parameters, prove that the maximum likelihood estimates of  $\phi$ ,  $\Gamma$ ,  $\mu_0$  and  $\mu_1$  are indeed as given in the formulas above. (You

may assume that there is at least one positive and one negative example, so that the denominators in the definitions of  $\mu_0$  and  $\mu_1$  above are non-zero.)

a.)

Given the following:

$$p(y) = \phi^y(1-\phi)^{1-y}$$

$$p(x|y=0) = \frac{1}{(2\pi)^{d/2}|\Gamma|^{1/2}} \exp\left(-\frac{1}{2}(x - \mu_0)^\top \Gamma^{-1}(x - \mu_0)\right)$$

$$p(x|y=1) = \frac{1}{(2\pi)^{d/2}|\Gamma|^{1/2}} \exp\left(-\frac{1}{2}(x - \mu_1)^\top \Gamma^{-1}(x - \mu_1)\right)$$

Baye's Rule;  $p(Y=y | X=x) = \frac{p(Y=y) p(X=x | Y=y)}{p(X=x)}$

$$p(y=1) = \begin{cases} \phi \\ 1-\phi \end{cases}$$

$$p(y=0) = \begin{cases} 1-\phi \\ \phi \end{cases}$$

$$p(x) = p(x|y=1)p(y=1) + p(x|y=0)p(y=0)$$

therefore;

$$p(y=1|x) = \frac{\phi \cdot \frac{1}{(2\pi)^{d/2}|\Gamma|^{1/2}} \exp\left\{-\frac{1}{2}(x - \mu_1)^\top \Gamma^{-1}(x - \mu_1)\right\}}{\frac{1}{(2\pi)^{d/2}|\Gamma|^{1/2}} \left\{ \phi \exp\left(-\frac{1}{2}(x - \mu_1)^\top \Gamma^{-1}(x - \mu_1)\right) + (1-\phi) \exp\left(-\frac{1}{2}(x - \mu_0)^\top \Gamma^{-1}(x - \mu_0)\right) \right\}}$$

Divide numerator denominator by  $\phi$

$$p(y=1|x) = \frac{\frac{1}{(2\pi)^{d/2}|\Gamma|^{1/2}} \exp\left(-\frac{1}{2}(x - \mu_1)^\top \Gamma^{-1}(x - \mu_1)\right)}{1 + \frac{(1-\phi)}{\phi} \exp\left[-\frac{1}{2} \left\{ (x - \mu_0)^\top \Gamma^{-1}(x - \mu_0) - (x - \mu_1)^\top \Gamma^{-1}(x - \mu_1) \right\}\right]} + g(x)$$

Now the exponent:

$$(x - \mu_1 + \mu_1 - \mu_0)^\top \Gamma^{-1}(x - \mu_1 + \mu_1 - \mu_0) = (x - \mu_1)^\top \Gamma^{-1}(x - \mu_1)$$

$$= (x - \mu_1)^\top \Gamma^{-1}(x - \mu_1) + (\mu_1 - \mu_0)^\top \Gamma^{-1}(\mu_1 - \mu_0) + (x - \mu_1)^\top \Gamma^{-1}(\mu_1 - \mu_0) + (\mu_1 - \mu_0)^\top \Gamma^{-1}(x - \mu_1)$$
~~$$- (x - \mu_1)^\top \Gamma^{-1}(x - \mu_1)$$~~

$$\begin{aligned}
 &= (\mu_1 - \mu_0)^\top \Gamma^{-1} (\mu_1 - \mu_0) + 2(\mu_1 - \mu_0)^\top \Gamma^{-1} (x - \mu_1) \\
 &= (\mu_1 - \mu_0)^\top \Gamma^{-1} (\mu_1 - \mu_0) + 2(\mu_1 - \mu_0)^\top \Gamma^{-1} x - 2(\mu_1 - \mu_0)^\top \Gamma^{-1} \mu_1 \\
 &= (\mu_1 - \mu_0)^\top \Gamma^{-1} (\mu_1 - \mu_0) - 2(\mu_1 - \mu_0)^\top \Gamma^{-1} \mu_1 + 2(\mu_1 - \mu_0)^\top \Gamma^{-1} x
 \end{aligned}$$

term independent of  $x$       term involving  $x$

Suppose, we denote,  $(\mu_1 - \mu_0)^\top \Gamma^{-1} = \theta^\top$

$$\text{and } \ln\left(\frac{1-\phi}{\phi}\right) - \frac{1}{2} \left\{ (\mu_1 - \mu_0)^\top \Gamma^{-1} (\mu_1 - \mu_0) - 2(\mu_1 - \mu_0)^\top \Gamma^{-1} \mu_1 \right\} = \theta_0$$

then,

$$\begin{aligned}
 p(y=1|x) &= \frac{1}{1 + \exp\left[\ln\left(\frac{1-\phi}{\phi}\right) - \frac{1}{2} \left\{ (\mu_1 - \mu_0)^\top \Gamma^{-1} (\mu_1 - \mu_0) - 2(\mu_1 - \mu_0)^\top \Gamma^{-1} \mu_1 \right\} - (\mu_1 - \mu_0)^\top \Gamma^{-1} x\right]} \\
 &= \frac{1}{1 + \exp(-\theta^\top x + \theta_0)}
 \end{aligned}$$

$$\begin{aligned}
 b.) \quad &\log \prod_{i=1}^n \left( \frac{1}{(2\pi)^{\frac{d}{2}} |\Gamma|^{\frac{1}{2}}} \exp\left(-\frac{1}{2} \|x_i - \mu_0\|_\Gamma^2\right) \cdot \phi^y (1-\phi)^{1-y} \right) \\
 &= \sum_{i=1}^n \left[ -\frac{n}{2} \log 2\pi - \frac{1}{2} \log |\Gamma| - \frac{1}{2} (x_i - \mu_0)^\top \Gamma^{-1} (x_i - \mu_0) + y \log \phi + (1-y) \log (1-\phi) \right]
 \end{aligned}$$

Taking partial derivatives to each parameter and equating it to zero to find the maximum likelihood of that parameter

$$\text{For } \phi, \quad \frac{\partial}{\partial \phi} (\phi, \mu_0, \mu_1, \Gamma) = 0$$

$$\frac{\partial}{\partial \phi} (\phi, \mu_0, \mu_1, \Gamma) = \sum_{i=1}^n \left\{ -\frac{n}{2} \cdot 0 - \frac{1}{2} \cdot 0 - \frac{1}{2} \cdot 0 + \frac{y^{(i)}}{\phi} - \frac{(1-y^{(i)})}{(1-\phi)} \right\} = 0$$

$$\sum_{i=0}^n \left\{ y^{(i)} (1-\phi) - \phi (1-y^{(i)}) \right\} = 0$$

$$\sum_{i=1}^n \left\{ y^{(i)} - y^{(i)} \phi - \phi + y^{(i)} \phi \right\} = 0$$

$$\sum_{i=1}^n \left\{ y^{(i)} - \phi \right\} = 0 \Rightarrow \sum_{i=1}^n y^{(i)} - n\phi = 0 \quad \because \sum_{i=1}^n \phi = \phi \sum_{i=1}^n 1 = \phi n$$

$$\Rightarrow \Phi = \frac{1}{n} \sum_{i=1}^n y^{(i)} \Rightarrow \boxed{\Phi = \frac{1}{n} \sum_{i=1}^n I\{y^{(i)} = 1\}}$$

For  $\mu_0, \mu_1$ :

$$\frac{\partial}{\partial \mu_k} (\Phi, \mu_k, \Gamma) = 0 \Rightarrow \sum_{i=1}^n \left\{ -\frac{n}{2} \cdot 0 - \frac{1}{2} \cdot 0 - \frac{1}{2} \frac{\partial}{\partial \mu_k} [(x^{(i)} - \mu_k)^T \Gamma^{-1} (x^{(i)} - \mu_k)] + 0 + 0 \right\} = 0$$

Chain Rule:  $a = (x^{(i)} - \mu_k) \Rightarrow \frac{\partial}{\partial \mu_k} = \frac{1}{\partial a} \cdot \frac{\partial a}{\partial \mu_k} \quad \frac{\partial a}{\partial \mu_k} = I\{y^{(i)} = k\}$

$$-\frac{1}{2} \cdot 2 \sum_{i=1}^n I\{(x^{(i)} - \mu_k)^T \sum \frac{\partial a}{\partial \mu_k}\} = 0$$

$$\Rightarrow \sum_{i=1}^n x^{(i)} \frac{\partial \Phi}{\partial \mu_k} - \sum_{i=1}^n \mu_k \frac{\partial \Phi}{\partial \mu_k} = 0 \Rightarrow \mu_k = \frac{\sum_{i=1}^n I\{y^{(i)} = k\} x^{(i)}}{\sum_{i=1}^n I\{y^{(i)} = k\}}$$

since its  $\mu_0$  and  $\mu_1$  we change  $k$  respectively,

$$\Rightarrow \mu_0 = \frac{\sum_{i=1}^n I\{y^{(i)} = 0\} x^{(i)}}{\sum_{i=1}^n I\{y^{(i)} = 0\}}$$

$$\mu_1 = \frac{\sum_{i=1}^n I\{y^{(i)} = 1\} x^{(i)}}{\sum_{i=1}^n I\{y^{(i)} = 1\}}$$

For  $\Gamma$ :

$$\frac{\partial}{\partial \Gamma} (\Phi, \mu_k, \Gamma) = 0 \Rightarrow \sum_{i=1}^n \left\{ -\frac{n}{2} \cdot 0 - \frac{1}{2} \cdot 0 - \frac{\partial \log(|\Gamma|)}{\partial \Gamma} \cdot \frac{1}{2} \frac{\partial}{\partial \Gamma} [(x^{(i)} - \mu_k)^T \Gamma^{-1} (x^{(i)} - \mu_k)] + 0 + 0 \right\} = 0$$

$$\Rightarrow \sum_{i=1}^n \left\{ -\frac{1}{2} \Gamma^{-T} - \frac{1}{2} [\Gamma^{-T} (x^{(i)} - \mu_k) (x^{(i)} - \mu_k)^T \Gamma^{-T}] \right\} = 0 \quad \therefore \frac{\partial \log|\Gamma|}{\partial X} = X^{-T} \text{ and } \frac{\partial a^T X^{-1} b}{\partial X}$$

$$\Rightarrow \sum_{i=1}^n \left\{ 1 - \Gamma^{-1} (x^{(i)} - \mu_k) (x^{(i)} - \mu_k)^T \right\} = 0 \Rightarrow n = \sum_{i=1}^n \Gamma^{-1} (x^{(i)} - \mu_k) (x^{(i)} - \mu_k)^T = -X^{-T} a b^T X^{-T}$$

$$\Rightarrow n \Gamma = \sum_{i=1}^n (x^{(i)} - \mu_k) (x^{(i)} - \mu_k)^T \Rightarrow \boxed{\Gamma = \frac{1}{n} \sum_{i=1}^n (x^{(i)} - \mu_k) (x^{(i)} - \mu_k)^T}$$

where  $a_k = u_{y_k}$

### 3 Programming assignment: Linear Regression (40 pts)

For the following programming assignment, please download the datasets and iPython notebooks from Canvas and submit the following:

- Completed and ready-to-run iPython notebooks. Note: we will inspect the code and run your notebook if needed. If we cannot run any section of your notebook, you will not receive any points for the task related to that section.
- Responses (texts, codes, and/or figures) to the following problems/tasks

In this programming exercise, you will build a linear regression model and apply it to a covid-19 sample dataset.

**Task P1 (6 pts):** Complete the codes that generate the three visualization graphs that show the trend of the epidemic progression ("People tested", "Deaths", and "New positive cases"). Copy them to the solution file.

**Task P2 (4 pts):** Complete the function predict output. Copy the the outputs of the code to the solution file.

**Task P3 (6 pts):** Let the regression cost function be given by

$$L_D(w) = \frac{1}{n} \sum_{i=1}^n (y_i - w \cdot x_i)^2,$$

where  $x_i \in \mathbb{R}^d$  is the input feature of dimension  $d$ ,  $y_i \in \mathbb{R}$  is the output response, and  $w \in \mathbb{R}^d$  is the regression weights. Complete the function weight derivative to calculate the derivative of the cost function with respect to regression weights  $w$ , i.e.,  $\partial_w \partial L_D(w)$ . Note that this should be a  $d$  dimensional vector. Also copy the output of the code for the test example to the solution file.

**Task P4 (5 pts):** Complete the code section to perform the gradient decent in the function **regression gradient descent**. Copy the code to the solution file.

**Task P5 (3 pts):** Specify the initial weights, step size and tolerance for the function **regression gradient descent**. Print the outputs of the code.

**Task P6 (3 pts):** Use the learned weights to predict 'People tested' in the last three weeks in the dataset. Copy the predictions to the solution file, and calculate the test error

$$\frac{1}{n_{\text{tst}}} \sum_{i=1}^{n_{\text{tst}}} (y_{i,\text{tst}} - \hat{y}_{i,\text{tst}})^2, \quad n_{\text{tst}}$$

where  $n_{\text{tst}}$  is the number of test data,  $y_{i,\text{tst}}$  is the true label,  $\hat{y}_{i,\text{tst}}$  is the predicted label.

**Task P7 (3 pts):** Specify the initial weights, step size and tolerance for the function **regression gradient descent**. Print the outputs of the code.

**Task P8 (4 pts):** Use the learned weights to predict 'People tested' in the last three weeks in the dataset. Find the value of the model predictions on the 10th day of the forecasting period. Also print the actual number of people tested on that particular day. Copy the predictions to the solution file, and calculate the test error. Note: here we are asking you to report the number before normalization. So you need to convert the prediction back to the unit of people.

**Task P9 (6 pts):** Explore on your own. Report your question of investigation, as well as your results/interpretation in the solution file.

**ALL SOLUTIONS TO THE PROGRAMMING  
ASSIGNMENT ARE INCLUDED BELOW**

# Programming Assignment 2: Linear regression

As we know, the COVID-19 pandemic has been disrupting people's life around the world. To get it under control, a crucial aspect is to be able to accurate forecast the spread of the disease, which can be helpful as a planning tool for policymakers, clinicians, and public health officers to deal with this crisis. In this notebook, we will try to do some forecasting on the covid-19 epidemic progression using machine learning. We will use a dataset based on the COVID-19 Data Repository at John Hopkins university.

```
In [99]: import pandas as pd
from datetime import datetime, timedelta
import matplotlib.pyplot as plt
from matplotlib.dates import DateFormatter
import matplotlib.dates as mdates
import numpy as np
from math import sqrt
import sys
```

```
In [100]: print (sys.version)
```

```
3.8.1 (tags/v3.8.1:1b293b6, Dec 18 2019, 23:11:46) [MSC v.1916 64 bit (AMD64)]
```

First, let us load the data.

```
In [101]: data_orig = pd.read_csv("us_covid_data.csv")
data = data_orig.copy()
print (data_orig.columns)
data_orig
```

Index(['date', 'Country', 'hospitalized\_with\_symptom', 'Intensive\_care',  
 'Total\_hospitalized', 'Home\_Isolation', 'Total\_positive',  
 'Daily\_change\_in\_positive\_cases', 'New\_positive\_cases', 'Recovered',  
 'Deaths', 'Total\_cases', 'People\_tested'],  
 dtype='object')

Out[101]:

	date	Country	hospitalized_with_symptom	Intensive_care	Total_hospitalized	Home_I
0	2020-02-24T18:00:00	ITA		101	26	127
1	2020-02-25T18:00:00	ITA		114	35	150
2	2020-02-26T18:00:00	ITA		128	36	164
3	2020-02-27T18:00:00	ITA		248	56	304
4	2020-02-28T18:00:00	ITA		345	64	409
...	...	...		...	...	...
201	2020-09-12T17:00:00	ITA		1951	182	2133
202	2020-09-13T17:00:00	ITA		2042	187	2229
203	2020-09-14T17:00:00	ITA		2122	197	2319
204	2020-09-15T17:00:00	ITA		2222	201	2423
205	2020-09-16T17:00:00	ITA		2285	207	2492

206 rows × 13 columns

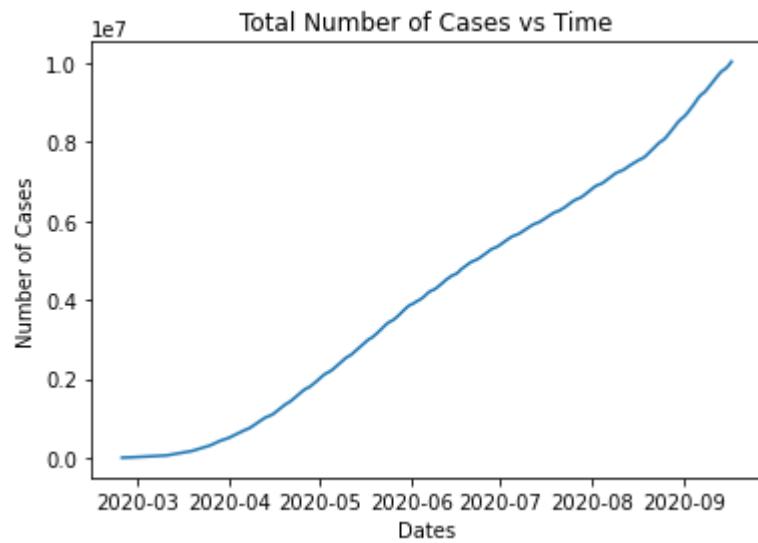
```
In [102]: # change the date format
dates = data['date']
date_format = [pd.to_datetime(d) for d in dates]
```

## Data Visualization

**Task P1:** complete the following **three** visualization graphs that show the trend of the epidemic progression.  
 Copy them to the solution file.

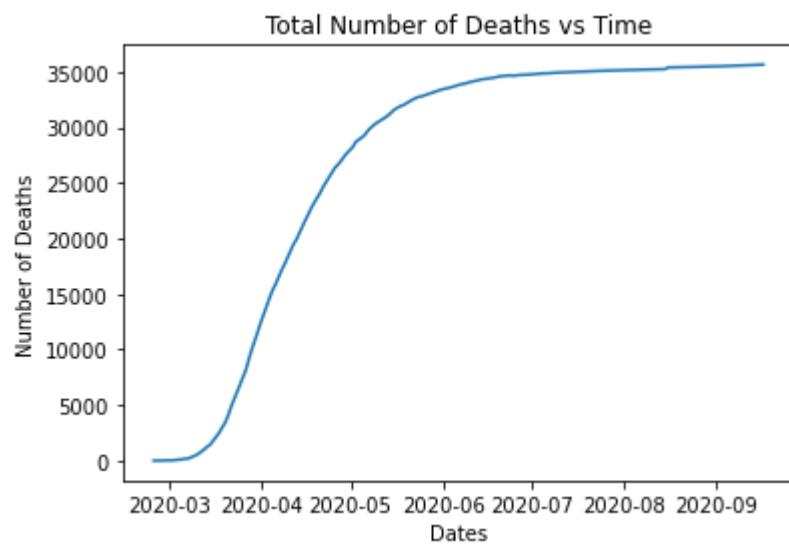
Graph 1: plot the total number of people tested for the entire period of the dataset. Your X axis will be the dates ("Dates") and Y-axis will be the total number of cases ("People\_tested") over the period of time.

```
In [103]: # Add code to plot the trend of the total number of people being tested as days progressed.  
# X axis -> dates('Dates')  
# Y axis -> number of people tested.('People_tested')  
  
### STUDENT: Start of Code ###  
plt.title("Total Number of Cases vs Time")  
plt.xlabel("Dates")  
plt.ylabel("Number of Cases")  
People_tested = data['People_tested']  
  
plt.plot(date_format, People_tested)  
  
plt.show()  
### End of code #####
```



Graph 2: plot the total number of deaths for the entire period. Your X axis will be the dates ("Dates") and Y-axis will be the total number of death cases("Deaths") over the period of time.

```
In [104]: # Add code to plot the trend of total deaths as days progressed.  
# X axis -> dates ('Dates')  
# Y axis -> number of deaths ('Deaths')  
  
### STUDENT: Start of Code ###  
plt.title("Total Number of Deaths vs Time")  
plt.xlabel("Dates")  
plt.ylabel("Number of Deaths")  
Deaths = data['Deaths']  
  
plt.plot(date_format, Deaths)  
  
plt.show()  
  
### End of code #####
```



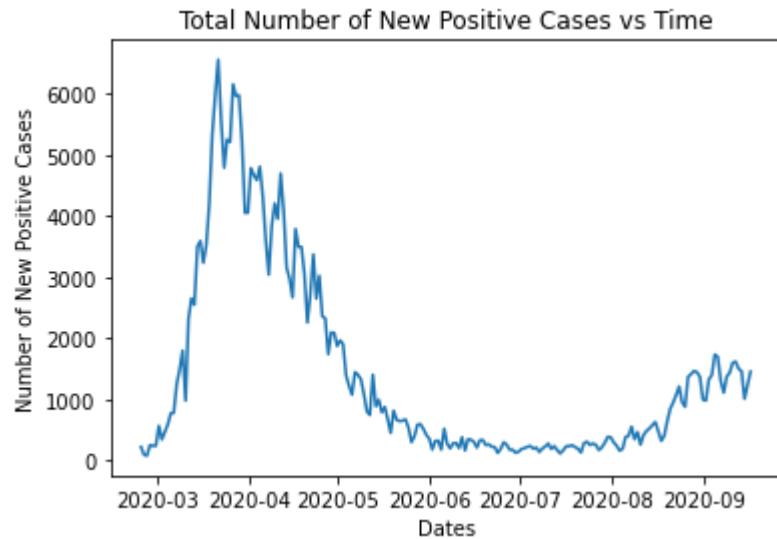
Graph 3: plot the total number of infected cases for the entire period. Your X axis will be the dates ("Dates") and Y-axis will be the total number of infected cases ('New\_positive\_cases') over the period of time.

```
In [105]: ### STUDENT: Start of Code ###
plt.title("Total Number of New Positive Cases vs Time")
plt.xlabel("Dates")
plt.ylabel("Number of New Positive Cases")
New_positive_cases = data['New_positive_cases']

plt.plot(date_format, New_positive_cases)

plt.show()

### End of code #####
```



As we can see that our data has different ranges of values for every feature and this can cause problems in our model, so here we will normalize our data (ignoring the categorical variables) so that our data is scaled between 0 and 1. The downside, however, is that the numbers are no longer interpretable. To interpret it, you need to multiply back by the scaling factor.

**IMPORTANT:** From now on, we will work with the normalized features to build the regression model. However, in **Task P8**, you need to convert the number back to the actual units.

```
In [106]: data_list = data_orig.columns.values.tolist()

for i in data_list[-11:]:
    data[[i]]=(data_orig[i]-data_orig[i].min())/(data_orig[i].max()-data_orig[i].min())

data
```

Out[106]:

	date	Country	hospitalized_with_symptom	Intensive_care	Total_hospitalized	Home_I
0	2020-02-24T18:00:00	ITA	0.000000	0.000000	0.000000	(
1	2020-02-25T18:00:00	ITA	0.000450	0.002227	0.000700	(
2	2020-02-26T18:00:00	ITA	0.000934	0.002474	0.001125	(
3	2020-02-27T18:00:00	ITA	0.005085	0.007422	0.005384	(
4	2020-02-28T18:00:00	ITA	0.008440	0.009401	0.008577	(
...	...	...	...	...	...	...
201	2020-09-12T17:00:00	ITA	0.063994	0.038595	0.061015	(
202	2020-09-13T17:00:00	ITA	0.067142	0.039832	0.063935	(
203	2020-09-14T17:00:00	ITA	0.069909	0.042306	0.066673	(
204	2020-09-15T17:00:00	ITA	0.073368	0.043295	0.069836	(
205	2020-09-16T17:00:00	ITA	0.075547	0.044780	0.071935	(

206 rows × 13 columns

## Calculate the feature matrix

The following is a function that accepts a list of feature names (e.g. ['Total\_Hospitalized', 'People\_tested']) and a target feature e.g. ('Deaths') and returns two things:

1. A numpy matrix whose columns are the desired features plus a column with a constant value 1, which is also known as the 'intercept'.
2. A numpy array that contains the values of the target output.

```
In [107]: def get_numpy_data(data_frame, features, output):
    # Steps
    # select the columns of data_Frame given by the features list into the variable features_sframe which will include the constant
    # Convert the features_frame into a numpy matrix
    # assign the column of data_frame associated with the output to the array output_array
    # convert the array into a numpy array by first converting it to a list
    # return feature_matrix,output_array

    data_frame['constant'] = 1 # here we are adding a constant column
    # add the column 'constant' to the front of the features list.
    features = ['constant'] + features

    # select the columns of data_Frame given by the features list into the variable features_sframe which will include the constant)
    features_frame = data_frame[features]

    # Convert the features_frame into a numpy matrix
    feature_matrix = features_frame.to_numpy()
    # print ("feature_matrix:", feature_matrix)

    # assign the column of data_frame associated with the output to the array output_array
    output_array = data_frame[output]

    # convert the array into a numpy array by first converting it to a list
    output_array = output_array.to_numpy()

    return(feature_matrix, output_array)
```

For dates, we need to convert them into a sequence of numbers. We now add a new column to our dataframe corresponding to the number of days since the start of the dataset.

```
In [108]: X = date_format
day_numbers = []
for i in range(1, len(X) + 1):
    day_numbers.append([i])

data['Days'] = pd.DataFrame(day_numbers,columns = ['Days'])
data["Days"] = data["Days"].astype(int)
```

Test the above function for a particular input and output feature.

```
In [109]: (example_features, example_output) = get_numpy_data(data, ['Days'], 'New_positive_cases')
print (example_features[0,:])
print (example_output[0])

[1 1]
0.022071307300509338
```

# Predict the outputs with given regression weights

Suppose we had the weights  $[1, 1]$  corresponding to the features  $[1, 100]$ , to compute the predicted output, we can simply take the dot product between them, so the output is  $1 * 1 + 1 * 100 = 101$ . Now, let's create the data with

```
In [110]: (test_features, output) = get_numpy_data(data, ['Days'], 'People_tested')
```

**Task P2:** Complete the following function 'predict\_output'. Copy the the outputs of the code to the solution file.

```
In [111]: def predict_output(feature_matrix, weights):
    # Inputs:
    # feature_matrix: a numpy matrix containing the features as columns (including the intercept),
    #                  and each row corresponds to a data point
    # weights: a numpy array for the corresponding regression weights (including the intercept)
    # Output:
    # a numpy array that contains the predicted outputs (according to the provided weights)
    # for all the data points in the feature_matrix

    # STUDENT: Start of code #####
    features = np.array(feature_matrix)
    regress_weights = np.array(weights)

    return np.dot(features, regress_weights)
    ## end of code
```

```
In [112]: # Copy the outputs of this code to the solution file
my_weights = np.array([1., 1.])
test_predictions = predict_output(example_features, my_weights)
print ("(normalized) prediction at day 5: ", test_predictions[5])
print ("(normalized) prediction at day 20 ", test_predictions[20])

(normalized) prediction at day 5:  7.0
(normalized) prediction at day 20  22.0
```

# Compute the derivative

We will now compute the derivative of the regression cost function:

$$L_D(w) = \frac{1}{n} \sum_{i=1}^n (y_i - w \cdot x_i)^2,$$

where  $x_i \in \mathbb{R}^d$  is the input feature of dimension  $d$ ,  $y_i \in \mathbb{R}$  is the output response, and  $w \in \mathbb{R}^d$  is the regression weights.

**Task P3:** Complete the function 'weight\_derivative' to calculate the derivative of the cost function with respect to regression weights  $w$ , i.e.,  $\frac{\partial}{\partial w} L_D(w)$ . Note that this should be a  $d$  dimensional vector. Also copy the output of the code for the test example to the solution file.

```
In [113]: def weight_derivative(weights, feature_matrix, labels):
    # Input:
    # weights: weight vector w, a numpy vector of dimension d
    # feature_matrix: numpy array of size n by d, where n is the number of data points, and d is the feature dimension
    # Labels: true labels y, a numpy vector of dimension d
    # Output:
    # Derivative of the regression cost function with respect to the weight w,
    # a numpy array of dimension d

    ## STUDENT: Start of code ##

    error = np.subtract( labels, np.dot(feature_matrix, weights) )
    derivative = -2/len(labels)*np.dot(np.transpose(feature_matrix), error)

    # print("Size of Weights:", weights.shape)
    # print("Size of features:", feature_matrix.shape)
    # print("Size of Labels:", labels.shape)

    return derivative
    # End of code ###
```

```
In [114]: # NOTE: copy the output to the solution file.

(example_features, example_output) = get_numpy_data(data, ['Days'], 'People_tested')
my_weights = np.array([0., 0.]) # this makes all the predictions 0
derivative = weight_derivative(my_weights, example_features, example_output)

print (derivative)

[ -0.82103242 -120.60087518]
```

## Gradient descent algorithm

Here, we will write a function to perform gradient descent algorithm on the linear regression cost. Given an initial point, we will update the current weights by moving in the negative gradient direction to minimize the cost function. Thus, in each iteration we obtain the updated weight  $w_{t+1}$  from the current iterate  $w_t$  as follows:

$$w_{t+1} = w_t - h \frac{\partial}{\partial w} L_D(w_t),$$

where  $h$  is the 'step\_size' that is the amount by which we move in the negative gradient direction.

We stop when we are sufficiently close to the optimum (where gradient is the zero vector) by checking the condition with respect to the magnitude (length) of the gradient vector:

$$\left\| \frac{\partial}{\partial w} L_D(w_t) \right\|_2 \leq \epsilon,$$

where  $\epsilon$  is the 'tolerance' parameter.

**Task P4:** Complete the code section to perform the gradient decent in the function `regression_gradient_descent`. Copy the code to the solution file.

```
In [115]: def regression_gradient_descent(feature_matrix, labels, initial_weights, step_size, tolerance):
    # Gradient descent algorithm for linear regression problem

    # Input:
    # feature_matrix: numpy array of size n by d, where n is the number of data points, and d is the feature dimension
    # labels: true labels y, a numpy vector of dimension d
    # initial_weights: initial weight vector to start with, a numpy vector of dimension d
    # step_size: step size of update
    # tolerance: tolerance epsilon for stopping condition
    # Output:
    # Weights obtained after convergence

    converged = False
    weights = np.array(initial_weights) # current iterate
    i = 0
    while not converged:
        i += 1
        # STUDENT: Start of code: your implementation of what the gradient descent algorithm does in every iteration
        # Refer back to the update rule listed above: update the weight
        derivative = weight_derivative(weights, feature_matrix, labels);
        weights = weights - step_size*derivative

        # Compute the gradient magnitude:
        gradient_magnitude = np.linalg.norm( weight_derivative(weights, feature_matrix, labels) )

        # Check the stopping condition to decide whether you want to stop the iterations
        if gradient_magnitude <= tolerance: # STUDENT: check the stopping condition here
            converged = True

        # End of code

        print ("Iteration: ",i,"gradient_magnitude: ", gradient_magnitude) # for us to check about convergence

    return(weights)
```

## Use gradient descent for linear regression

Let's test the gradient descent algorithm for linear regression with a single feature ('Day'). Here we are using first 180 days' data as our training data.

```
In [116]: #train_data
train_data = data[:180]
```

**Task P5:** Specify the initial\_weights, step\_size, and tolerance for the function regression\_gradient\_descent . Copy the outputs of the code to the solution file.

```
In [117]: simple_features = ['Days']
my_output = 'People_tested'

# Use get_numpy_data method to calculate the feature matrix and output.
(simple_feature_matrix, output) = get_numpy_data(train_data, simple_features,
my_output)

#Initialize the weights, step size and tolerance
# Start of code
#STUDENT: Specify the initial_weights, step_size, and tolerance
initial_weights = [1.0, 1.0]
step_size = 7e-8
tolerance = 1.2e4
# end of code

# Use the regression_gradient_descent function to calculate the gradient decent
and store it in the variable 'final_weights'
final_weights = regression_gradient_descent(simple_feature_matrix, output, ini
tial_weights, step_size, tolerance)

# end of code
print ("Here are the final weights after convergence:")
print (final_weights)
```

```
<ipython-input-107-8b2916f5b454>:9: SettingWithCopyWarning:  
A value is trying to be set on a copy of a slice from a DataFrame.  
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/table/user\_guide/indexing.html#returning-a-view-versus-a-copy  
data_frame['constant'] = 1 # here we are adding a constant column
```

```
Iteration: 1 gradient_magnitude: 21840.81707866705
Iteration: 2 gradient_magnitude: 21807.51575965956
Iteration: 3 gradient_magnitude: 21774.265216126485
Iteration: 4 gradient_magnitude: 21741.06537064902
Iteration: 5 gradient_magnitude: 21707.91614592638
Iteration: 6 gradient_magnitude: 21674.81746477566
Iteration: 7 gradient_magnitude: 21641.769250131623
Iteration: 8 gradient_magnitude: 21608.77142504654
Iteration: 9 gradient_magnitude: 21575.82391269002
Iteration: 10 gradient_magnitude: 21542.92663634879
Iteration: 11 gradient_magnitude: 21510.079519426563
Iteration: 12 gradient_magnitude: 21477.282485443844
Iteration: 13 gradient_magnitude: 21444.53545803773
Iteration: 14 gradient_magnitude: 21411.838360961778
Iteration: 15 gradient_magnitude: 21379.191118085775
Iteration: 16 gradient_magnitude: 21346.593653395597
Iteration: 17 gradient_magnitude: 21314.045890993017
Iteration: 18 gradient_magnitude: 21281.547755095533
Iteration: 19 gradient_magnitude: 21249.099170036196
Iteration: 20 gradient_magnitude: 21216.70006026343
Iteration: 21 gradient_magnitude: 21184.350350340832
Iteration: 22 gradient_magnitude: 21152.04996494705
Iteration: 23 gradient_magnitude: 21119.79882887556
Iteration: 24 gradient_magnitude: 21087.59686703451
Iteration: 25 gradient_magnitude: 21055.444004446545
Iteration: 26 gradient_magnitude: 21023.340166248632
Iteration: 27 gradient_magnitude: 20991.28527769187
Iteration: 28 gradient_magnitude: 20959.279264141343
Iteration: 29 gradient_magnitude: 20927.32205107593
Iteration: 30 gradient_magnitude: 20895.41356408814
Iteration: 31 gradient_magnitude: 20863.55372888393
Iteration: 32 gradient_magnitude: 20831.74247128252
Iteration: 33 gradient_magnitude: 20799.979717216258
Iteration: 34 gradient_magnitude: 20768.26539273041
Iteration: 35 gradient_magnitude: 20736.599423983014
Iteration: 36 gradient_magnitude: 20704.98173724469
Iteration: 37 gradient_magnitude: 20673.412258898476
Iteration: 38 gradient_magnitude: 20641.89091543965
Iteration: 39 gradient_magnitude: 20610.417633475583
Iteration: 40 gradient_magnitude: 20578.99233972552
Iteration: 41 gradient_magnitude: 20547.614961020485
Iteration: 42 gradient_magnitude: 20516.28542430301
Iteration: 43 gradient_magnitude: 20485.003656627076
Iteration: 44 gradient_magnitude: 20453.769585157825
Iteration: 45 gradient_magnitude: 20422.583137171507
Iteration: 46 gradient_magnitude: 20391.44424005523
Iteration: 47 gradient_magnitude: 20360.352821306817
Iteration: 48 gradient_magnitude: 20329.308808534643
Iteration: 49 gradient_magnitude: 20298.312129457467
Iteration: 50 gradient_magnitude: 20267.36271190423
Iteration: 51 gradient_magnitude: 20236.46048381396
Iteration: 52 gradient_magnitude: 20205.605373235514
Iteration: 53 gradient_magnitude: 20174.797308327477
Iteration: 54 gradient_magnitude: 20144.036217357967
Iteration: 55 gradient_magnitude: 20113.322028704482
Iteration: 56 gradient_magnitude: 20082.654670853706
Iteration: 57 gradient_magnitude: 20052.03407240138
```

Iteration: 58 gradient\_magnitude: 20021.46016205212  
Iteration: 59 gradient\_magnitude: 19990.932868619224  
Iteration: 60 gradient\_magnitude: 19960.45212102455  
Iteration: 61 gradient\_magnitude: 19930.017848298332  
Iteration: 62 gradient\_magnitude: 19899.629979579015  
Iteration: 63 gradient\_magnitude: 19869.28844411305  
Iteration: 64 gradient\_magnitude: 19838.993171254828  
Iteration: 65 gradient\_magnitude: 19808.744090466414  
Iteration: 66 gradient\_magnitude: 19778.54113131744  
Iteration: 67 gradient\_magnitude: 19748.38422348492  
Iteration: 68 gradient\_magnitude: 19718.273296753105  
Iteration: 69 gradient\_magnitude: 19688.208281013285  
Iteration: 70 gradient\_magnitude: 19658.189106263653  
Iteration: 71 gradient\_magnitude: 19628.215702609137  
Iteration: 72 gradient\_magnitude: 19598.28800026125  
Iteration: 73 gradient\_magnitude: 19568.405929537894  
Iteration: 74 gradient\_magnitude: 19538.56942086323  
Iteration: 75 gradient\_magnitude: 19508.7784047675  
Iteration: 76 gradient\_magnitude: 19479.03281188685  
Iteration: 77 gradient\_magnitude: 19449.33257296321  
Iteration: 78 gradient\_magnitude: 19419.677618844125  
Iteration: 79 gradient\_magnitude: 19390.06788048253  
Iteration: 80 gradient\_magnitude: 19360.503288936685  
Iteration: 81 gradient\_magnitude: 19330.98377536993  
Iteration: 82 gradient\_magnitude: 19301.50927105059  
Iteration: 83 gradient\_magnitude: 19272.07970735178  
Iteration: 84 gradient\_magnitude: 19242.69501575124  
Iteration: 85 gradient\_magnitude: 19213.355127831197  
Iteration: 86 gradient\_magnitude: 19184.059975278215  
Iteration: 87 gradient\_magnitude: 19154.809489882977  
Iteration: 88 gradient\_magnitude: 19125.603603540203  
Iteration: 89 gradient\_magnitude: 19096.442248248433  
Iteration: 90 gradient\_magnitude: 19067.325356109905  
Iteration: 91 gradient\_magnitude: 19038.25285933037  
Iteration: 92 gradient\_magnitude: 19009.224690218958  
Iteration: 93 gradient\_magnitude: 18980.240781187997  
Iteration: 94 gradient\_magnitude: 18951.301064752897  
Iteration: 95 gradient\_magnitude: 18922.405473531922  
Iteration: 96 gradient\_magnitude: 18893.55394024609  
Iteration: 97 gradient\_magnitude: 18864.74639771902  
Iteration: 98 gradient\_magnitude: 18835.982778876747  
Iteration: 99 gradient\_magnitude: 18807.26301674756  
Iteration: 100 gradient\_magnitude: 18778.58704446187  
Iteration: 101 gradient\_magnitude: 18749.954795252062  
Iteration: 102 gradient\_magnitude: 18721.366202452296  
Iteration: 103 gradient\_magnitude: 18692.821199498412  
Iteration: 104 gradient\_magnitude: 18664.319719927713  
Iteration: 105 gradient\_magnitude: 18635.861697378845  
Iteration: 106 gradient\_magnitude: 18607.447065591656  
Iteration: 107 gradient\_magnitude: 18579.075758407  
Iteration: 108 gradient\_magnitude: 18550.747709766623  
Iteration: 109 gradient\_magnitude: 18522.462853712976  
Iteration: 110 gradient\_magnitude: 18494.221124389092  
Iteration: 111 gradient\_magnitude: 18466.022456038405  
Iteration: 112 gradient\_magnitude: 18437.866783004625  
Iteration: 113 gradient\_magnitude: 18409.754039731557  
Iteration: 114 gradient\_magnitude: 18381.684160762976

Iteration: 115 gradient\_magnitude: 18353.657080742418  
Iteration: 116 gradient\_magnitude: 18325.672734413143  
Iteration: 117 gradient\_magnitude: 18297.731056617842  
Iteration: 118 gradient\_magnitude: 18269.83198229859  
Iteration: 119 gradient\_magnitude: 18241.975446496646  
Iteration: 120 gradient\_magnitude: 18214.161384352312  
Iteration: 121 gradient\_magnitude: 18186.389731104784  
Iteration: 122 gradient\_magnitude: 18158.660422092016  
Iteration: 123 gradient\_magnitude: 18130.97339275053  
Iteration: 124 gradient\_magnitude: 18103.328578615303  
Iteration: 125 gradient\_magnitude: 18075.7259153196  
Iteration: 126 gradient\_magnitude: 18048.165338594838  
Iteration: 127 gradient\_magnitude: 18020.646784270404  
Iteration: 128 gradient\_magnitude: 17993.17018827355  
Iteration: 129 gradient\_magnitude: 17965.735486629208  
Iteration: 130 gradient\_magnitude: 17938.34261545987  
Iteration: 131 gradient\_magnitude: 17910.991510985405  
Iteration: 132 gradient\_magnitude: 17883.68210952294  
Iteration: 133 gradient\_magnitude: 17856.414347486694  
Iteration: 134 gradient\_magnitude: 17829.18816138785  
Iteration: 135 gradient\_magnitude: 17802.00348783438  
Iteration: 136 gradient\_magnitude: 17774.86026353092  
Iteration: 137 gradient\_magnitude: 17747.75842527861  
Iteration: 138 gradient\_magnitude: 17720.69790997496  
Iteration: 139 gradient\_magnitude: 17693.678654613675  
Iteration: 140 gradient\_magnitude: 17666.700596284554  
Iteration: 141 gradient\_magnitude: 17639.763672173285  
Iteration: 142 gradient\_magnitude: 17612.867819561372  
Iteration: 143 gradient\_magnitude: 17586.012975825906  
Iteration: 144 gradient\_magnitude: 17559.199078439487  
Iteration: 145 gradient\_magnitude: 17532.426064970034  
Iteration: 146 gradient\_magnitude: 17505.693873080683  
Iteration: 147 gradient\_magnitude: 17479.0024405296  
Iteration: 148 gradient\_magnitude: 17452.351705169844  
Iteration: 149 gradient\_magnitude: 17425.741604949257  
Iteration: 150 gradient\_magnitude: 17399.17207791026  
Iteration: 151 gradient\_magnitude: 17372.643062189785  
Iteration: 152 gradient\_magnitude: 17346.15449601905  
Iteration: 153 gradient\_magnitude: 17319.706317723474  
Iteration: 154 gradient\_magnitude: 17293.298465722502  
Iteration: 155 gradient\_magnitude: 17266.93087852948  
Iteration: 156 gradient\_magnitude: 17240.60349475151  
Iteration: 157 gradient\_magnitude: 17214.31625308929  
Iteration: 158 gradient\_magnitude: 17188.06909233698  
Iteration: 159 gradient\_magnitude: 17161.86195138207  
Iteration: 160 gradient\_magnitude: 17135.694769205253  
Iteration: 161 gradient\_magnitude: 17109.567484880205  
Iteration: 162 gradient\_magnitude: 17083.480037573543  
Iteration: 163 gradient\_magnitude: 17057.432366544625  
Iteration: 164 gradient\_magnitude: 17031.42441114542  
Iteration: 165 gradient\_magnitude: 17005.45611082037  
Iteration: 166 gradient\_magnitude: 16979.527405106255  
Iteration: 167 gradient\_magnitude: 16953.63823363203  
Iteration: 168 gradient\_magnitude: 16927.78853611871  
Iteration: 169 gradient\_magnitude: 16901.978252379216  
Iteration: 170 gradient\_magnitude: 16876.207322318245  
Iteration: 171 gradient\_magnitude: 16850.47568593211

Iteration: 172 gradient\_magnitude: 16824.78328330862  
Iteration: 173 gradient\_magnitude: 16799.130054626938  
Iteration: 174 gradient\_magnitude: 16773.51594015744  
Iteration: 175 gradient\_magnitude: 16747.940880261543  
Iteration: 176 gradient\_magnitude: 16722.404815391645  
Iteration: 177 gradient\_magnitude: 16696.9076860909  
Iteration: 178 gradient\_magnitude: 16671.449432993144  
Iteration: 179 gradient\_magnitude: 16646.02999682271  
Iteration: 180 gradient\_magnitude: 16620.649318394317  
Iteration: 181 gradient\_magnitude: 16595.30733861292  
Iteration: 182 gradient\_magnitude: 16570.00399847359  
Iteration: 183 gradient\_magnitude: 16544.73923906137  
Iteration: 184 gradient\_magnitude: 16519.513001551102  
Iteration: 185 gradient\_magnitude: 16494.32522720736  
Iteration: 186 gradient\_magnitude: 16469.175857384234  
Iteration: 187 gradient\_magnitude: 16444.064833525255  
Iteration: 188 gradient\_magnitude: 16418.992097163245  
Iteration: 189 gradient\_magnitude: 16393.957589920148  
Iteration: 190 gradient\_magnitude: 16368.961253506948  
Iteration: 191 gradient\_magnitude: 16344.003029723479  
Iteration: 192 gradient\_magnitude: 16319.082860458315  
Iteration: 193 gradient\_magnitude: 16294.200687688655  
Iteration: 194 gradient\_magnitude: 16269.356453480146  
Iteration: 195 gradient\_magnitude: 16244.550099986782  
Iteration: 196 gradient\_magnitude: 16219.781569450759  
Iteration: 197 gradient\_magnitude: 16195.050804202318  
Iteration: 198 gradient\_magnitude: 16170.35774665966  
Iteration: 199 gradient\_magnitude: 16145.702339328747  
Iteration: 200 gradient\_magnitude: 16121.08452480324  
Iteration: 201 gradient\_magnitude: 16096.504245764301  
Iteration: 202 gradient\_magnitude: 16071.961444980509  
Iteration: 203 gradient\_magnitude: 16047.45606530769  
Iteration: 204 gradient\_magnitude: 16022.988049688804  
Iteration: 205 gradient\_magnitude: 15998.557341153812  
Iteration: 206 gradient\_magnitude: 15974.163882819536  
Iteration: 207 gradient\_magnitude: 15949.807617889523  
Iteration: 208 gradient\_magnitude: 15925.48848965393  
Iteration: 209 gradient\_magnitude: 15901.206441489368  
Iteration: 210 gradient\_magnitude: 15876.961416858809  
Iteration: 211 gradient\_magnitude: 15852.753359311393  
Iteration: 212 gradient\_magnitude: 15828.582212482359  
Iteration: 213 gradient\_magnitude: 15804.447920092867  
Iteration: 214 gradient\_magnitude: 15780.35042594992  
Iteration: 215 gradient\_magnitude: 15756.289673946161  
Iteration: 216 gradient\_magnitude: 15732.2656080598  
Iteration: 217 gradient\_magnitude: 15708.278172354467  
Iteration: 218 gradient\_magnitude: 15684.32731097907  
Iteration: 219 gradient\_magnitude: 15660.412968167697  
Iteration: 220 gradient\_magnitude: 15636.53508823943  
Iteration: 221 gradient\_magnitude: 15612.693615598278  
Iteration: 222 gradient\_magnitude: 15588.88849473301  
Iteration: 223 gradient\_magnitude: 15565.119670217022  
Iteration: 224 gradient\_magnitude: 15541.387086708244  
Iteration: 225 gradient\_magnitude: 15517.69068894896  
Iteration: 226 gradient\_magnitude: 15494.030421765736  
Iteration: 227 gradient\_magnitude: 15470.406230069242  
Iteration: 228 gradient\_magnitude: 15446.818058854153

Iteration: 229 gradient\_magnitude: 15423.265853199007  
Iteration: 230 gradient\_magnitude: 15399.749558266089  
Iteration: 231 gradient\_magnitude: 15376.269119301289  
Iteration: 232 gradient\_magnitude: 15352.824481633985  
Iteration: 233 gradient\_magnitude: 15329.415590676917  
Iteration: 234 gradient\_magnitude: 15306.042391926057  
Iteration: 235 gradient\_magnitude: 15282.704830960472  
Iteration: 236 gradient\_magnitude: 15259.402853442207  
Iteration: 237 gradient\_magnitude: 15236.136405116169  
Iteration: 238 gradient\_magnitude: 15212.905431809966  
Iteration: 239 gradient\_magnitude: 15189.709879433845  
Iteration: 240 gradient\_magnitude: 15166.549693980482  
Iteration: 241 gradient\_magnitude: 15143.424821524923  
Iteration: 242 gradient\_magnitude: 15120.335208224422  
Iteration: 243 gradient\_magnitude: 15097.280800318347  
Iteration: 244 gradient\_magnitude: 15074.261544128023  
Iteration: 245 gradient\_magnitude: 15051.277386056612  
Iteration: 246 gradient\_magnitude: 15028.328272589026  
Iteration: 247 gradient\_magnitude: 15005.41415029174  
Iteration: 248 gradient\_magnitude: 14982.534965812718  
Iteration: 249 gradient\_magnitude: 14959.690665881262  
Iteration: 250 gradient\_magnitude: 14936.881197307921  
Iteration: 251 gradient\_magnitude: 14914.106506984313  
Iteration: 252 gradient\_magnitude: 14891.366541883053  
Iteration: 253 gradient\_magnitude: 14868.66124905759  
Iteration: 254 gradient\_magnitude: 14845.99057564212  
Iteration: 255 gradient\_magnitude: 14823.354468851443  
Iteration: 256 gradient\_magnitude: 14800.752875980828  
Iteration: 257 gradient\_magnitude: 14778.185744405911  
Iteration: 258 gradient\_magnitude: 14755.653021582573  
Iteration: 259 gradient\_magnitude: 14733.154655046808  
Iteration: 260 gradient\_magnitude: 14710.690592414594  
Iteration: 261 gradient\_magnitude: 14688.260781381796  
Iteration: 262 gradient\_magnitude: 14665.865169724017  
Iteration: 263 gradient\_magnitude: 14643.503705296482  
Iteration: 264 gradient\_magnitude: 14621.17633603394  
Iteration: 265 gradient\_magnitude: 14598.883009950518  
Iteration: 266 gradient\_magnitude: 14576.623675139603  
Iteration: 267 gradient\_magnitude: 14554.39827977373  
Iteration: 268 gradient\_magnitude: 14532.206772104455  
Iteration: 269 gradient\_magnitude: 14510.049100462236  
Iteration: 270 gradient\_magnitude: 14487.925213256318  
Iteration: 271 gradient\_magnitude: 14465.835058974593  
Iteration: 272 gradient\_magnitude: 14443.778586183527  
Iteration: 273 gradient\_magnitude: 14421.75574352797  
Iteration: 274 gradient\_magnitude: 14399.766479731088  
Iteration: 275 gradient\_magnitude: 14377.810743594251  
Iteration: 276 gradient\_magnitude: 14355.888483996861  
Iteration: 277 gradient\_magnitude: 14333.999649896292  
Iteration: 278 gradient\_magnitude: 14312.144190327723  
Iteration: 279 gradient\_magnitude: 14290.32205440405  
Iteration: 280 gradient\_magnitude: 14268.533191315772  
Iteration: 281 gradient\_magnitude: 14246.777550330822  
Iteration: 282 gradient\_magnitude: 14225.055080794524  
Iteration: 283 gradient\_magnitude: 14203.365732129414  
Iteration: 284 gradient\_magnitude: 14181.709453835161  
Iteration: 285 gradient\_magnitude: 14160.086195488404

Iteration: 286 gradient\_magnitude: 14138.495906742706  
Iteration: 287 gradient\_magnitude: 14116.938537328359  
Iteration: 288 gradient\_magnitude: 14095.414037052322  
Iteration: 289 gradient\_magnitude: 14073.922355798077  
Iteration: 290 gradient\_magnitude: 14052.46344352552  
Iteration: 291 gradient\_magnitude: 14031.03725027085  
Iteration: 292 gradient\_magnitude: 14009.643726146443  
Iteration: 293 gradient\_magnitude: 13988.28282134074  
Iteration: 294 gradient\_magnitude: 13966.954486118135  
Iteration: 295 gradient\_magnitude: 13945.658670818848  
Iteration: 296 gradient\_magnitude: 13924.39532585882  
Iteration: 297 gradient\_magnitude: 13903.164401729602  
Iteration: 298 gradient\_magnitude: 13881.965848998223  
Iteration: 299 gradient\_magnitude: 13860.79961830708  
Iteration: 300 gradient\_magnitude: 13839.66566037384  
Iteration: 301 gradient\_magnitude: 13818.563925991308  
Iteration: 302 gradient\_magnitude: 13797.494366027302  
Iteration: 303 gradient\_magnitude: 13776.456931424578  
Iteration: 304 gradient\_magnitude: 13755.451573200671  
Iteration: 305 gradient\_magnitude: 13734.478242447809  
Iteration: 306 gradient\_magnitude: 13713.536890332789  
Iteration: 307 gradient\_magnitude: 13692.627468096869  
Iteration: 308 gradient\_magnitude: 13671.74992705565  
Iteration: 309 gradient\_magnitude: 13650.904218598953  
Iteration: 310 gradient\_magnitude: 13630.090294190737  
Iteration: 311 gradient\_magnitude: 13609.30810536894  
Iteration: 312 gradient\_magnitude: 13588.557603745418  
Iteration: 313 gradient\_magnitude: 13567.838741005793  
Iteration: 314 gradient\_magnitude: 13547.151468909335  
Iteration: 315 gradient\_magnitude: 13526.495739288908  
Iteration: 316 gradient\_magnitude: 13505.871504050783  
Iteration: 317 gradient\_magnitude: 13485.278715174582  
Iteration: 318 gradient\_magnitude: 13464.71732471313  
Iteration: 319 gradient\_magnitude: 13444.187284792366  
Iteration: 320 gradient\_magnitude: 13423.688547611224  
Iteration: 321 gradient\_magnitude: 13403.221065441525  
Iteration: 322 gradient\_magnitude: 13382.784790627848  
Iteration: 323 gradient\_magnitude: 13362.379675587461  
Iteration: 324 gradient\_magnitude: 13342.005672810148  
Iteration: 325 gradient\_magnitude: 13321.66273485816  
Iteration: 326 gradient\_magnitude: 13301.35081436607  
Iteration: 327 gradient\_magnitude: 13281.069864040664  
Iteration: 328 gradient\_magnitude: 13260.819836660852  
Iteration: 329 gradient\_magnitude: 13240.600685077521  
Iteration: 330 gradient\_magnitude: 13220.412362213463  
Iteration: 331 gradient\_magnitude: 13200.254821063256  
Iteration: 332 gradient\_magnitude: 13180.128014693135  
Iteration: 333 gradient\_magnitude: 13160.031896240891  
Iteration: 334 gradient\_magnitude: 13139.966418915794  
Iteration: 335 gradient\_magnitude: 13119.931535998428  
Iteration: 336 gradient\_magnitude: 13099.927200840631  
Iteration: 337 gradient\_magnitude: 13079.953366865357  
Iteration: 338 gradient\_magnitude: 13060.009987566575  
Iteration: 339 gradient\_magnitude: 13040.09701650918  
Iteration: 340 gradient\_magnitude: 13020.21440732885  
Iteration: 341 gradient\_magnitude: 13000.362113731955  
Iteration: 342 gradient\_magnitude: 12980.540089495467

```
Iteration: 343 gradient_magnitude: 12960.748288466819
Iteration: 344 gradient_magnitude: 12940.98666456382
Iteration: 345 gradient_magnitude: 12921.255171774554
Iteration: 346 gradient_magnitude: 12901.553764157237
Iteration: 347 gradient_magnitude: 12881.882395840155
Iteration: 348 gradient_magnitude: 12862.24102102152
Iteration: 349 gradient_magnitude: 12842.629593969388
Iteration: 350 gradient_magnitude: 12823.04806902155
Iteration: 351 gradient_magnitude: 12803.496400585398
Iteration: 352 gradient_magnitude: 12783.974543137867
Iteration: 353 gradient_magnitude: 12764.48245122528
Iteration: 354 gradient_magnitude: 12745.020079463275
Iteration: 355 gradient_magnitude: 12725.587382536696
Iteration: 356 gradient_magnitude: 12706.184315199462
Iteration: 357 gradient_magnitude: 12686.810832274497
Iteration: 358 gradient_magnitude: 12667.466888653595
Iteration: 359 gradient_magnitude: 12648.152439297344
Iteration: 360 gradient_magnitude: 12628.867439234982
Iteration: 361 gradient_magnitude: 12609.611843564328
Iteration: 362 gradient_magnitude: 12590.385607451675
Iteration: 363 gradient_magnitude: 12571.188686131654
Iteration: 364 gradient_magnitude: 12552.02103490717
Iteration: 365 gradient_magnitude: 12532.882609149267
Iteration: 366 gradient_magnitude: 12513.773364297036
Iteration: 367 gradient_magnitude: 12494.69325585752
Iteration: 368 gradient_magnitude: 12475.642239405594
Iteration: 369 gradient_magnitude: 12456.620270583873
Iteration: 370 gradient_magnitude: 12437.627305102602
Iteration: 371 gradient_magnitude: 12418.663298739562
Iteration: 372 gradient_magnitude: 12399.728207339955
Iteration: 373 gradient_magnitude: 12380.821986816301
Iteration: 374 gradient_magnitude: 12361.944593148355
Iteration: 375 gradient_magnitude: 12343.095982382998
Iteration: 376 gradient_magnitude: 12324.276110634088
Iteration: 377 gradient_magnitude: 12305.484934082435
Iteration: 378 gradient_magnitude: 12286.72240897566
Iteration: 379 gradient_magnitude: 12267.988491628072
Iteration: 380 gradient_magnitude: 12249.283138420615
Iteration: 381 gradient_magnitude: 12230.606305800718
Iteration: 382 gradient_magnitude: 12211.957950282225
Iteration: 383 gradient_magnitude: 12193.338028445283
Iteration: 384 gradient_magnitude: 12174.746496936252
Iteration: 385 gradient_magnitude: 12156.183312467574
Iteration: 386 gradient_magnitude: 12137.648431817715
Iteration: 387 gradient_magnitude: 12119.141811831036
Iteration: 388 gradient_magnitude: 12100.663409417679
Iteration: 389 gradient_magnitude: 12082.21318155351
Iteration: 390 gradient_magnitude: 12063.791085279998
Iteration: 391 gradient_magnitude: 12045.397077704087
Iteration: 392 gradient_magnitude: 12027.031115998143
Iteration: 393 gradient_magnitude: 12008.693157399823
Iteration: 394 gradient_magnitude: 11990.383159211986
Here are the final weights after convergence:
[0.99621425 0.54625306]
```

**Task P6:** Use the learned weights to predict 'People tested' in the last three weeks in the dataset. Copy the predictions to the solution file, and calculate the test error  $\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$  where  $y_i$  is the number of test data,  $y_i$  is the true label,  $\hat{y}_i$  is the predicted label.

```
In [118]: # Create the test data
test_data = data.iloc[-21:]
(test_simple_feature_matrix, test_output) = get_numpy_data(test_data, simple_features, my_output)
test_predictions = predict_output(test_simple_feature_matrix, final_weights)
print (test_predictions)

[102.59928352 103.14553658 103.69178964 104.2380427 104.78429576
 105.33054882 105.87680188 106.42305494 106.969308 107.51556106
 108.06181412 108.60806718 109.15432024 109.7005733 110.24682637
 110.79307943 111.33933249 111.88558555 112.43183861 112.97809167
 113.52434473]

<ipython-input-107-8b2916f5b454>:9: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/table/user_guide/indexing.html#returning-a-view-versus-a-copy
    data_frame['constant'] = 1 # here we are adding a constant column
```

```
In [121]: # Calculate the test error
# STUDENT: Start of code

test_error = (1/len(test_predictions))* np.sum(np.square( np.subtract(test_data.People_tested, test_predictions)))
print(test_error)

#end of code
```

11490.99138344532

## Linear regression using multiple features

Here, we will be considering multiple input features ( Intensive\_care , New\_positive\_cases , Days ) to predict the People\_tested in the future.

**Task P7:** Specify the initial\_weights, step\_size, and tolerance for the function regression\_gradient\_descent . Print the outputs of the code.

```
In [127]: model_features = ['Intensive_care', 'New_positive_cases', 'Days']
my_output = 'People_tested'

#call the get_numpy_data method to calculate the feature matrix and output. Store them in the variables "multi_feature_matrix" & "output"

(multi_feature_matrix, output) = get_numpy_data(data, model_features, my_output)

# Initialize the weights, step size and tolerance
# STUDENT: Start of code
# STUDENT: Specify the initial_weights, step_size, and tolerance
initial_weights = [ 1.0, 1.0, 1.0, 1.0 ]
step_size = 7e-8
tolerance = 1.2e4
# end of code
weight_2 = regression_gradient_descent(multi_feature_matrix, output, initial_weights, step_size, tolerance)
print ("Here are the final weights after convergence:")
print (weight_2)
```

Iteration: 1 gradient\_magnitude: 28577.826184864996  
Iteration: 2 gradient\_magnitude: 28520.816323869836  
Iteration: 3 gradient\_magnitude: 28463.920191758247  
Iteration: 4 gradient\_magnitude: 28407.13756165268  
Iteration: 5 gradient\_magnitude: 28350.468207128142  
Iteration: 6 gradient\_magnitude: 28293.911902211352  
Iteration: 7 gradient\_magnitude: 28237.46842137985  
Iteration: 8 gradient\_magnitude: 28181.137539561012  
Iteration: 9 gradient\_magnitude: 28124.91903213125  
Iteration: 10 gradient\_magnitude: 28068.812674915087  
Iteration: 11 gradient\_magnitude: 28012.818244184222  
Iteration: 12 gradient\_magnitude: 27956.93551665667  
Iteration: 13 gradient\_magnitude: 27901.164269495923  
Iteration: 14 gradient\_magnitude: 27845.50428030994  
Iteration: 15 gradient\_magnitude: 27789.955327150372  
Iteration: 16 gradient\_magnitude: 27734.517188511614  
Iteration: 17 gradient\_magnitude: 27679.18964332996  
Iteration: 18 gradient\_magnitude: 27623.972470982688  
Iteration: 19 gradient\_magnitude: 27568.8654512872  
Iteration: 20 gradient\_magnitude: 27513.86836450015  
Iteration: 21 gradient\_magnitude: 27458.98099131656  
Iteration: 22 gradient\_magnitude: 27404.203112868905  
Iteration: 23 gradient\_magnitude: 27349.53451072633  
Iteration: 24 gradient\_magnitude: 27294.974966893693  
Iteration: 25 gradient\_magnitude: 27240.52426381075  
Iteration: 26 gradient\_magnitude: 27186.182184351255  
Iteration: 27 gradient\_magnitude: 27131.948511822106  
Iteration: 28 gradient\_magnitude: 27077.82302996248  
Iteration: 29 gradient\_magnitude: 27023.805522943003  
Iteration: 30 gradient\_magnitude: 26969.895775364814  
Iteration: 31 gradient\_magnitude: 26916.09357225877  
Iteration: 32 gradient\_magnitude: 26862.398699084588  
Iteration: 33 gradient\_magnitude: 26808.810941729942  
Iteration: 34 gradient\_magnitude: 26755.330086509646  
Iteration: 35 gradient\_magnitude: 26701.955920164815  
Iteration: 36 gradient\_magnitude: 26648.688229861964  
Iteration: 37 gradient\_magnitude: 26595.526803192206  
Iteration: 38 gradient\_magnitude: 26542.47142817038  
Iteration: 39 gradient\_magnitude: 26489.521893234232  
Iteration: 40 gradient\_magnitude: 26436.677987243518  
Iteration: 41 gradient\_magnitude: 26383.93949947924  
Iteration: 42 gradient\_magnitude: 26331.306219642735  
Iteration: 43 gradient\_magnitude: 26278.77793785487  
Iteration: 44 gradient\_magnitude: 26226.3544446552  
Iteration: 45 gradient\_magnitude: 26174.03553100114  
Iteration: 46 gradient\_magnitude: 26121.82098826711  
Iteration: 47 gradient\_magnitude: 26069.710608243724  
Iteration: 48 gradient\_magnitude: 26017.704183136964  
Iteration: 49 gradient\_magnitude: 25965.801505567313  
Iteration: 50 gradient\_magnitude: 25914.00236856898  
Iteration: 51 gradient\_magnitude: 25862.306565589042  
Iteration: 52 gradient\_magnitude: 25810.71389048662  
Iteration: 53 gradient\_magnitude: 25759.22413753208  
Iteration: 54 gradient\_magnitude: 25707.83710140618  
Iteration: 55 gradient\_magnitude: 25656.552577199294  
Iteration: 56 gradient\_magnitude: 25605.370360410525  
Iteration: 57 gradient\_magnitude: 25554.290246946995

Iteration: 58 gradient\_magnitude: 25503.312033122922  
Iteration: 59 gradient\_magnitude: 25452.435515658886  
Iteration: 60 gradient\_magnitude: 25401.660491680952  
Iteration: 61 gradient\_magnitude: 25350.98675871996  
Iteration: 62 gradient\_magnitude: 25300.41411471058  
Iteration: 63 gradient\_magnitude: 25249.94235799065  
Iteration: 64 gradient\_magnitude: 25199.571287300263  
Iteration: 65 gradient\_magnitude: 25149.300701781005  
Iteration: 66 gradient\_magnitude: 25099.130400975177  
Iteration: 67 gradient\_magnitude: 25049.06018482496  
Iteration: 68 gradient\_magnitude: 24999.089853671623  
Iteration: 69 gradient\_magnitude: 24949.21920825475  
Iteration: 70 gradient\_magnitude: 24899.44804971141  
Iteration: 71 gradient\_magnitude: 24849.776179575398  
Iteration: 72 gradient\_magnitude: 24800.203399776434  
Iteration: 73 gradient\_magnitude: 24750.729512639347  
Iteration: 74 gradient\_magnitude: 24701.35432088332  
Iteration: 75 gradient\_magnitude: 24652.077627621096  
Iteration: 76 gradient\_magnitude: 24602.899236358197  
Iteration: 77 gradient\_magnitude: 24553.81895099208  
Iteration: 78 gradient\_magnitude: 24504.83657581148  
Iteration: 79 gradient\_magnitude: 24455.95191549551  
Iteration: 80 gradient\_magnitude: 24407.16477511294  
Iteration: 81 gradient\_magnitude: 24358.47496012139  
Iteration: 82 gradient\_magnitude: 24309.88227636661  
Iteration: 83 gradient\_magnitude: 24261.38653008164  
Iteration: 84 gradient\_magnitude: 24212.987527886078  
Iteration: 85 gradient\_magnitude: 24164.685076785267  
Iteration: 86 gradient\_magnitude: 24116.47898416962  
Iteration: 87 gradient\_magnitude: 24068.369057813707  
Iteration: 88 gradient\_magnitude: 24020.355105875624  
Iteration: 89 gradient\_magnitude: 23972.436936896145  
Iteration: 90 gradient\_magnitude: 23924.614359798004  
Iteration: 91 gradient\_magnitude: 23876.8871838851  
Iteration: 92 gradient\_magnitude: 23829.25521884177  
Iteration: 93 gradient\_magnitude: 23781.718274731982  
Iteration: 94 gradient\_magnitude: 23734.276161998634  
Iteration: 95 gradient\_magnitude: 23686.928691462752  
Iteration: 96 gradient\_magnitude: 23639.675674322774  
Iteration: 97 gradient\_magnitude: 23592.516922153765  
Iteration: 98 gradient\_magnitude: 23545.452246906676  
Iteration: 99 gradient\_magnitude: 23498.4814609076  
Iteration: 100 gradient\_magnitude: 23451.604376857034  
Iteration: 101 gradient\_magnitude: 23404.8208078291  
Iteration: 102 gradient\_magnitude: 23358.130567270826  
Iteration: 103 gradient\_magnitude: 23311.533469001388  
Iteration: 104 gradient\_magnitude: 23265.02932721139  
Iteration: 105 gradient\_magnitude: 23218.617956462087  
Iteration: 106 gradient\_magnitude: 23172.29917168467  
Iteration: 107 gradient\_magnitude: 23126.072788179543  
Iteration: 108 gradient\_magnitude: 23079.93862161555  
Iteration: 109 gradient\_magnitude: 23033.896488029244  
Iteration: 110 gradient\_magnitude: 22987.94620382419  
Iteration: 111 gradient\_magnitude: 22942.08758577021  
Iteration: 112 gradient\_magnitude: 22896.32045100263  
Iteration: 113 gradient\_magnitude: 22850.644617021586  
Iteration: 114 gradient\_magnitude: 22805.059901691275

Iteration: 115 gradient\_magnitude: 22759.566123239263  
Iteration: 116 gradient\_magnitude: 22714.1631002555697  
Iteration: 117 gradient\_magnitude: 22668.850651692635  
Iteration: 118 gradient\_magnitude: 22623.62859686332  
Iteration: 119 gradient\_magnitude: 22578.496755441407  
Iteration: 120 gradient\_magnitude: 22533.45494746034  
Iteration: 121 gradient\_magnitude: 22488.502993312522  
Iteration: 122 gradient\_magnitude: 22443.640713748704  
Iteration: 123 gradient\_magnitude: 22398.867929877186  
Iteration: 124 gradient\_magnitude: 22354.18446316315  
Iteration: 125 gradient\_magnitude: 22309.590135427945  
Iteration: 126 gradient\_magnitude: 22265.08476884836  
Iteration: 127 gradient\_magnitude: 22220.668185955918  
Iteration: 128 gradient\_magnitude: 22176.340209636175  
Iteration: 129 gradient\_magnitude: 22132.100663128036  
Iteration: 130 gradient\_magnitude: 22087.949370022987  
Iteration: 131 gradient\_magnitude: 22043.88615426447  
Iteration: 132 gradient\_magnitude: 21999.910840147117  
Iteration: 133 gradient\_magnitude: 21956.023252316074  
Iteration: 134 gradient\_magnitude: 21912.223215766324  
Iteration: 135 gradient\_magnitude: 21868.510555841935  
Iteration: 136 gradient\_magnitude: 21824.885098235423  
Iteration: 137 gradient\_magnitude: 21781.34666898702  
Iteration: 138 gradient\_magnitude: 21737.895094483985  
Iteration: 139 gradient\_magnitude: 21694.53020145993  
Iteration: 140 gradient\_magnitude: 21651.251816994103  
Iteration: 141 gradient\_magnitude: 21608.059768510713  
Iteration: 142 gradient\_magnitude: 21564.953883778257  
Iteration: 143 gradient\_magnitude: 21521.933990908787  
Iteration: 144 gradient\_magnitude: 21478.999918357273  
Iteration: 145 gradient\_magnitude: 21436.151494920898  
Iteration: 146 gradient\_magnitude: 21393.388549738378  
Iteration: 147 gradient\_magnitude: 21350.710912289276  
Iteration: 148 gradient\_magnitude: 21308.118412393327  
Iteration: 149 gradient\_magnitude: 21265.61088020977  
Iteration: 150 gradient\_magnitude: 21223.188146236633  
Iteration: 151 gradient\_magnitude: 21180.8500413101  
Iteration: 152 gradient\_magnitude: 21138.59639660382  
Iteration: 153 gradient\_magnitude: 21096.42704362824  
Iteration: 154 gradient\_magnitude: 21054.341814229905  
Iteration: 155 gradient\_magnitude: 21012.340540590827  
Iteration: 156 gradient\_magnitude: 20970.423055227795  
Iteration: 157 gradient\_magnitude: 20928.5891909917  
Iteration: 158 gradient\_magnitude: 20886.8387810669  
Iteration: 159 gradient\_magnitude: 20845.171658970514  
Iteration: 160 gradient\_magnitude: 20803.58765855178  
Iteration: 161 gradient\_magnitude: 20762.086613991396  
Iteration: 162 gradient\_magnitude: 20720.668359800842  
Iteration: 163 gradient\_magnitude: 20679.33273082175  
Iteration: 164 gradient\_magnitude: 20638.0795622252  
Iteration: 165 gradient\_magnitude: 20596.90868951112  
Iteration: 166 gradient\_magnitude: 20555.81994850757  
Iteration: 167 gradient\_magnitude: 20514.813175370142  
Iteration: 168 gradient\_magnitude: 20473.88820658125  
Iteration: 169 gradient\_magnitude: 20433.044878949542  
Iteration: 170 gradient\_magnitude: 20392.28302960919  
Iteration: 171 gradient\_magnitude: 20351.60249601929

Iteration: 172 gradient\_magnitude: 20311.003115963165  
Iteration: 173 gradient\_magnitude: 20270.48472754777  
Iteration: 174 gradient\_magnitude: 20230.047169202993  
Iteration: 175 gradient\_magnitude: 20189.69027968107  
Iteration: 176 gradient\_magnitude: 20149.413898055875  
Iteration: 177 gradient\_magnitude: 20109.217863722337  
Iteration: 178 gradient\_magnitude: 20069.102016395773  
Iteration: 179 gradient\_magnitude: 20029.066196111242  
Iteration: 180 gradient\_magnitude: 19989.110243222924  
Iteration: 181 gradient\_magnitude: 19949.233998403484  
Iteration: 182 gradient\_magnitude: 19909.43730264341  
Iteration: 183 gradient\_magnitude: 19869.719997250413  
Iteration: 184 gradient\_magnitude: 19830.081923848764  
Iteration: 185 gradient\_magnitude: 19790.522924378693  
Iteration: 186 gradient\_magnitude: 19751.042841095747  
Iteration: 187 gradient\_magnitude: 19711.641516570133  
Iteration: 188 gradient\_magnitude: 19672.318793686132  
Iteration: 189 gradient\_magnitude: 19633.074515641456  
Iteration: 190 gradient\_magnitude: 19593.908525946623  
Iteration: 191 gradient\_magnitude: 19554.82066842431  
Iteration: 192 gradient\_magnitude: 19515.810787208786  
Iteration: 193 gradient\_magnitude: 19476.87872674522  
Iteration: 194 gradient\_magnitude: 19438.02433178914  
Iteration: 195 gradient\_magnitude: 19399.247447405724  
Iteration: 196 gradient\_magnitude: 19360.547918969252  
Iteration: 197 gradient\_magnitude: 19321.92559216248  
Iteration: 198 gradient\_magnitude: 19283.38031297599  
Iteration: 199 gradient\_magnitude: 19244.911927707606  
Iteration: 200 gradient\_magnitude: 19206.52028296177  
Iteration: 201 gradient\_magnitude: 19168.20522564893  
Iteration: 202 gradient\_magnitude: 19129.966602984943  
Iteration: 203 gradient\_magnitude: 19091.80426249045  
Iteration: 204 gradient\_magnitude: 19053.718051990258  
Iteration: 205 gradient\_magnitude: 19015.707819612762  
Iteration: 206 gradient\_magnitude: 18977.77341378933  
Iteration: 207 gradient\_magnitude: 18939.91468325369  
Iteration: 208 gradient\_magnitude: 18902.131477041323  
Iteration: 209 gradient\_magnitude: 18864.42364448887  
Iteration: 210 gradient\_magnitude: 18826.791035233553  
Iteration: 211 gradient\_magnitude: 18789.233499212514  
Iteration: 212 gradient\_magnitude: 18751.75088666228  
Iteration: 213 gradient\_magnitude: 18714.343048118146  
Iteration: 214 gradient\_magnitude: 18677.009834413548  
Iteration: 215 gradient\_magnitude: 18639.751096679523  
Iteration: 216 gradient\_magnitude: 18602.56668634407  
Iteration: 217 gradient\_magnitude: 18565.45645513159  
Iteration: 218 gradient\_magnitude: 18528.42025506224  
Iteration: 219 gradient\_magnitude: 18491.45793845142  
Iteration: 220 gradient\_magnitude: 18454.569357909146  
Iteration: 221 gradient\_magnitude: 18417.75436633944  
Iteration: 222 gradient\_magnitude: 18381.01281693977  
Iteration: 223 gradient\_magnitude: 18344.344563200477  
Iteration: 224 gradient\_magnitude: 18307.749458904156  
Iteration: 225 gradient\_magnitude: 18271.227358125103  
Iteration: 226 gradient\_magnitude: 18234.7781152287  
Iteration: 227 gradient\_magnitude: 18198.40158487089  
Iteration: 228 gradient\_magnitude: 18162.097621997542

Iteration: 229 gradient\_magnitude: 18125.86608184388  
Iteration: 230 gradient\_magnitude: 18089.706819933945  
Iteration: 231 gradient\_magnitude: 18053.619692079978  
Iteration: 232 gradient\_magnitude: 18017.60455438186  
Iteration: 233 gradient\_magnitude: 17981.661263226557  
Iteration: 234 gradient\_magnitude: 17945.789675287495  
Iteration: 235 gradient\_magnitude: 17909.989647524046  
Iteration: 236 gradient\_magnitude: 17874.26103718093  
Iteration: 237 gradient\_magnitude: 17838.603701787648  
Iteration: 238 gradient\_magnitude: 17803.01749915791  
Iteration: 239 gradient\_magnitude: 17767.50228738908  
Iteration: 240 gradient\_magnitude: 17732.057924861598  
Iteration: 241 gradient\_magnitude: 17696.684270238424  
Iteration: 242 gradient\_magnitude: 17661.38118246447  
Iteration: 243 gradient\_magnitude: 17626.148520766048  
Iteration: 244 gradient\_magnitude: 17590.98614465028  
Iteration: 245 gradient\_magnitude: 17555.893913904558  
Iteration: 246 gradient\_magnitude: 17520.87168859601  
Iteration: 247 gradient\_magnitude: 17485.91932907089  
Iteration: 248 gradient\_magnitude: 17451.036695954062  
Iteration: 249 gradient\_magnitude: 17416.223650148426  
Iteration: 250 gradient\_magnitude: 17381.480052834348  
Iteration: 251 gradient\_magnitude: 17346.80576546915  
Iteration: 252 gradient\_magnitude: 17312.200649786537  
Iteration: 253 gradient\_magnitude: 17277.664567796004  
Iteration: 254 gradient\_magnitude: 17243.197381782364  
Iteration: 255 gradient\_magnitude: 17208.798954305123  
Iteration: 256 gradient\_magnitude: 17174.469148198008  
Iteration: 257 gradient\_magnitude: 17140.207826568334  
Iteration: 258 gradient\_magnitude: 17106.014852796532  
Iteration: 259 gradient\_magnitude: 17071.89009053557  
Iteration: 260 gradient\_magnitude: 17037.83340371041  
Iteration: 261 gradient\_magnitude: 17003.84465651747  
Iteration: 262 gradient\_magnitude: 16969.923713424083  
Iteration: 263 gradient\_magnitude: 16936.070439167965  
Iteration: 264 gradient\_magnitude: 16902.284698756645  
Iteration: 265 gradient\_magnitude: 16868.566357466974  
Iteration: 266 gradient\_magnitude: 16834.915280844536  
Iteration: 267 gradient\_magnitude: 16801.33133470317  
Iteration: 268 gradient\_magnitude: 16767.814385124373  
Iteration: 269 gradient\_magnitude: 16734.36429845681  
Iteration: 270 gradient\_magnitude: 16700.980941315756  
Iteration: 271 gradient\_magnitude: 16667.664180582597  
Iteration: 272 gradient\_magnitude: 16634.413883404257  
Iteration: 273 gradient\_magnitude: 16601.229917192686  
Iteration: 274 gradient\_magnitude: 16568.112149624354  
Iteration: 275 gradient\_magnitude: 16535.06044863969  
Iteration: 276 gradient\_magnitude: 16502.074682442566  
Iteration: 277 gradient\_magnitude: 16469.15471949978  
Iteration: 278 gradient\_magnitude: 16436.300428540522  
Iteration: 279 gradient\_magnitude: 16403.51167855585  
Iteration: 280 gradient\_magnitude: 16370.788338798186  
Iteration: 281 gradient\_magnitude: 16338.130278780762  
Iteration: 282 gradient\_magnitude: 16305.53736827713  
Iteration: 283 gradient\_magnitude: 16273.009477320624  
Iteration: 284 gradient\_magnitude: 16240.546476203855  
Iteration: 285 gradient\_magnitude: 16208.14823547819

Iteration: 286 gradient\_magnitude: 16175.81462595321  
Iteration: 287 gradient\_magnitude: 16143.545518696244  
Iteration: 288 gradient\_magnitude: 16111.340785031816  
Iteration: 289 gradient\_magnitude: 16079.200296541152  
Iteration: 290 gradient\_magnitude: 16047.123925061655  
Iteration: 291 gradient\_magnitude: 16015.11154268639  
Iteration: 292 gradient\_magnitude: 15983.163021763603  
Iteration: 293 gradient\_magnitude: 15951.278234896186  
Iteration: 294 gradient\_magnitude: 15919.457054941156  
Iteration: 295 gradient\_magnitude: 15887.699355009194  
Iteration: 296 gradient\_magnitude: 15856.005008464104  
Iteration: 297 gradient\_magnitude: 15824.373888922306  
Iteration: 298 gradient\_magnitude: 15792.805870252356  
Iteration: 299 gradient\_magnitude: 15761.300826574421  
Iteration: 300 gradient\_magnitude: 15729.85863225979  
Iteration: 301 gradient\_magnitude: 15698.479161930365  
Iteration: 302 gradient\_magnitude: 15667.162290458165  
Iteration: 303 gradient\_magnitude: 15635.907892964831  
Iteration: 304 gradient\_magnitude: 15604.715844821121  
Iteration: 305 gradient\_magnitude: 15573.586021646408  
Iteration: 306 gradient\_magnitude: 15542.51829930821  
Iteration: 307 gradient\_magnitude: 15511.512553921655  
Iteration: 308 gradient\_magnitude: 15480.568661849027  
Iteration: 309 gradient\_magnitude: 15449.686499699244  
Iteration: 310 gradient\_magnitude: 15418.865944327374  
Iteration: 311 gradient\_magnitude: 15388.106872834163  
Iteration: 312 gradient\_magnitude: 15357.409162565516  
Iteration: 313 gradient\_magnitude: 15326.772691112012  
Iteration: 314 gradient\_magnitude: 15296.197336308449  
Iteration: 315 gradient\_magnitude: 15265.682976233307  
Iteration: 316 gradient\_magnitude: 15235.229489208303  
Iteration: 317 gradient\_magnitude: 15204.836753797883  
Iteration: 318 gradient\_magnitude: 15174.504648808746  
Iteration: 319 gradient\_magnitude: 15144.233053289365  
Iteration: 320 gradient\_magnitude: 15114.021846529487  
Iteration: 321 gradient\_magnitude: 15083.870908059673  
Iteration: 322 gradient\_magnitude: 15053.780117650804  
Iteration: 323 gradient\_magnitude: 15023.749355313605  
Iteration: 324 gradient\_magnitude: 14993.778501298179  
Iteration: 325 gradient\_magnitude: 14963.867436093502  
Iteration: 326 gradient\_magnitude: 14934.016040426975  
Iteration: 327 gradient\_magnitude: 14904.224195263918  
Iteration: 328 gradient\_magnitude: 14874.49178180714  
Iteration: 329 gradient\_magnitude: 14844.818681496416  
Iteration: 330 gradient\_magnitude: 14815.204776008044  
Iteration: 331 gradient\_magnitude: 14785.64994725437  
Iteration: 332 gradient\_magnitude: 14756.154077383298  
Iteration: 333 gradient\_magnitude: 14726.71704877786  
Iteration: 334 gradient\_magnitude: 14697.338744055693  
Iteration: 335 gradient\_magnitude: 14668.01904606863  
Iteration: 336 gradient\_magnitude: 14638.757837902172  
Iteration: 337 gradient\_magnitude: 14609.55500287508  
Iteration: 338 gradient\_magnitude: 14580.410424538863  
Iteration: 339 gradient\_magnitude: 14551.323986677338  
Iteration: 340 gradient\_magnitude: 14522.295573306172  
Iteration: 341 gradient\_magnitude: 14493.325068672395  
Iteration: 342 gradient\_magnitude: 14464.412357253954

Iteration: 343 gradient\_magnitude: 14435.55732375926  
Iteration: 344 gradient\_magnitude: 14406.759853126712  
Iteration: 345 gradient\_magnitude: 14378.019830524245  
Iteration: 346 gradient\_magnitude: 14349.33714134888  
Iteration: 347 gradient\_magnitude: 14320.711671226243  
Iteration: 348 gradient\_magnitude: 14292.143306010146  
Iteration: 349 gradient\_magnitude: 14263.631931782098  
Iteration: 350 gradient\_magnitude: 14235.177434850855  
Iteration: 351 gradient\_magnitude: 14206.779701752002  
Iteration: 352 gradient\_magnitude: 14178.438619247454  
Iteration: 353 gradient\_magnitude: 14150.15407432503  
Iteration: 354 gradient\_magnitude: 14121.925954197994  
Iteration: 355 gradient\_magnitude: 14093.754146304615  
Iteration: 356 gradient\_magnitude: 14065.6385383077  
Iteration: 357 gradient\_magnitude: 14037.579018094166  
Iteration: 358 gradient\_magnitude: 14009.57547377458  
Iteration: 359 gradient\_magnitude: 13981.62779368273  
Iteration: 360 gradient\_magnitude: 13953.735866375147  
Iteration: 361 gradient\_magnitude: 13925.899580630687  
Iteration: 362 gradient\_magnitude: 13898.118825450083  
Iteration: 363 gradient\_magnitude: 13870.393490055514  
Iteration: 364 gradient\_magnitude: 13842.723463890115  
Iteration: 365 gradient\_magnitude: 13815.108636617611  
Iteration: 366 gradient\_magnitude: 13787.548898121806  
Iteration: 367 gradient\_magnitude: 13760.04413850619  
Iteration: 368 gradient\_magnitude: 13732.59424809348  
Iteration: 369 gradient\_magnitude: 13705.199117425193  
Iteration: 370 gradient\_magnitude: 13677.858637261194  
Iteration: 371 gradient\_magnitude: 13650.57269857928  
Iteration: 372 gradient\_magnitude: 13623.341192574737  
Iteration: 373 gradient\_magnitude: 13596.164010659906  
Iteration: 374 gradient\_magnitude: 13569.041044463738  
Iteration: 375 gradient\_magnitude: 13541.972185831382  
Iteration: 376 gradient\_magnitude: 13514.957326823753  
Iteration: 377 gradient\_magnitude: 13487.996359717074  
Iteration: 378 gradient\_magnitude: 13461.089177002483  
Iteration: 379 gradient\_magnitude: 13434.235671385573  
Iteration: 380 gradient\_magnitude: 13407.435735785997  
Iteration: 381 gradient\_magnitude: 13380.689263337006  
Iteration: 382 gradient\_magnitude: 13353.996147385045  
Iteration: 383 gradient\_magnitude: 13327.356281489321  
Iteration: 384 gradient\_magnitude: 13300.769559421387  
Iteration: 385 gradient\_magnitude: 13274.235875164695  
Iteration: 386 gradient\_magnitude: 13247.755122914203  
Iteration: 387 gradient\_magnitude: 13221.327197075942  
Iteration: 388 gradient\_magnitude: 13194.951992266573  
Iteration: 389 gradient\_magnitude: 13168.629403313013  
Iteration: 390 gradient\_magnitude: 13142.359325251959  
Iteration: 391 gradient\_magnitude: 13116.141653329525  
Iteration: 392 gradient\_magnitude: 13089.976283000782  
Iteration: 393 gradient\_magnitude: 13063.863109929367  
Iteration: 394 gradient\_magnitude: 13037.802029987046  
Iteration: 395 gradient\_magnitude: 13011.792939253324  
Iteration: 396 gradient\_magnitude: 12985.835734015016  
Iteration: 397 gradient\_magnitude: 12959.930310765816  
Iteration: 398 gradient\_magnitude: 12934.076566205924  
Iteration: 399 gradient\_magnitude: 12908.274397241605

```
Iteration: 400 gradient_magnitude: 12882.52370098478
Iteration: 401 gradient_magnitude: 12856.824374752629
Iteration: 402 gradient_magnitude: 12831.176316067173
Iteration: 403 gradient_magnitude: 12805.579422654859
Iteration: 404 gradient_magnitude: 12780.03359244616
Iteration: 405 gradient_magnitude: 12754.538723575179
Iteration: 406 gradient_magnitude: 12729.094714379225
Iteration: 407 gradient_magnitude: 12703.701463398409
Iteration: 408 gradient_magnitude: 12678.358869375248
Iteration: 409 gradient_magnitude: 12653.06683125426
Iteration: 410 gradient_magnitude: 12627.82524818155
Iteration: 411 gradient_magnitude: 12602.634019504425
Iteration: 412 gradient_magnitude: 12577.49304477098
Iteration: 413 gradient_magnitude: 12552.4022237297
Iteration: 414 gradient_magnitude: 12527.361456329065
Iteration: 415 gradient_magnitude: 12502.370642717155
Iteration: 416 gradient_magnitude: 12477.429683241218
Iteration: 417 gradient_magnitude: 12452.53847844733
Iteration: 418 gradient_magnitude: 12427.696929079948
Iteration: 419 gradient_magnitude: 12402.904936081546
Iteration: 420 gradient_magnitude: 12378.1624005922
Iteration: 421 gradient_magnitude: 12353.469223949198
Iteration: 422 gradient_magnitude: 12328.82530768666
Iteration: 423 gradient_magnitude: 12304.23055353513
Iteration: 424 gradient_magnitude: 12279.684863421187
Iteration: 425 gradient_magnitude: 12255.188139467067
Iteration: 426 gradient_magnitude: 12230.740283990246
Iteration: 427 gradient_magnitude: 12206.341199503086
Iteration: 428 gradient_magnitude: 12181.990788712408
Iteration: 429 gradient_magnitude: 12157.688954519137
Iteration: 430 gradient_magnitude: 12133.435600017889
Iteration: 431 gradient_magnitude: 12109.230628496609
Iteration: 432 gradient_magnitude: 12085.073943436166
Iteration: 433 gradient_magnitude: 12060.965448509976
Iteration: 434 gradient_magnitude: 12036.905047583612
Iteration: 435 gradient_magnitude: 12012.892644714433
Iteration: 436 gradient_magnitude: 11988.928144151192
Here are the final weights after convergence:
[0.99572553 0.99950436 0.99941219 0.41591547]
```

**Task P8:** Use the learned weights to predict 'People\_tested' in the last three weeks in the dataset. Find the value of the model predictions on the 10th day of the forecasting period. Also print the actual number of people tested on that particular day. Copy the predictions to the solution file, and calculate the test error. Note: here we are asking you to report the number before normalization. So you need to convert the prediction back to the unit of people.

```
In [128]: (test_feature_matrix, test_output) = get_numpy_data(test_data, model_features,
my_output)

test_predictions_2 = predict_output(test_feature_matrix, weight_2)

#Prediction for the 10th day of the forecasting period.
print (test_predictions_2[10])

#Convert the normalized data back to original figures using the same min-max normalization
prediction_10th_day = test_predictions_2[10] * (data_orig['People_tested'].max()
() - data_orig['People_tested'].min()) + data_orig['People_tested'].min()

print ("Model prediction of the 10th day:",int(prediction_10th_day))

# Get the actual number of people tested from our test data on 10 th day of forecasting period.
actual_people_tested = data_orig["People_tested"].iloc[190]

print ("Actual number of people tested on the 10th day:",actual_people_tested)
```

82.72965202021162

Model prediction of the 10th day: 830628809

Actual number of people tested on the 10th day: 8725909

<ipython-input-107-8b2916f5b454>:9: SettingWithCopyWarning:  
A value is trying to be set on a copy of a slice from a DataFrame.  
Try using .loc[row\_indexer,col\_indexer] = value instead

See the caveats in the documentation: [https://pandas.pydata.org/pandas-docs/table/user\\_guide/indexing.html#returning-a-view-versus-a-copy](https://pandas.pydata.org/pandas-docs/table/user_guide/indexing.html#returning-a-view-versus-a-copy)  
data\_frame['constant'] = 1 # here we are adding a constant column

```
In [129]: # Calculate the test error
# STUDENT: Start of code
test_error = (1/len(test_predictions_2))* np.sum(np.square( np.subtract(test_data.People_tested, test_predictions_2)))
print(test_error)

# end of code
```

6701.844086335183

## Explore on your own

Now that you have tried two models for predictions, in this section, you can explore on your own an aspect of the problem that interests you. Here are some examples:

- What features or what combination of features are most predictive for 'People\_tested'?
- How does tolerance for convergence affect prediction errors?
- How does step size affect prediction errors?
- How can we use validation to select the set of features to improve prediction?

Report your question of investigation, as well as your results/interpretation in the solution file.

```
In [138]: def regression_gradient_descent_2(feature_matrix, labels, initial_weights, step_size, tolerance):
    # Gradient descent algorithm for linear regression problem

    # Input:
    # feature_matrix: numpy array of size n by d, where n is the number of data points, and d is the feature dimension
    # Labels: true Labels y, a numpy vector of dimension d
    # initial_weights: initial weight vector to start with, a numpy vector of dimension d
    # step_size: step size of update
    # tolerance: tolerance epsilon for stopping condition
    # Output:
    # Weights obtained after convergence

    converged = False
    weights = np.array(initial_weights) # current iterate
    i = 0
    while not converged:
        i += 1
        # STUDENT: Start of code: your implementation of what the gradient descent algorithm does in every iteration
        # Refer back to the update rule listed above: update the weight
        derivative = weight_derivative(weights, feature_matrix, labels);
        weights = weights - step_size*derivative

        # Compute the gradient magnitude:

        gradient_magnitude = np.linalg.norm( weight_derivative(weights, feature_matrix, labels) )

        # Check the stopping condition to decide whether you want to stop the iterations
        if gradient_magnitude <= tolerance: # STUDENT: check the stopping condition here
            converged = True

        # End of code

        #print ("Iteration: ",i,"gradient_magnitude: ", gradient_magnitude) # for us to check about convergence

    return(weights)
```

```
In [141]: # Explore an aspect of the model that interests you
### STUDENT: Start of code

simple_features = ['Days']
my_output = 'People_tested'

# Use get_numpy_data method to calculate the feature matrix and output.
(simple_feature_matrix, output) = get_numpy_data(train_data, simple_features,
my_output)

#Initialize the weights, step size and tolerance
# Start of code
#STUDENT: Specify the initial_weights, step_size, and tolerance
initial_weights = [1.0, 1.0]
step_size = 7e-8

tolerance_1 = 0.8e4
tolerance_2 = 1.0e4
tolerance_3 = 1.2e4
tolerance_4 = 1.4e4
# end of code

# Use the regression_gradient_descent function to calculate the gradient decent and store it in the variable 'final_weights'
final_weights_1 = regression_gradient_descent_2(simple_feature_matrix, output,
initial_weights, step_size, tolerance_1)
final_weights_2 = regression_gradient_descent_2(simple_feature_matrix, output,
initial_weights, step_size, tolerance_2)
final_weights_3 = regression_gradient_descent_2(simple_feature_matrix, output,
initial_weights, step_size, tolerance_3)
final_weights_4 = regression_gradient_descent_2(simple_feature_matrix, output,
initial_weights, step_size, tolerance_4)
# end of code

#print ("Here are the final weights after convergence with tolerance of 0.8e4:")
#print (final_weights_1)
#print ("Here are the final weights after convergence with tolerance of 1.0e4:")
#print (final_weights_2)
#print ("Here are the final weights after convergence with tolerance of 1.2e4:")
#print (final_weights_3)
#print ("Here are the final weights after convergence with tolerance of 1.4e4:")
#print (final_weights_4)

test_data = data.iloc[-21:]
(test_simple_feature_matrix, test_output) = get_numpy_data(test_data, simple_features, my_output)
test_predictions_1 = predict_output(test_simple_feature_matrix, final_weights_1)
test_predictions_2 = predict_output(test_simple_feature_matrix, final_weights_2)
test_predictions_3 = predict_output(test_simple_feature_matrix, final_weights_3)
```

```
test_predictions_4 = predict_output(test_simple_feature_matrix, final_weights_
4)

test_error = (1/len(test_predictions_1))* np.sum(np.square( np.subtract(test_d
ata.People_tested, test_predictions_1)))
print("Error for tolerance of 0.8e4:", test_error)
test_error = (1/len(test_predictions_2))* np.sum(np.square( np.subtract(test_d
ata.People_tested, test_predictions_2)))
print("Error for tolerance of 1.0e4:", test_error)
test_error = (1/len(test_predictions_3))* np.sum(np.square( np.subtract(test_d
ata.People_tested, test_predictions_3)))
print("Error for tolerance of 1.2e4:", test_error)
test_error = (1/len(test_predictions_4))* np.sum(np.square( np.subtract(test_d
ata.People_tested, test_predictions_4)))
print("Error for tolerance of 1.4e4:", test_error)
#end of code

### End of code
```

```
Error for tolerance of 0.8e4: 5067.1321292306275
Error for tolerance of 1.0e4: 7969.441808885362
Error for tolerance of 1.2e4: 11490.99138344532
Error for tolerance of 1.4e4: 15670.65863747879
```

```
<ipython-input-107-8b2916f5b454>:9: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy
data_frame['constant'] = 1 # here we are adding a constant column
```

My question of investigation was how does tolerance for convergence affect the test error. I used 4 different tolerance values ranging from 0.8e4 to 1.4e4. As I increased the tolerance value, the error also increased as well. It seems like the smaller the tolerance I give it, the less room for error there is for the model to make.