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Problem Chosen

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**2018 ICM**
**Summary Sheet**

(Your team's summary should be included as the first page of your electronic submission.)
Type a summary of your results on this page. Do not include the name of your school, advisor, or team members on this page.

Peace and development has become the theme in this day and age. However, climate change has been causing serious threat to people's survival and the national vulnerability has increased dramatically. Combining with previous researches, we add 9 indicators related to national vulnerability, so it is influenced by 21 indicators. Our research aims to establish multi-layer deep neural networks model. Based on gradient descent algorithm, Momentum algorithm and Adam algorithm, the mapping between input and output of deep neural networks and the continuous mapping function of m-dimensional Euclidean space in a highly non-linear Euclidean space finite domain come out. Coupled with the data processing of the complexity of simple non-linear functions, two links (forward and backward-propagation and weights update) iterations are repeatedly adopted to overcome the limitations of traditional regression models in building complex mapping relations and extracting high-level data characteristics. In our research, the training sets containing 21 factors corresponding countries data from 2013 to 2016 are used to achieve the prediction of the influence of climate factors on the national vulnerability.

Firstly, the model can determine national vulnerability by the impact of climate change on national vulnerability from two aspects, single climate factors and comprehensive climate factors. We have concluded that the single factor of climate change has a certain impact on national vulnerability and the comprehensive factors of climate have a great impact on national vulnerability. However, huge fluctuations cannot be caused by changing single factor, which reflects the stability of this model.

Secondly, by analyzing the vulnerability of one of the ten vulnerable countries, Sudan, we get the optimal climate factor model and Sudan could not be so vulnerable if comprehensive climate factors improve. And we used the "threshold mechanism" to determine the appropriate threshold to determine the selection of the critical point in order to make the model to achieve the best results, which can effectively reduce the vulnerability of the Sudan.

Thirdly, we chose Britain, which is in top 10 non-fragile countries to predict the national vulnerability. We can draw a conclusion that the improvement of the comprehensive factors of climate change can make the U.K. have more solid strength. And we calculated the cost of education, health care, welfare and protection to determine the government budget under artificial intervention.

Finally, after a comprehensive analysis of the correlation between urban vulnerability and national vulnerability, due to the cumulative process effect and cumulative amplification effect, we determined that the neural network model can be applied to smaller "continent" or larger “continent". Therefore, our model can be applied to not only national vulnerability detection, prediction and prevention, but also a tiny area, such as township, or a great area, such as the earth. This will bring great help to the development of local conditions and point out the direction for the progress and development of the world.

# The Impact of Climate Change on National Vulnerability Based on Deep Neural Networks

## Abstract

National vulnerability has complex effects of many variables, which also have correlations with each other. In our research, we established a multilayer deep neural network model using 21 indicators of national vulnerability data from 2013 to 2016 for 4 years to learn the characteristics of data for achieving the best forecast of regression. We also optimize the algorithm and use momentum algorithm and Adam algorithm to make the model more reliable and robust.

Firstly, we show the influence of single and comprehensive climate change factors on national vulnerability. And we concluded that the single factor of climate change has certain influence on the national stability and comprehensive factors have a strong impact on national vulnerability. However, huge fluctuations cannot be caused by changing single factor, which reflects the stability of this model.

Secondly, after analyzing the relationship between Sudan's national stability and its characteristics, we find that the comprehensive factors of climate change have great influence on the national vulnerability of Sudan.

Thirdly, after analyzing the vulnerability of UK countries, it is concluded that climate change factors have a great influence on the fragile factors of the UK countries. The UK can improve its national strength by improving climate conditions, such as increasing greening area and planting trees. At the same time, the threshold is used to analyze the critical point which is the most suitable to distinguish the country's vulnerability, so that the model can be used to predict the true state of the country.

Finally, we demonstrated the generality of the neural network model. The multi-layer deep neural network is also suitable for cities, states, even continents.

**Key Words:** National Vulnerability; Climate Change; Machine Learning; Deep Neural Networks Model; Momentum Algorithm; Adam Algorithm.

# Table of Contents

# 1 Introduction

Climate change can affect the vulnerability of a country or region. Climate change varies by region. Much of the impact it brings can change the way people live, leading to fragility in the country.

National vulnerability means the state's ability or legitimacy is weak, unable to meet the basic needs and expectations of the people, and unable to resist the internal and external risks in the fields of nature, society and security. Vulnerability is a manifestation of internal contradictions in the country. The phenomenon of "weak countries" has become a global and regional issue. Since 1980s, climate warming marked by the global climate change has attracted the attention of governments, international organizations and scientists. After that, some scholars began to introduce the concept of vulnerability into the field of climate change research. In 2001 IPCC (Intergovernmental Panel on Climate Change) third assessment report on climate change, the vulnerability was revised as a clear concept. From then, it has gradually become the focus of global climate change research and hot fields.

With the increasing global population pressure, climate change especially the greenhouse effect has been affected at human living needs, such as food and increasing number of private cars. The changing climate also caused deterioration of the environment, such as drought, rising sea levels and the environmental performance index (EPI) decreased. In order to survive, people live away from their homes to the stable state and make a mass migration. This directly results in that migration of people can't get the basic guarantee of their good education, health care, credit and during the rush, the infant mortality rate and life expectancy are greatly shortened. And because of human migration, domestic labor shortage, economic and public service collapse come out. At the same time, people's rights are not guaranteed, and the crime rate is rising sharply. Moreover, the defense is weak, and the political economy is vulnerable to external intervention, which all lead to national vulnerability increase. For the country, which people have migrated to, the racial conflicts are bound to occur. The surplus labor force has led to a rise in the unemployment rate in the country. Under such a vicious circle, the world's development imbalance will be more serious, and the world economy will collapse sharply. Therefore, it is of great significance to the human society to study the impact of climate change on the vulnerability of the country.

This article will focus on the following aspects of the impact of single climate change factor and comprehensive climate factors on the country's vulnerability.

# 2 Basic assumptions

1) There is no sharp deterioration of the environment caused by the war led to an increase in the national vulnerability.
2) There is no sudden outbreak of large-scale influenza and viruses, such as Ebola virus, SARS and so on.
3) There is no planetary collision exactly on a certain country.

# 3 Nomenclatures

| Symbol | Meaning |
|---|---|
| $M$ | number of examples in the dataset |
| $n_x$ | input size |
| $n_y$ | output size |
| $n_h^{[l]}$ | number of hidden units |
| $X$ | input matrix |
| $x^{(i)}$ | $\mathrm{I}^{th}$ example |
| $Y$ | label matrix |
| $y^{[i]}$ | output label |
| $W^{[l]}$ | weight matrix |
| $b^{[l]}$ | bias vector |
| $\hat{Y}$ | predicted output vector |
| $L$ | number of layers in the network |
| HP | Homeless People due to Natural Disaster |
| LE | Life expectancy at birth |
| TU | Total unemployment rate |
| EPI | Environmental Performance Index |
| PP | Prison Population |
| IM | Infant mortality rate |
| UED | Uneven Economic Development |
| DC | Domestic credit provided by financial sector |
| GTI | Global Terrorism Index |

# 4 Deep Neural Networks Model with Gradient Descent

## 4.1 Model Establishment & Model Preparation

### 4.1.1 Model Establishment

(1) The Choice of Influencing Factors

In view of the fact that is the national vulnerability determined by a variety of factors, in addition to the 12 indicators in the Fragile States Index, Demographic Pressures, Refugees and IDPs, Group Grievance, Human Flight, Poverty and Economic Decline, Uneven Development, State Legitimacy, Public Services, Human Rights, Security Apparatus, Factionalized Elites, External Intervention), there are 9 factors also influencing the national vulnerability (Homeless People due to Natural Disaster, Life expectancy at birth, Total unemployment rate, Environmental Performance Index, Prison Population, Infant mortality rate, Education Index, Domestic credit provided by financial sector, Global Terrorism Index) based on the Dr. Zbigniew W. Ras, Department of Computer Science, University of North Carolina Charlotte, NC, USA. After the data preprocessing, the data having significant impact on national vulnerability has been got for 2013-2016 years. The added dataset including 9 features is listed in Appendix 10.

(2) Algorithm Choice

National vulnerability is influenced by many variables. There is a certain correlation between variables. We propose to build a multilayer deep neural network model, using 21 indicators in four years to learn the characteristics of memory data, so as to achieve the best regression for data.

Deep neural network is a learning algorithm for multilayer neural networks under the guidance of a tutor. It is based on the gradient descent method. The relationship between input and output in real deep network is a mapping between an input m and output of the deep neural network to complete the functions of continuous mapping to m dimensional Euclidean space in a finite domain in Euclidean space, which is highly nonlinear. Its information processing capability is derived from the multiple complex of simple nonlinear function, so it has a strong ability to reproduce the function. It iteratively iterates through two links (incentive propagation and weight updating), until the input reaches a predetermined target range.

(3) Algorithm Implementation

The learning process of deep neural network is composed of forward propagation process and reverse propagation process. In the forward propagation process, the input information is processed and transmitted to the output layer by the hidden layer through the input layer. If the expected output value is not in the output layer, the objective function is replaced by output and the expected sum of squares and reversed to the spread. And then, partial derivatives of the objective function of the neuron weight layer are obtained, which forms a ladder of objective function of the weight vector, as the basis of modifying the weights. Lastly, network-learning is completing in the process of modification of weights. When the error reaches the desired value, the network learning is finished[1].

In the forward propagation process:

Input: $a^{[l-1]}$ Output: $a^{[l]}$, cache($z^{[l]}$)

$$z^{[l]}=W^{[l]}\cdot a^{[l-1]}+b^{[l]}$$

$$a^{[l]}=g^{[l]}(z^{[l]})$$

For the backward propagation process:

Input: $\mathrm{d}a^{[l]}$ Output: $\mathrm{d}a^{[l-1]}$, $\mathrm{d}W^{[l]}$ , $\mathrm{d}b^{[l]}$

$$\mathrm{d}z^{[l]}= \mathrm{d}a^{[l]}*g^{[l]}(z^{[l]})$$

$$\mathrm{d}W^{[l]}=\frac{1}{m}dz^{[l]}\cdot a^{[l-1]}$$

$$db^{[l]}=dz^{[l]}$$

$$\mathrm{d}a^{[l-1]} =W^{[l+1]T}\cdot \mathrm{d}z^{[l+1]}*g^{[l]}(z^{[l]})$$

Then

$$\mathrm{d}z^{[l]}=W^{[l+1]T}\cdot dz^{[l+1]}*g^{[l]}(z^{[l]})$$

There are three types of deep neural network models: the input layer, the hidden layer and the output layer. A neuron model is a model that contains input, output, and computing functions. The input can be analogous to the dendrite of the neuron, and the output can be analogous to the axon of the neuron, and the calculation can be analogous to the nucleus.

The training algorithm of the deep neural network model is to adjust the value of the weight to the best, so the whole network has the best prediction effect. The purpose of the machine learning model training is to make the parameters as possible as possible with the real model.

First, we assign random values to all the parameters. We use these randomly generated parameter values to predict the samples in the training data. The prediction target of the sample is ŷ, and the real target is y. So, we define a value loss, and the calculation formula is as follows.

The Loss Function:

$$\mathrm{J}(\omega,\mathrm{b})=-\frac{1}{m}\sum_{i=1}^{m}(y\log\hat{y}+(1-y)\log(1-\hat{y}))$$

$$=-\frac{1}{m}\sum_{i=1}^{m}(y\log a+(1-y)\log(1-a))$$

If we introduce the matrix formula of the previous neural network into $\hat{y}$, the loss can be imported to function of the parameter, which is called the loss function. At this point, the problem is transformed into an optimization problem. Gradient descent algorithm is used. Gradient descent algorithm calculates the parameters at the current gradient every time, then let the parameters move towards a distance in the opposite direction of the gradient and repeat until the gradient is close to zero. At this time, all the parameters happen to achieve a state that makes the loss function reach a minimum. In the neural network model, because of the complex structure, the cost of calculating the gradient is very high. So, it is necessary to use the back-propagation algorithm. The backpropagation algorithm is used to calculate the structure of the neural network. The gradient of all the parameters is calculated not once, but from the back.

Then, we calculate the gradient of the output layer, then the gradient of the second parameter matrix, middle layer, first parameter matrix.

Finally, the gradient of the input layer. After the end of the calculation, the gradient of the two parameter matrices is available.

Updating the parameters:

$$W = W - \alpha \frac{\partial J(W,b)}{\partial W}$$

$$b = b - \alpha \frac{\partial J(W,b)}{\partial b}$$

The value of parameters *W* and *b* trained in our model are listed in the Appendix 11

In a multilayer neural network, the output is also calculated in a layer of one layer. Starting from the outermost layer, the calculation is calculating the value of all the units, then continues to calculate the deeper layer. The next layer will be calculated only after the values of all the units in the current layer have been calculated. So, this process is called "forward propagation". The more in-depth representation features can be understood that as the number of networks increases, each layer is more in-depth for the previous level of abstract representation. In neural networks, each layer of neurons presents a more abstract representation of the value of the previous layer of neurons. The network has stronger ability to distinguish and classify things by extracting more abstract features. This is why we choose multi-layer deep neural network model.

### 4.1.2 Model Preparation

We first import the Python related libraries (Numpy, Pandas, Sklearn, Matplotlib), then read the data and preprocess the data. The model we built is a functional model of multivariate and national vulnerability. *X* represents all the corresponding characteristic data in 4 years and *Y* is the corresponding national ranks. And the Python Codes are listed in Appendix 1.

(1) Data Standardization

We normalize the *X* data based on the characteristics of the sigmoid and ReLu functions that make the most of the data around the function point 0 in order to avoid the loss of weight.

Sigmoid Activation Function:

$$\sigma(z) = \frac{1}{1+e^{z}} = \hat{y} = a$$

$$\sigma'(z) = \frac{e^{-z}}{(1+e^{-z})^2} = \hat{y}(1 - \hat{y}) = a(1 - a)$$

(2) Threshold Selection

According to the national vulnerability data, we selected 50 as the threshold. The rank is less than 50, the *x* is 0, which shows the country is more fragile. On the contrary, if the rank is more than 50, the *x* is 1, representing the country has more solid national strength. At the same time, four data sets (train_*x*, train_*y*, test_*x* and test_*y*) set up to train the model. (The corresponding Python Codes are in Appendix 1 for data processing.)

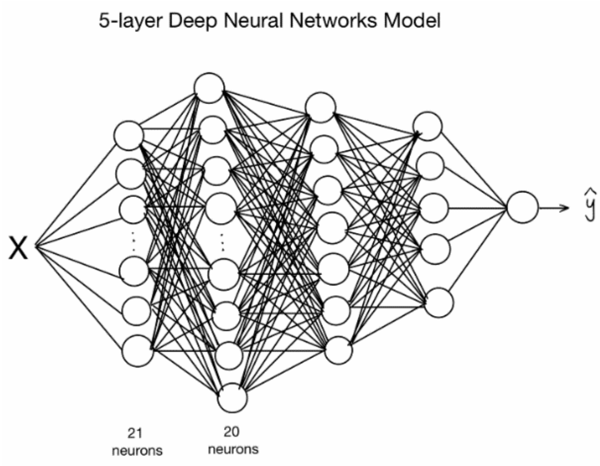
ReLu Activation Function[2-3]:

$$g(z) = \max(0, z)$$

$$g'(z) = \begin{cases} 0, \text{ if } & z \le 0 \\ 1, \text{ if } & z > 0 \end{cases}$$

(3) The Choice of Neural Networks

We have established 5 layers of deep neural networks, including 4 hidden layers and one output layer. The number of neurons in each layer respectively is 21, 20, 7, 5, 1. The hidden layer is used the ReLu activation function, and the output layer is used the Sigmoid activation function[3]. (The Python Codes are in the Appendix 3 and Appendix 5.)



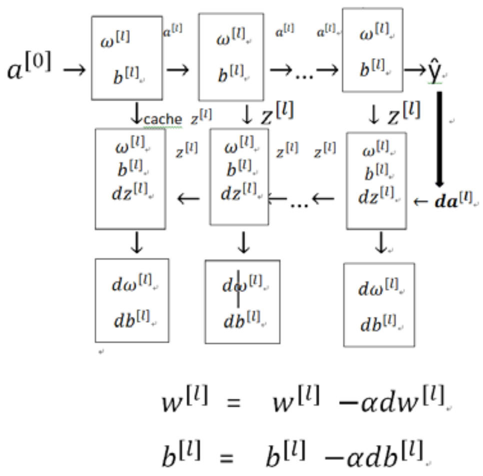
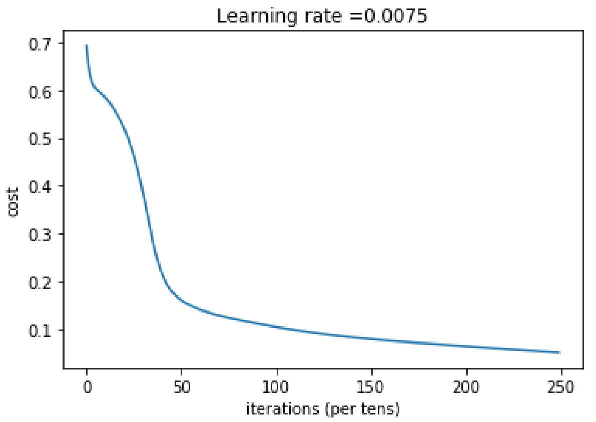




**Figure 1** **Figure 2**

Figure 1 shows our 5-layer deep neural networks model. ($X$ is the dataset inputted. $\hat{y}$ is the prediction value.) Figure 2 shows how forward and back-propagation happens.

The learning rate is 0.0075. After 25000 iterations of the model, we get the deep neural network model. The Python Codes are listed in Appendix 4.




```
Cost after iteration 0: 0.701325
Cost after iteration 100: 0.666666
Cost after iteration 200: 0.644502
Cost after iteration 300: 0.629774
Cost after iteration 400: 0.619712
Cost after iteration 24600: 0.058187
Cost after iteration 24700: 0.057891
Cost after iteration 24800: 0.057593
Cost after iteration 24900: 0.057350
Accuracy: 0.9876977152899822
Accuracy: 0.979020979020979
```

**Figure 3** **Figure 4**

Figure 3 shows the cost decrease after 25000 iterations. As for the prediction in Figure 4, the accuracy of the training set is 0.9876977152899822, and the test set is 0.979020979020979.

## 4.2 Climate change impacts on national vulnerability

The 5 layers depth neural network model has been built, which is a general description of national vulnerability based on multivariable and multi parameter conditions.

The change of climate will change many factors, such as Refugees and Internally-Displaced Persons Group Grievance, Human Flight and Brain Drain, Uneven Economic Development, Economic Decline, Human Rights and Rule of Law, Security Apparatus, Homeless People due to Natural Disaster, Environmental Performance Index (EPI), Global Terrorism Index (GTI), which all have a direct impact on national vulnerability. Subsequently, the analysis between single climate factor and mixed factors dominated by climate is as following.

### 4.2.1 Single factors of climate change Influence

In order to display the single and comprehensive factors influencing the national vulnerability, the result shows as following respectively.

In the study of the single factors of climate showed in Figure 5, the climate factors of the various countries are expanding which change from 0 to 10 by per 0.001 increasing and then it is tested the accuracy illustrating by images. Under the study of the comprehensive factors of climate change, the multi factor factors are respectively expanded (Refugees and Internally-Displaced Persons Group Grievance, Human Flight and Brain Drain, Uneven Economic Development, Economic Decline, Human Rights and Rule of Law, Security Apparatus, Homeless People due to Natural Disaster, Environmental Performance Index (EPI), Global Terrorism Index(GTI)) from 0 to 10 by 0.001 increasing, and the accuracy is tested and the image is drawn.

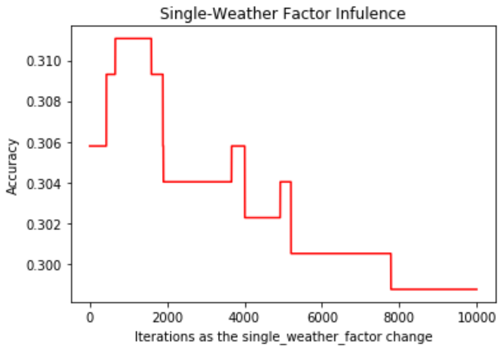



**Figure 5**

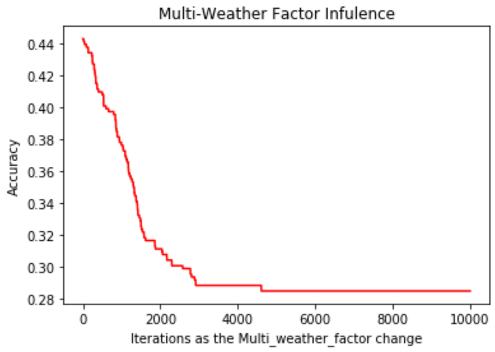



**Figure 6**

Figure 5 shows the impacts of single climate change factor on the training accuracy. Figure 6 shows the impacts of comprehensive climate change factors on the training accuracy

The Python Codes are listed in Appendix 6.

### 4.2.2 Comprehensive factors of climate change Influence

(1) When the climate change factor is synchronous in each country showed in Figure 6, the factor value is from 0 to 10 increasing by 0.001.

(2) when factor value is 1-2, the accuracy is up to 0.315, which means climate is less affected on national vulnerability;

(3) When the factor value is 2-4, 4-5 or 5-7.8, the accuracy is under gradient descent;

(4) when the factor value>8, the accuracy reaches the minimum, which means it has dominant influence on the national vulnerability.

Conclusion: The accuracy of the factor values in the vicinity of 4 and 5 has a large fluctuation, and the impact on the country is not very large because of the single factor influence of some countries.

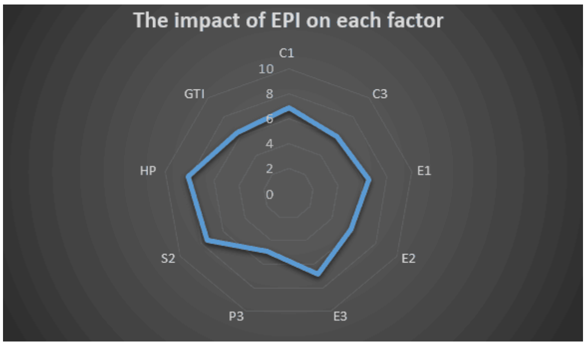



Figure7

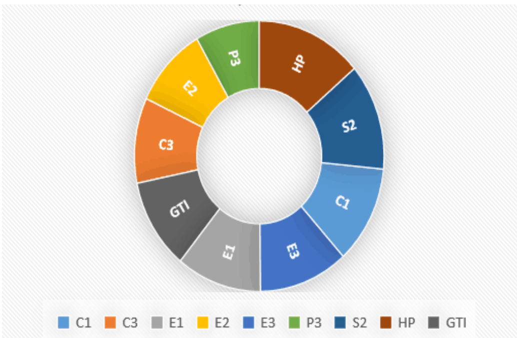



Figure 8

Figure 7 and Figure 8 both show the different impacts of C1, C3, E1, E2, E3, P3, S2, HP and GTI on single weather factor EPI using the dataset.

When the climate change factor and other indirect factors' effects are synchronous in each country, the comprehensive factors of climate change have great influence on national vulnerability.

When the factor value is from 0 to 10 increasing by 0.001.

(1)When factor value <1.8, the climate change factors have significant influence on national vulnerability and the accuracy rate is relatively high;

(2)When the factor value is between 1.8 and 3, the accuracy slow down;

(3)When the factor value is greater than 3, the accuracy rate stay constant, but low accuracy, which states that climate change factors have a strong impact on national vulnerability.

**Conclusion**: When factor value <1.8, the climate change factors have significant influence on national vulnerability and the accuracy rate is relatively high;

All in all, the model is stable basically if the single climate weather factor changes a little bit, and the single weather factor EPI could make an influence on the model. Besides, the model is affected by comprehensive weather factors greatly if the values of these factors change simultaneous.

## 4.3 4.3 Sudan Climate improvement reduce national vulnerability

Sudan is chosen as an object of study.The results of the related calculations are as Follows:

Table 1

| factors | C1 | C2 | C3 | E1 | E2 | E3 | P1 |
|---|---|---|---|---|---|---|---|
| count | 4 | 4 | 4 | 4 | 4 | 4 | 4 |
| mean | 9.5 | 9.9 | 9.8 | 8.425 | 7.975 | 8.775 | 9.65 |
| std | 0.244948974 | 0.115470054 | 0.141421356 | 0.419324854 | 0.377491722 | 0.287228132 | 0.1 |
| min | 9.2 | 9.8 | 9.7 | 7.8 | 7.6 | 8.4 | 9.6 |
| 25% | 9.425 | 9.8 | 9.7 | 8.4 | 7.825 | 8.7 | 9.6 |
| 50% | 9.5 | 9.9 | 9.75 | 8.6 | 7.9 | 8.8 | 9.6 |
| 75% | 9.575 | 10 | 9.85 | 8.625 | 8.05 | 8.875 | 9.65 |
| max | 9.8 | 10 | 10 | 8.7 | 8.5 | 9.1 | 9.8 |

| factors | P2 | P3 | S1 | S2 | X1 | HP | LE |
|---|---|---|---|---|---|---|---|
| count | 4 | 4 | 4 | 4 | 4 | 4 | 4 |
| mean | 8.875 | 9.45 | 8.8 | 10 | 9.875 | 2.743 | 2.7105 |
| std | 0.15 | 0.173205081 | 0.141421356 | 0 | 0.095742711 | 3.804667134 | 3.739667142 |
| min | 8.8 | 9.3 | 8.7 | 10 | 9.8 | 0.838 | 0.838 |
| 25% | 8.8 | 9.3 | 8.7 | 10 | 9.8 | 0.841 | 0.841 |
| 50% | 8.8 | 9.45 | 8.75 | 10 | 9.85 | 0.842 | 0.842 |
| 75% | 8.875 | 9.6 | 8.85 | 10 | 9.925 | 2.744 | 2.7115 |
| max | 9.1 | 9.6 | 9 | 10 | 10 | 8.45 | 8.32 |

| factors | TU | EPI | PP | IM | ED | DC | GTI |
|---|---|---|---|---|---|---|---|
| count | 4 | 4 | 4 | 4 | 4 | 4 | 4 |
| mean | 7.4925 | 5.739 | 7.945303105 | 1.1925 | 2.67275 | 10.745 | 2.6025 |
| std | 1.58184228 | 0.873310178 | 0.989419057 | 0.020615528 | 3.704833363 | 1.074197375 | 1.062780473 |
| min | 5.12 | 5.22 | 6.461212421 | 1.17 | 0.82 | 9.68 | 1.84 |
| 25% | 7.4675 | 5.22 | 7.941553105 | 1.185 | 0.82 | 10.3175 | 1.84 |
| 50% | 8.275 | 5.35 | 8.435 | 1.19 | 0.8205 | 10.53 | 2.238 |
| 75% | 8.3 | 5.869 | 8.43875 | 1.1975 | 2.67325 | 10.9575 | 3.0005 |
| max | 8.3 | 7.036 | 8.45 | 1.22 | 8.23 | 12.24 | 4.094 |

Table 1 summarizes the 21 indicators in 2013-2016 in Sudan, each mean value and maximum value of climate change factors (C1: 9.5/9.8, C3: 9.8/10, E1: 8.425/8.7, E2: 7.975/8.5, E3: 8.775/8.875, P3: 9.45/9.6, S2: 10/10) are greater than 5. Among these, mean EPI is 5.739 and its maximum value is up to 7.036.

After summarizing the 21 indicators in 2013-2016 in Sudan, each mean value and maximum value of climate change factors (C1: 9.5/9.8, C3: 9.8/10, E1: 8.425/8.7, E2: 7.975/8.5, E3: 8.775/8.875, P3: 9.45/9.6, S2: 10/10) are greater than 5. Among these, mean EPI is 5.739 and its maximum value is up to 7.036. (The Python Codes are in Appendix 2.)

After testing the Sudan's data set in the task on, the accuracy is low, which shows it has a great impact on the national vulnerability. Meanwhile, in the model training set and the Sultan test, after the removal of the impact factors of climate change factors, the prad_Sudan output is Array [1, 0, 1, 0] showing that the comprehensive factors of climate change have a great impact on Sudan.

In conclusion, the Sudan national vulnerability would be improved if the comprehensive climate change factors get better value listed above.

## 4.4 U.K. Climate improvement makes nation stronger

### 4.4.1 U.K. climate change influence analysis

Britain is chosen as a research object.

**Table 2**

| uk | | | | | | | |
|---|---|---|---|---|---|---|---|
| factors | C1 | C2 | C3 | E1 | E2 | E3 | P1 |
| count | 4 | 4 | 4 | 4 | 4 | 4 | 4 |
| mean | 2.275 | 2.975 | 5.2 | 3.525 | 3.2 | 1.975 | 1.55 |
| std | 0.5909 | 1.05 | 0.4899 | 0.8884 | 0.9345 | 0.25 | 0.6608 |
| min | 1.4 | 1.4 | 4.6 | 2.2 | 1.8 | 1.6 | 0.6 |
| 25% | 2.225 | 2.975 | 4.9 | 3.475 | 3.15 | 1.975 | 1.35 |
| 50% | 2.5 | 3.5 | 5.3 | 3.9 | 3.65 | 2.1 | 1.8 |
| 75% | 2.55 | 3.5 | 5.6 | 3.95 | 3.7 | 2.1 | 2 |
| max | 2.7 | 3.5 | 5.6 | 4.1 | 3.7 | 2.1 | 2 |
| factors | P2 | P3 | S1 | S2 | X1 | HP | LE |
| count | 4 | 4 | 4 | 4 | 4 | 4 | 4 |
| mean | 1.9 | 1.775 | 2.475 | 2.325 | 1.2 | 1.5445 | 6.945 |
| std | 0.5416 | 0.05 | 0.1893 | 0.3775 | 0.0816 | 2.1303 | 1.1701 |
| min | 1.1 | 1.7 | 2.2 | 1.8 | 1.1 | 0.47 | 5.19 |
| 25% | 1.85 | 1.775 | 2.425 | 2.25 | 1.175 | 0.4805 | 6.93 |
| 50% | 2.1 | 1.8 | 2.55 | 2.4 | 1.2 | 0.484 | 7.525 |
| 75% | 2.15 | 1.8 | 2.6 | 2.475 | 1.225 | 1.548 | 7.54 |
| max | 2.3 | 1.8 | 2.6 | 2.7 | 1.3 | 4.74 | 7.54 |
| factors | TU | EPI | PP | IM | ED | DC | GTI |
| count | 4 | 4 | 4 | 4 | 4 | 4 | 4 |
| mean | 3.7 | 8.0841 | 1.5445 | 4.445 | 1.402 | 0.5925 | 0.5978 |
| std | 4.723 | 0.944 | 2.1303 | 1.4817 | 1.832 | 0.4013 | 0.5888 |
| min | 1.22 | 6.6765 | 0.47 | 3.62 | 0.48 | 0 | 0.115 |
| 25% | 1.22 | 8.0299 | 0.4805 | 3.62 | 0.4868 | 0.5175 | 0.3363 |
| 50% | 1.4 | 8.481 | 0.484 | 3.75 | 0.489 | 0.765 | 0.41 |
| 75% | 3.88 | 8.5353 | 1.548 | 4.575 | 1.4043 | 0.84 | 0.6715 |
| max | 10.78 | 8.698 | 4.74 | 6.66 | 4.15 | 0.84 | 1.456 |

Table 2 Summarizes the 21 indexes of 2013-2016 years in the UK for four years, and the mean of climate change factors (C1: 2.275, C3: 5.2, E1: 3.525, E2: 3.2, E3: 1.975, P3: 1.775, S2: 2.325) were less than 6, but the single index EPI mean climate change is 8.084122 and the maximum value is up to 8.698. the factors of climate change have a great influence on the national vulnerability factors.

### 4.4.2 The determination of the critical point

Due to the "threshold mechanism" established in the model: 50 is the threshold, and the value less than 50 is "0" showing the country is more fragile and the more than 50 is “1” showing country has strong national strength. So, the critical point is defined as the threshold value of a model that distinguishes the country's vulnerability.

Next, select the appropriate threshold to distinguish the size of the country's vulnerability.

In the program, we increase the threshold from 0 to 178 by 1 each step. We use training set to train the model, and then test the accuracy with the training set and the test set respectively, so as to confirm the influence of the model on the national vulnerability by increasing 1 each step.

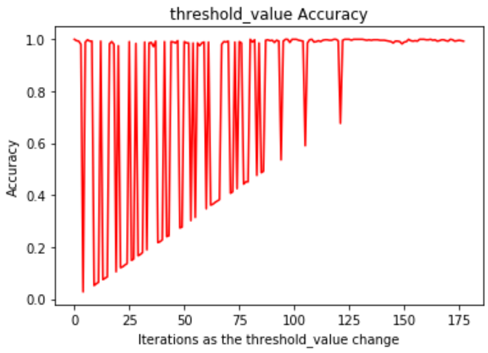



**Figure9**

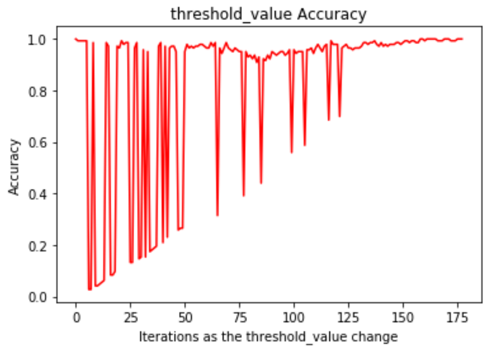



**Figure 10**

Figure 9 is the photo of training set accuracy and Figure 10 is the test set accuracy.

The Python Codes are listed in Appendix 7.

So, as the threshold increasing, the accuracy is up and down. And as the figure shows, the better threshold is between 25-75. And the model is robust using the value of 50.

## 4.5 Comprehensive intervention reduce national vulnerability

### 4.5.1 Comprehensive factors of climate change Influence

According to the results of Problem 1, the comprehensive factors of climate change have a great impact on the accuracy. When climate change factors change synchronously in different countries, the factor value should try to be located between 0-1.8. The accuracy rate is the highest and the vulnerability of the country is the least.

### 4.5.2 Total budget of human intervention

The annual input of education is appropriate, which is about 5% in gross national product, especially in those more vulnerable countries which should pay more attention to education. Investment in science and technology should be mainly considered by underdeveloped countries. Underdeveloped areas should increase investment in infrastructure, create a favorable investment environment, and develop domestic technology through introducing foreign capital.

Education, health care, welfare and protection should be the top priority for the country to address the problem of climate change influence.

Table 3

| Category | Detail | Budget\billions of Pounds | Total |
|---|---|---|---|
| Education | Pre-primary and primary education | 0.8 | 84.4 |
| | Secondary education | 27.2 | |
| | Tertiary education | 6.2 | |
| | Education not definable by level | 46.2 | |
| | Subsidiary services to education | 0.5 | |
| | R&D Education | 1.6 | |
| | Education n.e.c. | 2.3 | |
| Health Care | Medical service | 129.6 | 138.5 |
| | Public health services | 3.5 | |
| | R&D Health | 2.2 | |
| | Health n.e.c. | 3.2 | |
| Welfare | Family and children | 15.7 | 113.6 |
| | Unemployment | 2.7 | |
| | Housing | 4.0 | |
| | Social exclusion n.e.c. | 31.6 | |
| | Social protection n.e.c. | 59.7 | |
| Protection | Police services | 3.6 | 29.9 |
| | Fire-protection services | 0.5 | |
| | Law courts | 5.3 | |
| | Prisons | 4.2 | |
| | R&D Public order and safety | 1.1 | |
| | Public order and safety n.e.c. | 15.2 | |

The total amount of budget: 84.4 + 138.5 + 113.6 + 29.9 = 366.4 billion pounds.

All in all, the country could be stronger if it spends around 366.4 billion pounds per year for education, welfare, health care and protection to address the problem comprehensive climate weather factors.

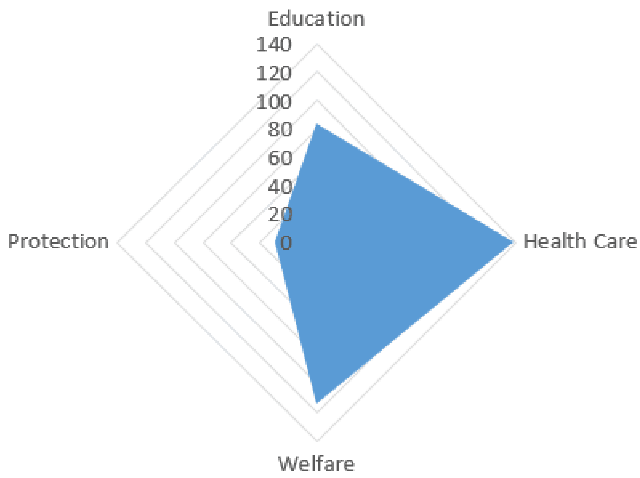



**Figure 11**

Figure 11 shows the percentage of fields including education, health care, welfare and protection for national budget. It clearly shows that health care should be spent more than others.

## 4.6 Model Applicability and Universality

The neural networks models can be applied to smaller "continents" or larger "continents", such as cities and continents.

Urban vulnerability is the comprehensive embodiment of economic fragility, social vulnerability and ecological environment vulnerability. Urban vulnerability's evaluation and regulation is of great significance to the promotion of the quality of urbanization and the realization of sustainable development. With a large population and economic agglomeration to the city, the city is a disaster and risk prone land leading to increase the vulnerability of the city. With the passage of time, chronic deposition effect is increasingly enlarged, which results in the formation of "cumulative" process and cumulative amplification effect. With the slow deposition and amplification process in the course of time accumulated more than a certain the threshold, the city will escape from the state of sustainable development[3]. As gradually increasing the vulnerability, and when the external interference factors of "catalytic", vulnerability state will accelerate the amplification effect even mutation effect, leading to the city system collapse.

The new type of urbanization development model requires continuous reduction of urban vulnerability and continuous improvement of the quality of urbanization. In order to improve the comprehensive response ability of cities, it is very necessary to use neural network to carry out urban vulnerability research and grasp the change of urban vulnerability. We believe that the city comprehensive vulnerability comprehensively reflects the city under the comprehensive disaster factors with the attribute disturbance, which is measurement of natural system, social system, economic system and many other city system sensitivity, coping ability and degree of exposure and is defects and shortcomings of internal system, closely related to social factors, the city's political and economic factors, and geographical factors. Urban vulnerability is affected by population density, economic density index, proportion of disadvantaged groups, tree greening rate, regional unemployment rate and per capita GDP and at the same time, they have an impact on each other.

Conclusion: Our model, using the neural network, integrates relevant data to determine the vulnerability of the city and to measure the impact of various factors. The continent is a collection of n countries. Each country can be understood as a factor in the study of continent vulnerability. N factors affect the vulnerability of continents, and the links between countries are close and estranged. The same neural network model can also be used to determine the fragility of the continent.

# 5 Evaluation and optimization of model

## 5.1 Model Evaluation: Pros and Cons of Gradient Descent Algorithm

Until now, we have used Gradient Descent algorithm (Python Codes are in Appendix 3) in our 5-layer deep neural networks to update the parameters (w and b) and minimize the cost function. Because gradient descent algorithm makes the parameters update after hundreds or thousands of iterations, the direction of the update has some variance, and the path taken by gradient descent algorithm will oscillate toward the convergence. Using momentum or Adam algorithm can reduce these oscillations and get a better model[1].

## 5.2 Model Optimization

### 5.2.1 Deep Neural Networks with Momentum Algorithm

Momentum takes into account the past gradients to smooth out the update. We will store the 'direction' of the previous gradients in the variable *v*. Formally, this will be the exponentially weighted average of the gradient on previous steps[4].

$$S_{dw}=\beta S_{dw}+(1-\beta)dw^2$$

$$S_{db}=\beta S_{db}+(1-\beta)db^2$$

$$\omega=\omega-\alpha\frac{dw}{\sqrt{S_{dw}}+\varepsilon}$$

$$b=b-\alpha\frac{db}{\sqrt{S_{db}}+\varepsilon}$$

$$(\varepsilon=10^{-8})$$

(Python Codes are in Appendix 8.)

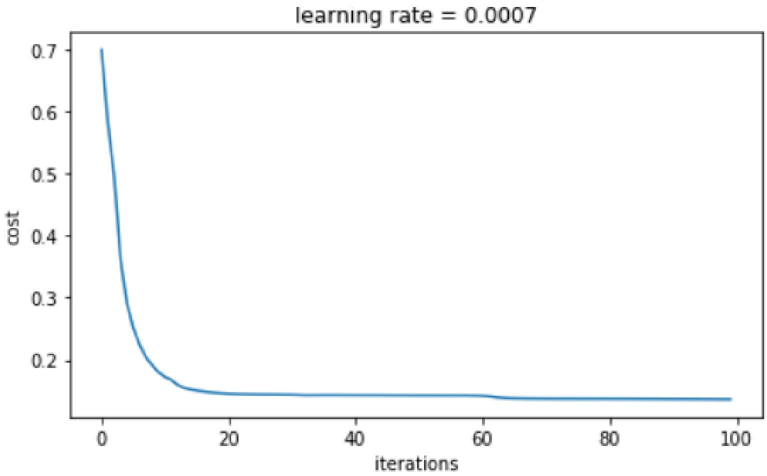



**Figure 12**

Figure 12 shows the cost decrease using the momentum algorithm.

As we can see, after using the momentum algorithm, the 5-layer deep neural networks become more robust.

### 5.2.2 Deep Neural Networks with Adam Algorithm

Adam algorithm is one of the most effective optimization algorithms for training multi-layer deep neural networks. It combines ideas from RMSProp and Momentum algorithm[5].

Firstly, it calculates an exponentially weighted average of past gradients, and stores it in variable *v* and *v_corrected*. Then it calculates an exponentially weighted average of the squares of the gradients and stores it in variables *s* and *s_corrected*. Finally, it updates parameters in a direction[6].

$$v_{dw^{[l]}}=\beta_1 v_{dw^{[l]}}+(1-\beta_1)\frac{\partial J}{\partial W^{[l]}}$$

$$v_{dW^{[l]}}^{corrected}=\frac{v_{dw^{[l]}}}{1-(\beta_1)^t}$$

$$S_{dw^{[l]}}=\beta_2 S_{dw^{[l]}}+(1-\beta_2)\left(\frac{\partial J}{\partial W^{[l]}}\right)^2$$

$$S_{dW^{[l]}}^{corrected}=\frac{S_{dw^{[l]}}}{1-(\beta_1)^t}$$

$$W^{[l]}=W^{[l]}-\alpha\frac{v_{dW^{[l]}}^{corrected}}{\sqrt{S_{dW^{[l]}}^{corrected}}+\varepsilon}$$

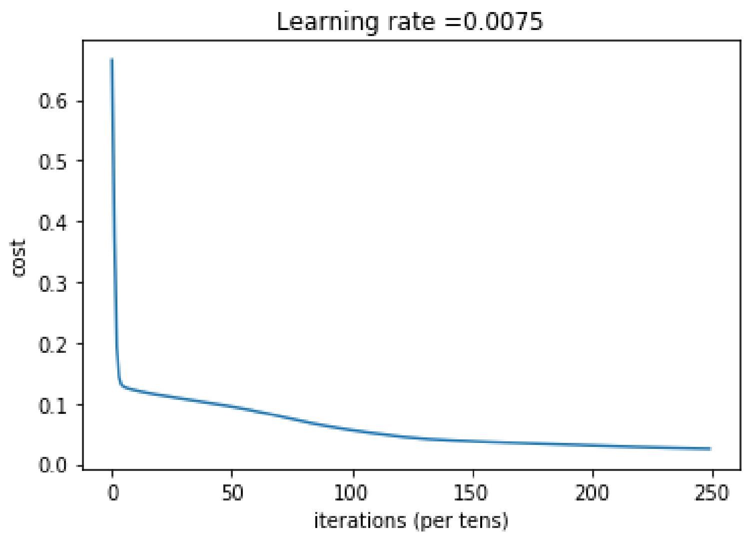



**Figure 13**

Figure 13 shows the cost decrease using the Adam algorithm. (Python Codes are in Appendix 9)

As you can see, the cost decreases fast and steadily, which is very good for training a better model.

# 6 Conclusion

Peace and development has become the theme in this day and age. However, climate change has been causing serious threat to people's survival and the national vulnerability has increased dramatically.

Combining with previous researches of *Analysis on Fragile States Data* by Dr. Zbigniew W. Ras, Department of Computer Science, University of North Carolina Charlotte, NC, USA, we increased 9 indicators (Homeless People due to Natural Disaster(HP), Life Expectancy(LE), Total Unemployment Rate(TU), Environmental Performance Index(PEI), Prison Population(PP), Infant Mortality Rate(IM), Education Index(EI), Domestic Credit Provided by financial sector(DC), Global Terrorism Index(GTI)) related to national vulnerability, so it is determined by 21 indicators.

Our research aims to establish multilayer deep neural network model. Based on gradient descent method, Momentum algorithm and Adam algorithm, the mapping between input and output of deep neural networks and the continuous mapping function of m dimensional Euclidean space in a highly nonlinear Euclidean space finite domain come out[6]. Coupled with the data processing of the complexity of simple nonlinear functions, two links (Forward and backward-propagation and weights update) iterations are repeatedly adopted to overcome the limitations of traditional regression models in building complex mapping relations and extracting high-level data characteristics[7].

In our research, the training sets containing 21 factors corresponding countries data from 2013 to 016 was used to achieve the prediction of the influence of climate factors on the national vulnerability.

Firstly, the model can determine national vulnerability by the impact of climate change on national vulnerability from two aspects, single climate factors and climatic comprehensive factors. We have concluded that the single factor of climate change has a certain impact on national vulnerability and the comprehensive factors of climate change have a great impact on national vulnerability.

Secondly, by analyzing the vulnerability of the country to top ten vulnerable countries, Sudan, we get the optimal climate change factor model and used the "threshold mechanism" to determine the appropriate threshold to determine the selection of the critical point in order to make the model to achieve the best results, which can effectively reduce the vulnerability of the Sudan. However, huge fluctuations cannot be caused by changing single factor, which reflects the stability of this model.

Thirdly, we chose Britain, which is in top 10 non-fragile countries to predict the national vulnerability. We can draw a conclusion that the improvement of the comprehensive factors of climate change can make the UK have more solid strength. And we calculated the cost of education, medical, welfare and security to determine the government budget under artificial intervention.

Finally, after a comprehensive analysis of the correlation between urban vulnerability and national vulnerability, due to the cumulative process effect and cumulative amplification effect, we determined that the neural network model can be applied to smaller "continent" or larger “continent". Therefore, our model can be applied to not only national vulnerability detection, prediction and prevention, but also a tiny area, such as township, or a great area, such as the earth. This will bring great help to the development of local conditions and point out the direction for the progress and development of the world.

# 7 References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6. Ernest Istook, Tony Martinez. Improved Backpropagation Learning in Neural Networks with Windowed Momentum[J]. In International Journal of Neural Systems, vol. 12, no.3&4, pp. 303-318.
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# 8 Appendix

## Appendix 1

Python Codes for data cleaning, pre-processing and reading the dataset

(in **Appendix 10**)

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

dataset = pd.read_csv("Final_Data_Train.csv")
x = dataset.iloc[: ,3:].values
y = dataset.iloc[: ,2:3].values

x = x / 10
from sklearn import preprocessing
binarizer = preprocessing.Binarizer(threshold=50)
y = binarizer.transform(y)

from sklearn.cross_validation import train_test_split
train_x, test_x, train_y, test_y = train_test_split(x, y, test_size = 0.2, random_state = 2)
train_x = np.transpose(train_x)
train_y = np.transpose(train_y)
test_x = np.transpose(test_x)
test_y = np.transpose(test_y)
```

## Appendix 2

Python Codes for reading the Sudan_Dataset for Task 2

```
Sudan_Dataset = pd.read_excel('task2.xlsx')
Sudan_Dataset.iloc[: ,[3, 9, 11, 12, 13, 15, 16, 18, 19, 20, 21]] = 0
Sudan_x = Sudan_Dataset.iloc[: ,[3, 9, 11, 12, 13, 15, 16, 18, 19, 20, 21]]
Sudan_y = Sudan_Dataset.iloc[:, 1:2].values
#Sudan_y = Sudan_y / 178
Sudan_x = np.transpose(Sudan_x)
Sudan_y = np.transpose(Sudan_y)
pred_Sudan, Accuracy = predict(Sudan_x, Sudan_y, parameters)
```

# Appendix 3

Python Codes for establish the model

```python
def sigmoid(Z):

    A = 1/(1+np.exp(-Z))
    cache = Z

    return A, cache

def sigmoid_backward(dA, cache):

    Z = cache
    s = 1/(1+np.exp(-Z))
    dZ = dA * s * (1-s)

    assert (dZ.shape == Z.shape)
    return dZ

def relu(Z):

    A = np.maximum(0,Z)

    assert(A.shape == Z.shape)
    cache = Z

    return A, cache

def relu_backward(dA, cache):

    Z = cache
    dZ = np.array(dA, copy=True)
    dZ[Z <= 0] = 0

    assert (dZ.shape == Z.shape)
    return dZ
```

```python
def linear_forward(A, W, b):

    Z = np.dot(W, A) + b

    assert(Z.shape == (W.shape[0], A.shape[1]))
    cache = (A, W, b)
    return Z, cache

def linear_activation_forward(A_prev, W, b, activation):

    if activation == "sigmoid":
        Z, linear_cache = linear_forward(A_prev, W, b)
        A, activation_cache = sigmoid(Z)

    elif activation == "relu":
        Z, linear_cache = linear_forward(A_prev, W, b)
        A, activation_cache = relu(Z)

    assert (A.shape == (W.shape[0], A_prev.shape[1]))
    cache = (linear_cache, activation_cache)

    return A, cache
```

```
def initialize_parameters_deep(layer_dims):

    parameters = {}
    L = len(layer_dims)

    for l in range(1, L):

        parameters['W' + str(l)] = np.random.randn(layer_dims[l],
                    layer_dims[l-1])/ np.sqrt(layer_dims[l-1])
        parameters['b' + str(l)] = np.zeros((layer_dims[l], 1))

        assert(parameters['W' + str(l)].shape == (layer_dims[l],
                            layer_dims[l-1]))
        assert(parameters['b' + str(l)].shape == (layer_dims[l], 1))

    return parameters

def L_model_forward(X, parameters):

    caches = []
    A = X
    L = len(parameters) // 2

    for l in range(1, L):
        A_prev = A
        A, cache = linear_activation_forward(A_prev,
                                             parameters['W' + str(l)],
                                             parameters['b' + str(l)], "relu")
        caches.append(cache)

    AL, cache = linear_activation_forward(A,
                                          parameters['W' + str(L)],
                                          parameters['b' + str(L)], "sigmoid")
    caches.append(cache)

    assert(AL.shape == (1,X.shape[1]))
    return AL, caches

def compute_cost(AL, Y):

    m = Y.shape[1]
    cost = -np.sum(np.multiply(np.log(AL),Y) +
                np.multiply(np.log(1 - AL), 1-Y)) / m
    cost = np.squeeze(cost)
    assert(cost.shape == ())
    return cost
```

```
def linear_backward(dZ, cache):

    A_prev, W, b = cache
    m = A_prev.shape[1]

    dW = np.dot(dZ, A_prev.T) / m
    db = np.sum(dZ, axis=1, keepdims=True) / m
    dA_prev = np.dot(W.T, dZ)

    assert (dA_prev.shape == A_prev.shape)
    assert (dW.shape == W.shape)
    assert (db.shape == b.shape)

    return dA_prev, dW, db

def linear_activation_backward(dA, cache, activation):

    linear_cache, activation_cache = cache
    if activation == "relu":
        dZ = relu_backward(dA, activation_cache)
        dA_prev, dW, db = linear_backward(dZ, linear_cache)

    elif activation == "sigmoid":
        dZ = sigmoid_backward(dA, activation_cache)
        dA_prev, dW, db = linear_backward(dZ, linear_cache)

    return dA_prev, dW, db

def L_model_backward(AL, Y, caches):

    grads = {}
    L = len(caches)
    Y = Y.reshape(AL.shape)

    dAL = - (np.divide(Y, AL) - np.divide(1 - Y, 1 - AL))
    current_cache = caches[L-1]
    grads["dA" + str(L)], grads["dW" + str(L)], grads["db" + str(L)] =
              linear_activation_backward(dAL,current_cache,activation="sigmoid")
    for l in reversed(range(L-1)):
        current_cache = caches[l]
        dA_prev_temp, dW_temp, db_temp =
          linear_activation_backward(grads["dA"+str(l+2)],current_cache,"relu")
        grads["dA" + str(l + 1)] = dA_prev_temp
        grads["dW" + str(l + 1)] = dW_temp
        grads["db" + str(l + 1)] = db_temp

    return grads
```

```
def update_parameters(parameters, grads, learning_rate):

    L = len(parameters) // 2
    # Update rule for each parameter. Use a for loop.
    for l in range(L):
        parameters["W" + str(l+1)] = parameters["W" + str(l+1)] -
                                        learning_rate * grads["dW" + str(l+1)]
        parameters["b" + str(l+1)] = parameters["b" + str(l+1)] -
                                        learning_rate * grads["db" + str(l+1)]

    return parameters

def L_layer_model(X, Y, layers_dims, learning_rate,
                  num_iterations = 3000, print_cost=False):
    costs = []
    parameters = initialize_parameters_deep(layers_dims)
    for i in range(0, num_iterations):

        AL, caches = L_model_forward(X, parameters)
        cost = compute_cost(AL, Y)
        grads = L_model_backward(AL, Y, caches)
        parameters = update_parameters(parameters, grads, learning_rate)

        if print_cost and i % 100 == 0:
            print ("Cost after iteration %i: %f" %(i, cost))
        if print_cost and i % 100 == 0:
            costs.append(cost)
    plt.plot(np.squeeze(costs))
    plt.ylabel('cost')
    plt.xlabel('iterations (per tens)')
    plt.title("Learning rate =" + str(learning_rate))
    plt.show()

    return parameters
```

# Appendix 4

Python Codes for predict the Accuracy

```
def predict(X, y, parameters):

    m = X.shape[1]
    p = np.zeros((1,m))

    probas, caches = L_model_forward(X, parameters)

    for i in range(0, probas.shape[1]):

        if probas[0,i] > 0.5:
            p[0,i] = 1

        else:
            p[0,i] = 0

    Accuracy = str(np.sum((p == y)/m))
    print("Accuracy: "  + Accuracy)
    Accuracy = float(Accuracy)

    return p, Accuracy
```

## **Appendix 5** Python Codes for establish 5-layer deep neural networks and make predictions

```
layers_dims = [21, 20, 7, 5, 1]
parameters = L_layer_model(train_x, train_y, layers_dims, learning_rate = 0.0075, num_iterations = 25000, print_cost = True)

pred_train, Accuracy = predict(train_x, train_y, parameters)
pred_test, Accuracy = predict(test_x, test_y, parameters)
```

## Appendix 6

Python Codes for discussing the influence of climate change factor for Task 1

```
Train_Accuracies = []
single_weather_factor = 0
while single_weather_factor <= 10:

    New_Dataset = dataset
    New_Dataset.iloc[:, 18] = single_weather_factor
#New_Dataset.iloc[:, [3, 5, 6, 7, 8, 9, 11, 15, 18, 23, 18]]
    Single_Weather_Affected_Dataset = dataset

    x_new = Single_Weather_Affected_Dataset.iloc[: ,3:].values
    y_new = Single_Weather_Affected_Dataset.iloc[: ,2:3].values

    from sklearn import preprocessing
    binarizer = preprocessing.Binarizer(threshold = 50)
    y_new = binarizer.transform(y_new)

    from sklearn.cross_validation import train_test_split
    train_x_new, test_x_new, train_y_new, test_y_new =
            train_test_split(x_new, y_new, test_size = 0.2, random_state = 2)

    train_x_new = np.transpose(train_x_new)
    train_y_new = np.transpose(train_y_new)
    test_x_new = np.transpose(test_x_new)
    test_y_new = np.transpose(test_y_new)

    pred_train_new, Accuracy = predict(train_x_new, train_y_new, parameters)
    Train_Accuracies.append(Accuracy)

    single_weather_factor += 0.001

plt.plot(np.squeeze(Train_Accuracies), color = 'r')
plt.ylabel('Accuracy')
plt.xlabel('Iterations as the single_weather_factor change')
plt.title("Single-Weather Factor Infulence")   #Multi-Weather Factor Infulence
plt.show()
```

# Appendix 7

Python Codes for Choosing suitable threshold

```
Train_Accuracies = []
threshold_value = 0

while threshold_value < 178:

    x_new = x / 10
    binarizer = preprocessing.Binarizer(threshold = threshold_value)
    y_new = binarizer.transform(y)

    train_x, test_x, train_y, test_y = train_test_split(x_new, y_new,
                                                        test_size = 0.2,
                                                        random_state = 2)
    train_x = np.transpose(train_x)
    train_y = np.transpose(train_y)
    test_x = np.transpose(test_x)
    test_y = np.transpose(test_y)

    layers_dims = [21, 20, 7, 5, 1]
    parameters = L_layer_model(train_x, train_y, layers_dims,
                               learning_rate = 0.0075,
                               num_iterations = 25000,
                               print_cost = True)

    pred_train, Accuracy = predict(test_x, test_y, parameters)

    Train_Accuracies.append(Accuracy)

    threshold_value += 1

plt.plot(np.squeeze(Train_Accuracies), color = 'r')
plt.ylabel('Accuracy')
plt.xlabel('Iterations as the threshold_value change')
plt.title("threshold_value Accuracy")   #Multi-Weather Factor Infulence
plt.show()
```

# Appendix 8 Python Codes for Momentum Algorithm

```
def initialize_velocity(parameters):

    L = len(parameters) // 2 # number of layers in the neural networks
    v = {}

    for l in range(L):

        v["dW" + str(l+1)] = np.zeros(parameters["W"+str(l+1)].shape)
        v["db" + str(l+1)] = np.zeros(parameters["b"+str(l+1)].shape)

    return v

def update_parameters_with_momentum(parameters, grads, v, beta, learning_rate):

    L = len(parameters) // 2

    for l in range(L):

        v["dW" + str(l+1)] = beta*v["dW"+str(l+1)]+(1-beta)*grads["dW"+str(l+1)]
        v["db" + str(l+1)] = beta*v["db"+str(l+1)]+(1-beta)*grads["db"+str(l+1)]

        parameters["W" + str(l+1)] = parameters["W"+str(l+1)] - v["dW"+str(l+1)]*learning_rate
        parameters["b" + str(l+1)] = parameters["b"+str(l+1)] - v["db"+str(l+1)]*learning_rate

    return parameters, v
```

# Appendix 9 Python Codes for Adam Algorithm

```
def initialize_adam(parameters) :

    L = len(parameters) // 2
    v = {}
    s = {}

    for l in range(L):
        v["dW" + str(l+1)] = np.zeros(parameters["W"+str(l+1)].shape)
        v["db" + str(l+1)] = np.zeros(parameters["b"+str(l+1)].shape)
        s["dW" + str(l+1)] = np.zeros(parameters["W"+str(l+1)].shape)
        s["db" + str(l+1)] = np.zeros(parameters["b"+str(l+1)].shape)

    return v, s

def update_parameters_with_adam(parameters, grads, v, s, t, learning_rate = 0.01,
                                beta1 = 0.9, beta2 = 0.999,  epsilon = 1e-8):

    L = len(parameters) // 2
    v_corrected = {}
    s_corrected = {}
    for l in range(L):

        v["dW" + str(l+1)] = beta1*v["dW"+str(l+1)]+(1-beta1)*grads["dW"+str(l+1)]
        v["db" + str(l+1)] = beta1*v["db"+str(l+1)]+(1-beta1)*grads["db"+str(l+1)]

        v_corrected["dW" + str(l+1)] = v["dW"+str(l+1)]/(1-beta1**t)
        v_corrected["db" + str(l+1)] = v["db"+str(l+1)]/(1-beta1**t)

        s["dW" + str(l+1)] = beta2*s["dW"+str(l+1)]+(1-beta2)*np.power(grads["dW"+str(l+1)],2)
        s["db" + str(l+1)] = beta2*s["db"+str(l+1)]+(1-beta2)*np.power(grads["db"+str(l+1)],2)

        s_corrected["dW" + str(l+1)] = s["dW"+str(l+1)]/(1-beta2**t)
        s_corrected["db" + str(l+1)] = s["db"+str(l+1)]/(1-beta2**t)

        parameters["W" + str(l+1)] = parameters["W"+str(l+1)]-
            learning_rate*v_corrected["dW"+str(l+1)]/(np.sqrt(s_corrected["dW"+str(l+1)])+epsilon)
        parameters["b" + str(l+1)] = parameters["b"+str(l+1)]-
            learning_rate*v_corrected["db"+str(l+1)]/(np.sqrt(s_corrected["db"+str(l+1)])+epsilon)

    return parameters, v, s
```

# Appendix 10 **Added Dataset used to train the model** by

Dr. Zbigniew W. Ras, Department of Computer Science, University of North Carolina Charlotte, NC, USA.

| Country | Year | Rank | HP | LE | TU | EPI | PP | IM | ED | DC | GTI |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Sudan | 2013 | 3 | 0.838 | 8.25 | 5.48 | 6.461212 | 0.838 | 1.22 | 0.821 | 12.24 | 2.636 |
| Somalia | 2013 | 1 | 0.83 | 6.62 | 1.5 | 6.711509 | 0.83 | 1.58 | 0.734 | 4.755 | 0 |
| South Suda | 2013 | 4 | 0.762 | 7.45 | 0.8 | 7.3541 | 0.762 | 1.38 | 0.666 | 0.59 | 3.086 |
| Yemen | 2013 | 6 | 0.478 | 7.47 | 0.36 | 8.822893 | 0.478 | 1.97 | 0.454 | 3.5 | 1.173 |
| Afghanista | 2013 | 7 | 0.47 | 5.97 | 1.66 | 0.987495 | 0.47 | 7.17 | 0.387 | 0.2 | 7.244 |
| Congo Den | 2013 | 2 | 0.49 | 6.26 | 0.74 | 0.976391 | 0.49 | 5.98 | 0.457 | 0.445 | 3.389 |
| Liberia | 2013 | 23 | 0.647 | 7.42 | 5.04 | 6.270738 | 0.647 | 2.29 | 0.704 | 8.765 | 1.168 |
| Chad | 2013 | 5 | 0.37 | 4.91 | 1.28 | 1.211863 | 0.37 | 9.77 | 0.338 | 0.275 | 0 |
| Zimbabwe | 2013 | 10 | 0.488 | 5.71 | 1.56 | 6.607026 | 0.488 | 1.42 | 0.677 | 5.245 | 0.069 |
| Iraq | 2013 | 11 | 0.599 | 6.73 | 2.94 | 3.27967 | 0.599 | 2.53 | 0.506 | 0 | 4.505 |
| Haiti | 2013 | 8 | 0.415 | 5.45 | 0.66 | 3.620776 | 0.415 | 6.74 | 0.346 | 1.05 | 0 |
| Kenya | 2013 | 17 | 0.894 | 8.32 | 1.36 | 4.805058 | 0.894 | 1.68 | 0.825 | 1.94 | 2.358 |
| Syria | 2013 | 21 | 0.874 | 5.63 | 0.64 | 5.909088 | 0.874 | 2.55 | 0.804 | 7.83 | 0 |
| Cote dIvoi | 2013 | 12 | 0.762 | 7.91 | 0.7 | 2.674599 | 0.762 | 0.88 | 0.659 | 4.43 | 0.119 |
| Central Afr | 2013 | 9 | 0.909 | 8.17 | 1.12 | 3.023417 | 0.909 | 0.47 | 0.871 | 1.315 | 0 |
| Pakistan | 2013 | 13 | 0.341 | 7.43 | 0.8 | 6.547982 | 0.341 | 0.49 | 0.199 | 2.295 | 0 |
| Niger | 2013 | 18 | 0.625 | 6.55 | 1.52 | 4.71251 | 0.625 | 4.32 | 0.537 | 2.32 | 0 |
| Banglades | 2013 | 29 | 0.815 | 7.63 | 2.32 | 2.553192 | 0.815 | 0.63 | 0.706 | 3 | 9.049 |
| Uzbekistar | 2013 | 44 | 0.72 | 7.25 | 2.06 | 6.868499 | 0.72 | 4.93 | 0.638 | 9.725 | 0.079 |
| Guinea | 2013 | 14 | 0.746 | 7.3 | 2.24 | 3.888358 | 0.746 | 1.15 | 0.721 | 1.08 | 0.415 |
| Mauritania | 2013 | 31 | 0.459 | 6.43 | 6.16 | 3.11094 | 0.459 | 0.66 | 0.443 | 7.81 | 2.491 |
| Burundi | 2013 | 20 | 0.392 | 5.8 | 2.1 | 2.611709 | 0.392 | 6.54 | 0.254 | 1.24 | 2.627 |
| Tajikistan | 2013 | 51 | 0.757 | 5.48 | 0.14 | 7.803491 | 0.757 | 9.26 | 0.744 | 9.15 | 0 |
| Ethiopia | 2013 | 19 | 0.414 | 6.27 | 1.8 | 3.705258 | 0.414 | 3.7 | 0.267 | 0 | 3.428 |
| Guinea Bis | 2013 | 15 | 0.611 | 7.14 | 1.4 | 4.065906 | 0.611 | 2.66 | 0.454 | 0.84 | 0 |
| Uganda | 2013 | 22 | 0.733 | 6.9 | 0.86 | 7.468032 | 0.733 | 0.37 | 0.635 | 1.77 | 2.037 |
| Nigeria | 2013 | 16 | 0.545 | 6.4 | 0.62 | 4.333577 | 0.545 | 3.55 | 0.466 | 0.64 | 0.119 |
| Israel and | 2013 | 67 | 0.769 | 7.48 | 2.14 | 2.060144 | 0.769 | 2.87 | 0.699 | 10.28 | 8.147 |
| Myanmar | 2013 | 26 | 0.686 | 6.89 | 5.48 | 3.607177 | 0.686 | 1.43 | 0.711 | 1.36 | 0.624 |
| Cambodia | 2013 | 41 | 0.398 | 5.58 | 0.04 | 4.64514 | 0.398 | 5.95 | 0.385 | 4.16 | 5.68 |
| Iran | 2013 | 37 | 0.907 | 8.22 | 3.04 | 4.045948 | 0.907 | 4.26 | 0.883 | 2.04 | 0.867 |
| Togo | 2013 | 42 | 0.904 | 7.08 | 0.96 | 6.73564 | 0.904 | 0.89 | 0.843 | 7.795 | 0 |
| Cameroon | 2013 | 27 | 0.643 | 7.3 | 0.82 | 1.758492 | 0.643 | 2.24 | 0.528 | 1.695 | 3.672 |
| Kyrgyz Rep | 2013 | 48 | 0.782 | 6.86 | 0.72 | 4.58393 | 0.782 | 3.92 | 0.801 | 7.79 | 0.585 |
| North Kore | 2013 | 23 | 0.922 | 6.88 | 1.28 | 2.241753 | 0.922 | 3.1 | 0.896 | 1.04 | 0 |
| Mali | 2013 | 38 | 0.892 | 7.28 | 1.38 | 4.179818 | 0.892 | 3.93 | 0.779 | 3.7 | 0 |
| Madagasca | 2013 | 61 | 0.419 | 4.89 | 0.26 | 4.412005 | 0.419 | 5.94 | 0.414 | 10.36 | 2.008 |
| Jordan | 2013 | 87 | 0.876 | 8.27 | 1.06 | 3.579069 | 0.876 | 1.48 | 0.789 | 17.59 | 1.369 |
| Eritrea | 2013 | 25 | 0.675 | 7.25 | 2 | 3.652729 | 0.675 | 1.6 | 0.585 | 0 | 0.01 |
| Zambia | 2013 | 45 | 0.744 | 6.53 | 3.54 | 6.990285 | 0.744 | 1.36 | 0.799 | 2.415 | 1.755 |
| Rwanda | 2013 | 38 | 0.671 | 7.41 | 3.82 | 4.246985 | 0.671 | 1.92 | 0.631 | 1.985 | 0 |
| Lebanon | 2013 | 46 | 0.891 | 6.97 | 3 | 4.28756 | 0.891 | 0.33 | 0.86 | 0 | 7.086 |
| Nepal | 2013 | 30 | 0.799 | 6.86 | 1.06 | 3.78417 | 0.799 | 2.21 | 0.794 | 2.485 | 0 |
| Venezuela | 2013 | 89 | 0.754 | 7.01 | 0.86 | 6.877636 | 0.754 | 5.65 | 0.652 | 11.65 | 1.129 |
| Solomon Is | 2013 | 51 | 0.559 | 7.29 | 6.84 | 6.560484 | 0.559 | 1.78 | 0.484 | 0.69 | 0.158 |
| TimorLeste | 2013 | 32 | 0.539 | 6.29 | 1.54 | 6.031659 | 0.539 | 0.37 | 0.544 | 0.9 | 1.731 |
| Congo Rep | 2013 | 36 | 0.576 | 6.1 | 1.56 | 2.707636 | 0.576 | 3.76 | 0.516 | 0.35 | 3.729 |
| Tanzania | 2013 | 65 | 0.478 | 8.22 | 6.2 | 5.68518 | 0.478 | 3.68 | 0.305 | 0 | 3.566 |
| Egypt | 2013 | 34 | 0.709 | 7.31 | 1.22 | 1.999986 | 0.709 | 2.71 | 0.614 | 3.695 | 0 |
| Sri Lanka | 2013 | 28 | 0.92 | 4.98 | 1.26 | 5.484258 | 0.92 | 0.62 | 0.812 | 0.32 | 0 |
| Papua Nev | 2013 | 53 | 0.942 | 5.21 | 0.98 | 3.996893 | 0.942 | 6.16 | 0.907 | 4.04 | 0 |
| Burkina Fa | 2013 | 35 | 0.781 | 7.39 | 0.32 | 1.753917 | 0.781 | 1.05 | 0.756 | 0.925 | 4.088 |
| Gambia | 2013 | 62 | 0.887 | 8.18 | 3 | 2.960703 | 0.887 | 0.35 | 0.82 | 2.205 | 6.801 |
| Comoros | 2013 | 56 | 0.712 | 7.37 | 1.46 | 4.189562 | 0.712 | 1.49 | 0.612 | 1.17 | 5.633 |
| Libya | 2013 | 54 | 0.563 | 6.97 | 0.74 | 3.950666 | 0.563 | 5.54 | 0.455 | 0.165 | 3.599 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Sierra Leor | 2013 | 33 | 0.749 | 6.31 | 0.66 | 6.108295 | 0.749 | 0.93 | 0.643 | 0.51 | 0.277 |
| Bolivia | 2013 | 67 | 0.589 | 6.87 | 5.62 | 1.727319 | 0.589 | 3.08 | 0.431 | 2.435 | 4.899 |
| Senegal | 2013 | 64 | 0.794 | 7.78 | 1.12 | 6.504403 | 0.794 | 0.31 | 0.769 | 2.92 | 4.597 |
| Bhutan | 2013 | 62 | 0.466 | 5.92 | 0.46 | 3.519697 | 0.466 | 6.85 | 0.386 | 2.625 | 3.732 |
| Swaziland | 2013 | 49 | 0.509 | 8 | 0.84 | 7.914588 | 0.509 | 0.22 | 0.438 | 1.36 | 0.522 |
| Mozambiq | 2013 | 59 | 0.641 | 7.64 | 0.88 | 3.846537 | 0.641 | 3.11 | 0.649 | 5.635 | 0 |
| China | 2013 | 66 | 0.831 | 8.1 | 2.12 | 3.827411 | 0.831 | 0.74 | 0.761 | 7.54 | 0 |
| Bosnia anc | 2013 | 83 | 0.661 | 6.75 | 3.54 | 4.666048 | 0.661 | 3.4 | 0.656 | 2.865 | 5.861 |
| Djibouti | 2013 | 50 | 0.924 | 7.98 | 2.94 | 2.73498 | 0.924 | 0.32 | 0.932 | 3.085 | 0.217 |
| Colombia | 2013 | 57 | 0.713 | 7.54 | 3.84 | 2.877063 | 0.713 | 1.15 | 0.599 | 3.48 | 0 |
| Thailand | 2013 | 90 | 0.719 | 7.46 | 0.74 | 7.055583 | 0.719 | 6.61 | 0.63 | 0.73 | 4.509 |
| Laos | 2013 | 58 | 0.541 | 6.03 | 1.68 | 3.945665 | 0.541 | 4.66 | 0.515 | 2.57 | 0 |
| Turkey | 2013 | 86 | 0.617 | 8.26 | 1.62 | 7.773454 | 0.617 | 5.15 | 0.656 | 1.85 | 1.743 |
| India | 2013 | 79 | 0.907 | 8.36 | 1.22 | 5.31246 | 0.907 | 0.54 | 0.809 | 7.82 | 0.679 |
| Guatemala | 2013 | 70 | 0.86 | 8.05 | 1.52 | 3.130576 | 0.86 | 0.39 | 0.819 | 1.955 | 4.992 |
| Malawi | 2013 | 40 | 0.735 | 6.02 | 1.28 | 2.752392 | 0.735 | 1.29 | 0.616 | 0.65 | 0 |
| Equatorial | 2013 | 47 | 0.681 | 7.07 | 1.58 | 1.613167 | 0.681 | 2.26 | 0.582 | 0.17 | 2.016 |
| Mexico | 2013 | 97 | 0.683 | 7.44 | 0.96 | 4.984946 | 0.683 | 7.92 | 0.531 | 5.685 | 0.188 |
| Georgia | 2013 | 55 | 0.678 | 6.33 | 1.08 | 2.078151 | 0.678 | 3.97 | 0.608 | 1.745 | 0.435 |
| Suriname | 2013 | 106 | 0.878 | 7.59 | 1.6 | 6.180724 | 0.878 | 9.79 | 0.864 | 2.71 | 0 |
| Angola | 2013 | 43 | 0.843 | 8.11 | 1.54 | 0.965486 | 0.843 | 0.23 | 0.695 | 0.775 | 0 |
| Fiji | 2013 | 67 | 0.856 | 7.62 | 1.54 | 2.224002 | 0.856 | 0.29 | 0.875 | 5.72 | 0 |
| Algeria | 2013 | 73 | 0.737 | 7.43 | 2.2 | 1.62615 | 0.737 | 2.24 | 0.65 | 0.105 | 6.304 |
| Indonesia | 2013 | 76 | 0.824 | 7.49 | 2.54 | 3.729984 | 0.824 | 0.17 | 0.817 | 3.855 | 1.225 |
| Philippines | 2013 | 59 | 0.779 | 6.57 | 2.02 | 4.055517 | 0.779 | 1 | 0.807 | 0.92 | 0 |
| Vietnam | 2013 | 97 | 0.678 | 7.46 | 1.62 | 7.196565 | 0.678 | 1.5 | 0.627 | 1.57 | 5.031 |
| Lesotho | 2013 | 71 | 0.796 | 8.13 | 1.24 | 4.165432 | 0.796 | 0.85 | 0.604 | 3.205 | 0 |
| Azerbaijan | 2013 | 76 | 0.887 | 8.1 | 2.8 | 4.326981 | 0.887 | 0.33 | 0.809 | 1.235 | 1.36 |
| Guyana | 2013 | 107 | 0.406 | 5.77 | 0.82 | 5.775291 | 0.406 | 6.68 | 0.316 | 2.53 | 5.155 |
| Maldives | 2013 | 88 | 0.834 | 7.98 | 2.24 | 3.746565 | 0.834 | 0.16 | 0.868 | 6.49 | 0 |
| Nicaragua | 2013 | 72 | 0.54 | 5.43 | 0.46 | 3.373418 | 0.54 | 6.36 | 0.403 | 0 | 2.163 |
| Sao Tome | 2013 | 91 | 0.827 | 7.69 | 1.74 | 4.009462 | 0.827 | 2.39 | 0.729 | 5.53 | 0 |
| Russia | 2013 | 80 | 0.731 | 7.26 | 0.68 | 3.436253 | 0.731 | 4.8 | 0.672 | 2.33 | 0 |
| Turkmenis | 2013 | 81 | 0.513 | 7.04 | 2.06 | 7.258439 | 0.513 | 0.24 | 0.43 | 1.35 | 1.408 |
| Ecuador | 2013 | 74 | 0.721 | 7.76 | 2.54 | 2.574222 | 0.721 | 1.87 | 0.614 | 1.395 | 0.059 |
| Jamaica | 2013 | 118 | 0.902 | 8.05 | 0.84 | 5.838507 | 0.902 | 0.34 | 0.878 | 8.87 | 4.256 |
| Benin | 2013 | 78 | 0.706 | 6.98 | 0.42 | 3.540409 | 0.706 | 1.55 | 0.708 | 0.92 | 3.266 |
| Paraguay | 2013 | 104 | 0.796 | 8.13 | 0.72 | 3.905804 | 0.796 | 7.62 | 0.648 | 1.95 | 0 |
| Honduras | 2013 | 75 | 0.633 | 6.62 | 2.2 | 1.096072 | 0.633 | 3.33 | 0.568 | 2.895 | 0.04 |
| Saudi Arab | 2013 | 102 | 0.843 | 8.03 | 2.72 | 3.944186 | 0.843 | 0.46 | 0.675 | 6.095 | 0 |
| Armenia | 2013 | 105 | 0.823 | 7.59 | 1.04 | 1.408003 | 0.823 | 1.23 | 0.808 | 2.07 | 8.669 |
| Tunisia | 2013 | 83 | 0.635 | 8.18 | 3.52 | 5.791098 | 0.635 | 2.08 | 0.57 | 2.63 | 0.069 |
| Morocco | 2013 | 93 | 0.753 | 7.4 | 4.52 | 2.003926 | 0.753 | 1.31 | 0.642 | 3.025 | 0 |
| Serbia | 2013 | 92 | 0.799 | 7.43 | 2.06 | 4.6127 | 0.799 | 0.73 | 0.807 | 3.06 | 0 |
| Belarus | 2013 | 81 | 0.792 | 7.53 | 1.5 | 2.880753 | 0.792 | 1.3 | 0.773 | 1.6 | 0.158 |
| South Afric | 2013 | 113 | 0.474 | 7.4 | 4.94 | 6.753734 | 0.474 | 0.29 | 0.329 | 3.16 | 2.066 |
| Gabon | 2013 | 99 | 0.887 | 8.04 | 5.96 | 2.32504 | 0.887 | 0.22 | 0.83 | 0.705 | 0.203 |
| Dominican | 2013 | 95 | 0.464 | 6.13 | 0.82 | 2.579795 | 0.464 | 5.89 | 0.309 | 2.26 | 0.395 |
| Cape Verd | 2013 | 94 | 0.501 | 5.46 | 1.52 | 1.804049 | 0.501 | 6.24 | 0.479 | 0 | 2.181 |
| Kazakhstar | 2013 | 109 | 0.727 | 7.53 | 1.84 | 4.045744 | 0.727 | 0.22 | 0.675 | 5.71 | 0.992 |
| El Salvador | 2013 | 95 | 0.725 | 7.54 | 1.52 | 2.339787 | 0.725 | 2.01 | 0.639 | 3.31 | 0 |
| Cuba | 2013 | 101 | 0.773 | 7.92 | 1.4 | 1.830711 | 0.773 | 0.46 | 0.791 | 3.435 | 1.696 |
| Moldova | 2013 | 83 | 0.828 | 5.71 | 1.64 | 2.345742 | 0.828 | 3.12 | 0.724 | 0.955 | 0.976 |
| Peru | 2013 | 103 | 0.538 | 7.63 | 1.4 | 6.358965 | 0.538 | 0.23 | 0.382 | 1.92 | 0.158 |
| Macedonia | 2013 | 112 | 0.484 | 7.88 | 1.02 | 3.122777 | 0.484 | 7.23 | 0.505 | 2.6 | 0 |
| Albania | 2013 | 119 | 0.759 | 7.73 | 2.68 | 1.676504 | 0.759 | 1.38 | 0.715 | 3.41 | 6.182 |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| Micronesia | 2013 | 99 | 0.421 | 7.65 | 1.12 | 4.441622 | 0.421 | 0.55 | 0.292 | 2.335 | 0 |
| Belize | 2013 | 114 | 0.889 | 8.04 | 0.2 | 2.470195 | 0.889 | 0.35 | 0.829 | 3.16 | 5.266 |
| Ukraine | 2013 | 117 | 0.741 | 6.35 | 1.5 | 6.525975 | 0.741 | 1.26 | 0.673 | 4.17 | 1.177 |
| Ghana | 2013 | 110 | 0.755 | 7.46 | 4.82 | 1.878831 | 0.755 | 1.28 | 0.778 | 1.565 | 0 |
| Samoa | 2013 | 111 | 0.838 | 6.79 | 3.68 | 4.821513 | 0.838 | 1.49 | 0.823 | 0 | 0 |
| Antigua an | 2013 | 128 | 0.523 | 5.15 | 1.46 | 2.669385 | 0.523 | 10.41 | 0.476 | 4.615 | 3.01 |
| Namibia | 2013 | 108 | 0.72 | 7.09 | 0.52 | 4.338718 | 0.72 | 0.31 | 0.735 | 1.205 | 0.054 |
| Trinidad ar | 2013 | 125 | 0.934 | 4.89 | 1 | 6.814059 | 0.934 | 5.11 | 0.885 | 2.605 | 0 |
| Bahrain | 2013 | 124 | 0.79 | 7.51 | 0.9 | 2.901002 | 0.79 | 1.09 | 0.713 | 3.605 | 3.99 |
| Seychelles | 2013 | 121 | 0.485 | 6.95 | 4.78 | 5.132506 | 0.485 | 1.09 | 0.425 | 1.745 | 0 |
| Croatia | 2013 | 135 | 0.817 | 7.7 | 2.36 | 1.897385 | 0.817 | 0.41 | 0.78 | 15.895 | 0 |
| Cyprus | 2013 | 115 | 0.85 | 7.98 | 1.88 | 3.2158 | 0.85 | 0.28 | 0.77 | 1.245 | 0.585 |
| Grenada | 2013 | 120 | 0.57 | 6.1 | 0.34 | 2.507989 | 0.57 | 4.7 | 0.547 | 4.56 | 0.119 |
| Bahamas | 2013 | 133 | 0.745 | 7.07 | 0.24 | 2.016541 | 0.745 | 3.12 | 0.704 | 5.195 | 9.556 |
| Botswana | 2013 | 121 | 0.735 | 7.62 | 1.22 | 2.920256 | 0.735 | 0.59 | 0.67 | 0.735 | 4.492 |
| Kuwait | 2013 | 127 | 0.737 | 7.37 | 0.64 | 4.686979 | 0.737 | 1.6 | 0.695 | 2.11 | 5.238 |
| Mongolia | 2013 | 129 | 0.501 | 8.02 | 3.92 | 3.016393 | 0.501 | 6.81 | 0.361 | 2.175 | 0 |
| Malaysia | 2013 | 116 | 0.908 | 7.16 | 0.6 | 3.517046 | 0.908 | 0.45 | 0.827 | 1.26 | 0 |
| Brazil | 2013 | 126 | 0.693 | 6.42 | 0.3 | 1.511949 | 0.693 | 3.82 | 0.654 | 5.065 | 0 |
| Brunei Dar | 2013 | 123 | 0.734 | 7.39 | 2.46 | 1.656498 | 0.734 | 1.43 | 0.633 | 0.675 | 0 |
| Romania | 2013 | 130 | 0.679 | 6.23 | 1.1 | 5.235916 | 0.679 | 1.6 | 0.606 | 3.92 | 0.741 |
| Hungary | 2013 | 141 | 0.483 | 6.21 | 1.2 | 4.1836 | 0.483 | 5.62 | 0.415 | 10.055 | 0 |
| Bulgaria | 2013 | 132 | 0.86 | 7.82 | 0.66 | 1.965212 | 0.86 | 0.81 | 0.71 | 3.39 | 3.917 |
| Greece | 2013 | 138 | 0.919 | 8.06 | 0.58 | 2.902316 | 0.919 | 0.33 | 0.905 | 6.955 | 3.864 |
| United Ara | 2013 | 142 | 0.62 | 7.41 | 0.82 | 7.895242 | 0.62 | 4.21 | 0.494 | 3.72 | 1.72 |
| Chile | 2013 | 152 | 0.387 | 5.08 | 0.9 | 5.737545 | 0.387 | 9.02 | 0.273 | 5.655 | 4.576 |
| Qatar | 2013 | 143 | 0.506 | 7.72 | 1.36 | 4.467031 | 0.506 | 1.94 | 0.417 | 10.06 | 0 |
| Monteneg | 2013 | 134 | 0.765 | 6.26 | 1.8 | 3.876586 | 0.765 | 1.28 | 0.696 | 1.29 | 2.804 |
| Spain | 2013 | 149 | 0.413 | 7.29 | 2.58 | 4.752135 | 0.413 | 4.41 | 0.364 | 9.035 | 0 |
| Oman | 2013 | 136 | 0.63 | 8.14 | 4.6 | 4.939654 | 0.63 | 0.35 | 0.529 | 1.81 | 0 |
| Costa Rica | 2013 | 139 | 0.412 | 5.79 | 3.18 | 3.402897 | 0.412 | 8.05 | 0.442 | 2.66 | 0 |
| Italy | 2013 | 147 | 0.659 | 6.9 | 2.74 | 3.796097 | 0.659 | 0.34 | 0.505 | 4.26 | 7.068 |
| Panama | 2013 | 131 | 0.514 | 6 | 0.72 | 4.120635 | 0.514 | 2.06 | 0.464 | 0.445 | 0.616 |
| Argentina | 2013 | 144 | 0.781 | 7.57 | 3.46 | 2.051205 | 0.781 | 0.68 | 0.697 | 1.52 | 7.305 |
| Slovak Rep | 2013 | 145 | 0.717 | 7.48 | 2.8 | 5.827862 | 0.717 | 0.93 | 0.653 | 2.865 | 2.68 |
| Estonia | 2013 | 145 | 0.586 | 5.68 | 1.16 | 3.163309 | 0.586 | 7.43 | 0.439 | 3.75 | 0.346 |
| Malta | 2013 | 151 | 0.508 | 8.11 | 1.26 | 6.521795 | 0.508 | 5.02 | 0.492 | 0.825 | 2.708 |
| Czech Repu | 2013 | 154 | 0.865 | 7.82 | 1.5 | 2.932325 | 0.865 | 0.32 | 0.856 | 11.6 | 0 |
| Poland | 2013 | 153 | 0.684 | 7.21 | 3.1 | 3.379114 | 0.684 | 7.06 | 0.661 | 2.545 | 0 |
| Barbados | 2013 | 137 | 0.565 | 7.08 | 1.18 | 1.650823 | 0.565 | 3.53 | 0.452 | 0 | 0 |
| Latvia | 2013 | 140 | 0.589 | 6.57 | 0.28 | 4.683896 | 0.589 | 2.27 | 0.59 | 0.64 | 1.62 |
| South Kore | 2013 | 157 | 0.766 | 6.54 | 4.96 | 4.998472 | 0.766 | 3.75 | 0.741 | 4.64 | 0 |
| Lithuania | 2013 | 150 | 0.814 | 6.53 | 4.12 | 3.89022 | 0.814 | 0.76 | 0.815 | 1.695 | 0 |
| Mauritius | 2013 | 148 | 0.779 | 6.01 | 1.74 | 2.500266 | 0.779 | 0.92 | 0.694 | 1.48 | 2.174 |
| Uruguay | 2013 | 155 | 0.773 | 5.86 | 1.3 | 8.090094 | 0.773 | 0.65 | 0.714 | 3.885 | 0 |
| Belgium | 2013 | 164 | 0.796 | 7.09 | 2.88 | 2.895078 | 0.796 | 0.4 | 0.836 | 5.665 | 7.242 |
| France | 2013 | 161 | 0.719 | 6.96 | 4.08 | 3.417975 | 0.719 | 2 | 0.753 | 7.39 | 0 |
| Denmark | 2013 | 174 | 0.452 | 5.08 | 11.84 | 3.927116 | 0.452 | 7.28 | 0.393 | 1.785 | 4.483 |
| Singapore | 2013 | 158 | 0.734 | 7.33 | 0.56 | 7.569365 | 0.734 | 3.71 | 0.677 | 1.565 | 0.079 |
| United Sta | 2013 | 159 | 0.718 | 6.78 | 1.64 | 6.737062 | 0.718 | 1.16 | 0.767 | 4.395 | 0 |
| United Kin | 2013 | 160 | 0.47 | 7.51 | 1.58 | 6.676487 | 0.47 | 3.88 | 0.48 | 0.69 | 1.456 |
| Germany | 2013 | 165 | 0.445 | 5.98 | 0.82 | 3.652601 | 0.445 | 5.01 | 0.348 | 7.855 | 1.235 |
| Japan | 2013 | 156 | 0.891 | 8.19 | 2.44 | 3.207578 | 0.891 | 0.32 | 0.86 | 2.59 | 0 |
| Austria | 2013 | 166 | 0.933 | 8.21 | 1.04 | 4.046799 | 0.933 | 0.36 | 0.936 | 6.795 | 4.844 |
| New Zeala | 2013 | 173 | 0.405 | 7.34 | 1.36 | 5.003618 | 0.405 | 2.64 | 0.363 | 11.7 | 0 |
| Slovenia | 2013 | 163 | 0.7 | 7.27 | 1.76 | 3.435098 | 0.7 | 1.36 | 0.699 | 1.705 | 1.475 |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| Portugal | 2013 | 161 | 0.773 | 7.26 | 0.1 | 3.441176 | 0.773 | 1.57 | 0.676 | 3.205 | 0 |
| Finland | 2013 | 178 | 0.427 | 6.28 | 1.88 | 3.731755 | 0.427 | 4.62 | 0.312 | 8.275 | 6.055 |
| Iceland | 2013 | 171 | 0.614 | 7.28 | 0.72 | 3.86805 | 0.614 | 1.92 | 0.504 | 3.425 | 5.831 |
| Canada | 2013 | 168 | 0.546 | 6.75 | 1.46 | 2.933048 | 0.546 | 3.07 | 0.451 | 0.72 | 5.017 |
| Netherland | 2013 | 166 | 0.634 | 7.58 | 1.38 | 5.72806 | 0.634 | 0.53 | 0.488 | 3.415 | 0.049 |
| Australia | 2013 | 169 | 0.736 | 7.44 | 0.98 | 0.997648 | 0.736 | 1.46 | 0.73 | 7.535 | 0.074 |
| Norway | 2013 | 175 | 0.908 | 8.12 | 1.14 | 3.516866 | 0.908 | 3.31 | 0.91 | 0 | 0 |
| Ireland | 2013 | 170 | 0.677 | 6.85 | 1.38 | 2.585198 | 0.677 | 1.51 | 0.61 | 0.09 | 0.03 |
| Switzerlan | 2013 | 175 | 0.417 | 5.47 | 2.2 | 6.670224 | 0.417 | 0.24 | 0.297 | 0.8 | 0.059 |
| Luxembou | 2013 | 172 | 0.766 | 7.36 | 2.68 | 4.086442 | 0.766 | 0.79 | 0.656 | 2.87 | 0 |
| Sweden | 2013 | 177 | 0.652 | 6.75 | 2.94 | 4.194991 | 0.652 | 0.65 | 0.686 | 1.28 | 0 |
| Sudan | 2014 | 4 | 0.842 | 8.3 | 5.22 | 8.435 | 0.842 | 1.19 | 0.82 | 10.53 | 1.84 |
| Somalia | 2014 | 2 | 0.845 | 6.65 | 1.5 | 8.1625 | 0.845 | 1.54 | 0.768 | 6.345 | 0.16 |
| Congo Den | 2014 | 5 | 0.498 | 6.33 | 0.76 | 6.378 | 0.498 | 5.66 | 0.469 | 0.04 | 6.5 |
| South Suda | 2014 | 1 | 0.781 | 7.49 | 0.86 | 7.9935 | 0.781 | 1.29 | 0.706 | 1.11 | 0 |
| Syria | 2014 | 9 | 0.882 | 5.74 | 0.62 | 7.647 | 0.882 | 2.42 | 0.818 | 7.875 | 0.01 |
| Yemen | 2014 | 7 | 0.488 | 7.53 | 0.38 | 8.247 | 0.488 | 1.87 | 0.462 | 3.605 | 3.57 |
| Central Afr | 2014 | 3 | 0.919 | 8.2 | 1.12 | 3.369 | 0.919 | 0.44 | 0.89 | 1.715 | 5.25 |
| Chad | 2014 | 6 | 0.347 | 5.07 | 1.28 | 4.95 | 0.347 | 9.35 | 0.338 | 0.55 | 1.59 |
| Afghanista | 2014 | 8 | 0.479 | 6.04 | 1.82 | 2.7165 | 0.479 | 6.81 | 0.398 | 0.115 | 5.6 |
| Liberia | 2014 | 21 | 0.662 | 7.44 | 5.28 | 7.39 | 0.662 | 2.01 | 0.721 | 9.745 | 0.58 |
| Guinea | 2014 | 10 | 0.751 | 7.34 | 2.24 | 6.018 | 0.751 | 1.11 | 0.725 | 1.42 | 5.52 |
| Haiti | 2014 | 11 | 0.421 | 5.52 | 0.66 | 5.6095 | 0.421 | 6.24 | 0.353 | 1.445 | 2.58 |
| Guinea Bis | 2014 | 17 | 0.637 | 7.18 | 1.38 | 4.2405 | 0.637 | 2.51 | 0.508 | 0.79 | 7.86 |
| Nigeria | 2014 | 14 | 0.555 | 6.48 | 0.7 | 6.095 | 0.555 | 3.34 | 0.475 | 0.61 | 4.41 |
| Zimbabwe | 2014 | 16 | 0.836 | 5.85 | 1.92 | 8.32 | 0.836 | 1.23 | 0.681 | 5.69 | 0 |
| Iraq | 2014 | 12 | 0.615 | 6.8 | 2.26 | 6.0785 | 0.615 | 2.36 | 0.525 | 0 | 0.24 |
| Pakistan | 2014 | 13 | 0.351 | 7.49 | 0.96 | 6.5935 | 0.351 | 0.48 | 0.206 | 2.395 | 1.72 |
| Burundi | 2014 | 18 | 0.399 | 5.87 | 2.14 | 3.821 | 0.399 | 6.22 | 0.261 | 1.17 | 4.24 |
| Banglades | 2014 | 32 | 0.823 | 7.66 | 2.46 | 4.3 | 0.823 | 0.56 | 0.717 | 2.99 | 9.37 |
| Niger | 2014 | 19 | 0.637 | 6.59 | 0.96 | 6.4215 | 0.637 | 4.07 | 0.546 | 2.365 | 1.45 |
| Mali | 2014 | 30 | 0.896 | 7.33 | 1.64 | 6.7645 | 0.896 | 3.7 | 0.783 | 3.535 | 2.71 |
| Tajikistan | 2014 | 57 | 0.764 | 5.57 | 0.16 | 7.612 | 0.764 | 8.74 | 0.752 | 8.8 | 4.71 |
| Rwanda | 2014 | 37 | 0.679 | 7.46 | 4.16 | 7.9545 | 0.679 | 1.81 | 0.637 | 2.4 | 4.73 |
| Kenya | 2014 | 21 | 0.902 | 8.35 | 1.34 | 6.256 | 0.902 | 1.58 | 0.842 | 1.755 | 1.18 |
| Uzbekistar | 2014 | 52 | 0.723 | 7.28 | 2.04 | 8.73 | 0.723 | 4.61 | 0.641 | 8.435 | 1.34 |
| Cote dIvoi | 2014 | 15 | 0.775 | 7.94 | 0.54 | 3.6905 | 0.775 | 0.86 | 0.684 | 4.5 | 0 |
| Jordan | 2014 | 81 | 0.881 | 8.31 | 1.02 | 5.405 | 0.881 | 1.39 | 0.804 | 18.85 | 5.21 |
| Myanmar | 2014 | 27 | 0.701 | 6.91 | 5.38 | 6.7055 | 0.701 | 1.39 | 0.725 | 1.75 | 0 |
| Uganda | 2014 | 23 | 0.738 | 6.94 | 0.76 | 8.248 | 0.738 | 0.35 | 0.641 | 1.455 | 0.24 |
| Iran | 2014 | 44 | 0.919 | 8.26 | 3.2 | 5.9255 | 0.919 | 3.93 | 0.906 | 2.17 | 2.38 |
| Nepal | 2014 | 35 | 0.804 | 6.94 | 1.36 | 7.3235 | 0.804 | 1.99 | 0.797 | 2.765 | 2.3 |
| Mauritania | 2014 | 26 | 0.473 | 6.51 | 6.18 | 5.6985 | 0.473 | 0.62 | 0.445 | 0 | 0 |
| Togo | 2014 | 47 | 0.909 | 7.11 | 1.06 | 8.2705 | 0.909 | 0.86 | 0.852 | 8.44 | 0 |
| Venezuela | 2014 | 74 | 0.764 | 7.04 | 0.9 | 8.4935 | 0.764 | 5.36 | 0.666 | 12.59 | 0 |
| TimorLeste | 2014 | 35 | 0.541 | 6.35 | 1.54 | 8.2365 | 0.541 | 0.36 | 0.545 | 1.01 | 5.17 |
| Ethiopia | 2014 | 20 | 0.418 | 6.37 | 1.66 | 4.533 | 0.418 | 3.5 | 0.267 | 0 | 0.08 |
| Eritrea | 2014 | 24 | 0.678 | 7.3 | 1.48 | 5.389 | 0.678 | 1.49 | 0.584 | 0 | 0 |
| Kyrgyz Rep | 2014 | 62 | 0.793 | 6.94 | 0.7 | 7.4995 | 0.793 | 3.66 | 0.805 | 8.115 | 2.85 |
| North Kore | 2014 | 29 | 0.923 | 6.96 | 1.26 | 4.926 | 0.923 | 2.97 | 0.897 | 1.09 | 0 |
| Libya | 2014 | 25 | 0.582 | 7.06 | 0.8 | 2.414 | 0.582 | 5.23 | 0.474 | 0.035 | 0 |
| Lebanon | 2014 | 40 | 0.899 | 7.03 | 2.16 | 6.1295 | 0.899 | 0.3 | 0.867 | 0 | 5.98 |
| Cameroon | 2014 | 28 | 0.646 | 7.33 | 0.88 | 3.1654 | 0.646 | 2.13 | 0.531 | 2.36 | 0 |
| Egypt | 2014 | 38 | 0.718 | 7.35 | 1.24 | 3.9275 | 0.718 | 2.62 | 0.622 | 4.41 | 0 |
| Laos | 2014 | 55 | 0.55 | 6.16 | 1.64 | 5.5105 | 0.55 | 4.46 | 0.518 | 3.035 | 4.67 |
| Cambodia | 2014 | 42 | 0.406 | 5.67 | 0.08 | 4.6905 | 0.406 | 5.58 | 0.395 | 4.23 | 1.45 |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| Angola | 2014 | 42 | 0.857 | 8.13 | 1.52 | 3.3445 | 0.857 | 0.21 | 0.718 | 1.21 | 5.77 |
| Gambia | 2014 | 51 | 0.894 | 8.22 | 2.48 | 5.228 | 0.894 | 0.36 | 0.832 | 2.685 | 3.55 |
| Solomon Is | 2014 | 50 | 0.565 | 7.34 | 6.78 | 6.447 | 0.565 | 1.7 | 0.489 | 0.715 | 0 |
| Sierra Leor | 2014 | 31 | 0.762 | 6.42 | 0.68 | 6.4695 | 0.762 | 0.85 | 0.659 | 0.09 | 1.73 |
| Madagasca | 2014 | 56 | 0.427 | 4.98 | 0.36 | 4.8335 | 0.427 | 5.47 | 0.423 | 9.725 | 0 |
| Colombia | 2014 | 61 | 0.734 | 7.58 | 3.88 | 4.3605 | 0.734 | 0.98 | 0.631 | 3.545 | 5.23 |
| Mozambiq | 2014 | 46 | 0.637 | 7.68 | 0.92 | 3.51 | 0.637 | 2.94 | 0.649 | 5.59 | 0 |
| Congo Rep | 2014 | 33 | 0.59 | 6.23 | 1.92 | 4.2115 | 0.59 | 3.44 | 0.52 | 0.435 | 0.7 |
| Sri Lanka | 2014 | 34 | 0.924 | 5.09 | 1.38 | 7.795 | 0.924 | 0.6 | 0.814 | 1.13 | 0 |
| Papua New | 2014 | 57 | 0.948 | 5.28 | 1.2 | 6.4555 | 0.948 | 5.84 | 0.916 | 3.93 | 0.19 |
| Israel and | 2014 | 68 | 0.774 | 7.54 | 2.54 | 5.4535 | 0.774 | 2.72 | 0.704 | 8.28 | 0.76 |
| Djibouti | 2014 | 41 | 0.923 | 8.02 | 2.9 | 3.7005 | 0.923 | 0.3 | 0.923 | 3 | 0 |
| Zambia | 2014 | 53 | 0.748 | 6.56 | 3.28 | 8.426 | 0.748 | 1.26 | 0.803 | 0 | 1.07 |
| Tanzania | 2014 | 63 | 0.488 | 8.26 | 5.6 | 8.441 | 0.488 | 3.44 | 0.318 | 0 | 0 |
| Honduras | 2014 | 76 | 0.638 | 6.64 | 1.54 | 6.1185 | 0.638 | 3.26 | 0.572 | 3.015 | 7.19 |
| Bosnia anc | 2014 | 78 | 0.671 | 6.83 | 3.58 | 4.974 | 0.671 | 3.17 | 0.656 | 2.935 | 6.58 |
| Georgia | 2014 | 70 | 0.694 | 6.44 | 1 | 6.335 | 0.694 | 3.7 | 0.618 | 2.43 | 6.24 |
| Thailand | 2014 | 71 | 0.723 | 7.49 | 0.88 | 7.9625 | 0.723 | 6.2 | 0.63 | 0.975 | 2.67 |
| Swaziland | 2014 | 48 | 0.514 | 8.04 | 0.9 | 8.307 | 0.514 | 0.22 | 0.445 | 1.045 | 0.81 |
| Bolivia | 2014 | 76 | 0.604 | 6.95 | 6.24 | 4.263 | 0.604 | 2.83 | 0.452 | 2.76 | 3.7 |
| Burkina Fa | 2014 | 39 | 0.792 | 7.42 | 0.32 | 3.675 | 0.792 | 0.97 | 0.778 | 1.44 | 0.56 |
| Philippines | 2014 | 48 | 0.783 | 6.62 | 1.8 | 6.4175 | 0.783 | 1 | 0.808 | 1.235 | 0.04 |
| Comoros | 2014 | 59 | 0.724 | 7.4 | 1.44 | 4.2875 | 0.724 | 1.41 | 0.63 | 1.46 | 4 |
| Maldives | 2014 | 91 | 0.846 | 8 | 2.32 | 6.431 | 0.846 | 0.16 | 0.882 | 7.025 | 4.66 |
| Algeria | 2014 | 67 | 0.743 | 7.48 | 2.12 | 4.47 | 0.743 | 2.2 | 0.658 | 0.9 | 5.19 |
| India | 2014 | 69 | 0.916 | 8.4 | 1.18 | 5.5925 | 0.916 | 0.53 | 0.822 | 5.805 | 0.16 |
| Equatorial | 2014 | 54 | 0.688 | 7.11 | 1.66 | 5.345 | 0.688 | 2.1 | 0.597 | 0.235 | 0.14 |
| Russia | 2014 | 65 | 0.737 | 7.29 | 0.54 | 6.688 | 0.737 | 4.57 | 0.671 | 1.9 | 0 |
| Malawi | 2014 | 44 | 0.719 | 6.09 | 1.32 | 4.548 | 0.719 | 1.19 | 0.616 | 0.81 | 0 |
| China | 2014 | 83 | 0.845 | 8.17 | 1.82 | 4.76 | 0.845 | 0.72 | 0.784 | 8.47 | 0 |
| Senegal | 2014 | 60 | 0.798 | 7.82 | 1.18 | 5.023 | 0.798 | 0.3 | 0.764 | 2.89 | 0 |
| Turkey | 2014 | 89 | 0.625 | 8.3 | 1.98 | 8.2365 | 0.625 | 4.58 | 0.658 | 2 | 1.02 |
| Mexico | 2014 | 99 | 0.701 | 7.47 | 0.98 | 6.428 | 0.701 | 7.59 | 0.561 | 5.785 | 0.47 |
| Bhutan | 2014 | 74 | 0.481 | 5.96 | 0.64 | 3.688 | 0.481 | 6.57 | 0.408 | 2.365 | 2.59 |
| Morocco | 2014 | 89 | 0.758 | 7.44 | 4.46 | 6.218 | 0.758 | 1.19 | 0.649 | 2.895 | 2.37 |
| Ukraine | 2014 | 84 | 0.746 | 6.5 | 1.86 | 7.91 | 0.746 | 1.17 | 0.673 | 4.32 | 0.95 |
| Dominican | 2014 | 104 | 0.47 | 6.2 | 0.76 | 5.886 | 0.47 | 5.58 | 0.31 | 2.52 | 7.29 |
| Paraguay | 2014 | 103 | 0.795 | 8.16 | 0.66 | 6.331 | 0.795 | 7.15 | 0.648 | 2.55 | 1.54 |
| Suriname | 2014 | 109 | 0.888 | 7.63 | 1.6 | 7.5395 | 0.888 | 9.02 | 0.886 | 3.02 | 0 |
| Guyana | 2014 | 107 | 0.414 | 5.88 | 0.78 | 7.196 | 0.414 | 6.28 | 0.33 | 3.04 | 4.66 |
| Belarus | 2014 | 87 | 0.794 | 7.56 | 1.7 | 4.9805 | 0.794 | 1.23 | 0.773 | 2.14 | 3.76 |
| Nicaragua | 2014 | 72 | 0.552 | 5.51 | 0.54 | 6.764 | 0.552 | 5.85 | 0.41 | 0 | 0 |
| Fiji | 2014 | 82 | 0.863 | 7.68 | 1.74 | 3.19 | 0.863 | 0.25 | 0.876 | 5.655 | 1.26 |
| Tunisia | 2014 | 86 | 0.553 | 8.22 | 3.06 | 8.2215 | 0.553 | 1.95 | 0.436 | 0.055 | 0.23 |
| Ghana | 2014 | 100 | 0.768 | 7.49 | 5.3 | 4.7265 | 0.768 | 1.13 | 0.794 | 1.91 | 3.71 |
| Guatemala | 2014 | 64 | 0.865 | 8.09 | 1.52 | 3.399 | 0.865 | 0.37 | 0.83 | 2.09 | 0.01 |
| Saudi Arab | 2014 | 101 | 0.855 | 8.09 | 2.78 | 7.4605 | 0.855 | 0.45 | 0.698 | 5.41 | 0.23 |
| Azerbaijan | 2014 | 80 | 0.892 | 8.14 | 3.02 | 4.1715 | 0.892 | 0.3 | 0.82 | 1.69 | 1.12 |
| Benin | 2014 | 73 | 0.706 | 7 | 0.52 | 3.4575 | 0.706 | 1.46 | 0.704 | 1.02 | 3.97 |
| Indonesia | 2014 | 88 | 0.834 | 7.52 | 2.12 | 6.7015 | 0.834 | 0.16 | 0.835 | 3.79 | 0.54 |
| Turkmenis | 2014 | 78 | 0.519 | 6.96 | 2.02 | 7.989 | 0.519 | 0.24 | 0.42 | 1.475 | 0.58 |
| Serbia | 2014 | 92 | 0.805 | 7.47 | 1.94 | 7.744 | 0.805 | 0.7 | 0.816 | 3.87 | 0.07 |
| Lesotho | 2014 | 66 | 0.799 | 8.19 | 1.34 | 2.855 | 0.799 | 0.77 | 0.611 | 2.7 | 0 |
| Sao Tome | 2014 | 93 | 0.841 | 7.74 | 1.32 | 5.796 | 0.841 | 2.28 | 0.756 | 4 | 0 |
| Ecuador | 2014 | 85 | 0.724 | 7.78 | 2.6 | 4.899 | 0.724 | 1.95 | 0.615 | 1.585 | 0 |
| Armenia | 2014 | 108 | 0.826 | 7.63 | 1.22 | 3.9975 | 0.826 | 1.15 | 0.807 | 2.555 | 7.31 |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| Vietnam | 2014 | 97 | 0.688 | 7.48 | 1.4 | 8.3065 | 0.688 | 1.47 | 0.629 | 1.78 | 0.19 |
| South Afric | 2014 | 113 | 0.491 | 7.43 | 4.98 | 7.942 | 0.491 | 0.27 | 0.355 | 3.285 | 2.55 |
| Kazakhstar | 2014 | 110 | 0.729 | 7.57 | 1.84 | 6.435 | 0.729 | 0.21 | 0.677 | 5.31 | 2.95 |
| Bahrain | 2014 | 119 | 0.79 | 7.54 | 0.88 | 4.868 | 0.79 | 1.02 | 0.713 | 3.755 | 10 |
| Jamaica | 2014 | 117 | 0.92 | 8.09 | 0.7 | 6.401 | 0.92 | 0.33 | 0.91 | 8.66 | 1.76 |
| Grenada | 2014 | 120 | 0.575 | 6.14 | 0.34 | 6.8485 | 0.575 | 4.42 | 0.546 | 3.42 | 6.76 |
| Gabon | 2014 | 104 | 0.893 | 8.08 | 6.04 | 4.0295 | 0.893 | 0.2 | 0.847 | 0.69 | 0 |
| Croatia | 2014 | 137 | 0.823 | 7.73 | 3.22 | 5.9645 | 0.823 | 0.38 | 0.795 | 15.39 | 6.4 |
| El Salvador | 2014 | 102 | 0.739 | 7.59 | 1.72 | 4.0695 | 0.739 | 1.9 | 0.665 | 3.685 | 0 |
| Micronesia | 2014 | 94 | 0.438 | 7.68 | 0.78 | 5.7275 | 0.438 | 0.52 | 0.312 | 2.505 | 0 |
| Namibia | 2014 | 106 | 0.733 | 7.16 | 0.62 | 6.2015 | 0.733 | 0.29 | 0.738 | 1.49 | 3.04 |
| Cape Verde | 2014 | 94 | 0.514 | 5.55 | 1.52 | 3.386 | 0.514 | 5.86 | 0.493 | 0 | 0 |
| Macedonia | 2014 | 118 | 0.495 | 7.93 | 1.18 | 6.5025 | 0.495 | 7.05 | 0.503 | 2.275 | 0.28 |
| Cyprus | 2014 | 114 | 0.854 | 8.02 | 1.88 | 5.87 | 0.854 | 0.26 | 0.786 | 1.46 | 4.9 |
| Peru | 2014 | 98 | 0.548 | 7.68 | 1.32 | 5.572 | 0.548 | 0.22 | 0.395 | 2.04 | 0 |
| Moldova | 2014 | 96 | 0.853 | 5.8 | 1.46 | 5.4605 | 0.853 | 3.02 | 0.781 | 1.31 | 0 |
| Albania | 2014 | 125 | 0.762 | 7.78 | 3.5 | 2.1565 | 0.762 | 1.29 | 0.715 | 3.385 | 7.41 |
| Antigua an | 2014 | 127 | 0.531 | 5.23 | 1.46 | 3.353 | 0.531 | 9.88 | 0.48 | 4.23 | 5.9 |
| Samoa | 2014 | 111 | 0.852 | 6.82 | 3.94 | 5.394 | 0.852 | 1.36 | 0.852 | 0 | 0 |
| Brazil | 2014 | 123 | 0.698 | 6.45 | 0.32 | 4.837 | 0.698 | 3.56 | 0.658 | 5.255 | 2.93 |
| Cuba | 2014 | 112 | 0.773 | 7.94 | 1.22 | 4.334 | 0.773 | 0.41 | 0.779 | 3.67 | 0.31 |
| Malaysia | 2014 | 115 | 0.911 | 7.16 | 0.58 | 5.9 | 0.911 | 0.36 | 0.818 | 0.755 | 2.96 |
| Mongolia | 2014 | 129 | 0.513 | 8.06 | 3.6 | 7.1635 | 0.513 | 6.61 | 0.377 | 1.94 | 0.27 |
| Seychelles | 2014 | 124 | 0.493 | 7.01 | 3.78 | 7.488 | 0.493 | 1.01 | 0.426 | 1.31 | 0 |
| Belize | 2014 | 116 | 0.895 | 8.08 | 0.22 | 4.209 | 0.895 | 0.34 | 0.841 | 2.85 | 0.35 |
| Brunei Dar | 2014 | 121 | 0.754 | 7.45 | 2.28 | 3.1245 | 0.754 | 1.44 | 0.677 | 1.275 | 2.45 |
| Trinidad ar | 2014 | 126 | 0.938 | 4.9 | 0.66 | 7.338 | 0.938 | 4.88 | 0.892 | 2.735 | 0.53 |
| Bulgaria | 2014 | 130 | 0.864 | 7.88 | 0.6 | 5.3005 | 0.864 | 0.85 | 0.714 | 3.125 | 6.25 |
| Kuwait | 2014 | 128 | 0.741 | 7.4 | 0.7 | 6.8135 | 0.741 | 1.35 | 0.701 | 2.215 | 3.29 |
| Hungary | 2014 | 139 | 0.49 | 6.28 | 0.98 | 5.7255 | 0.49 | 5.35 | 0.422 | 11.81 | 0 |
| Greece | 2014 | 134 | 0.924 | 8.09 | 0.56 | 5.885 | 0.924 | 0.32 | 0.914 | 6.93 | 2.61 |
| Botswana | 2014 | 122 | 0.747 | 7.65 | 1.36 | 3.3685 | 0.747 | 0.54 | 0.694 | 0.425 | 0.08 |
| Romania | 2014 | 132 | 0.692 | 6.26 | 1.04 | 6.7205 | 0.692 | 1.51 | 0.613 | 4.02 | 0.7 |
| Barbados | 2014 | 138 | 0.575 | 7.16 | 1.18 | 4.8735 | 0.575 | 3.21 | 0.457 | 0 | 8.58 |
| Oman | 2014 | 135 | 0.642 | 8.18 | 5.38 | 5.916 | 0.642 | 0.33 | 0.542 | 2.06 | 0 |
| United Ara | 2014 | 144 | 0.603 | 7.44 | 0.76 | 8.0635 | 0.603 | 3.97 | 0.494 | 4.405 | 3.09 |
| Spain | 2014 | 151 | 0.431 | 7.31 | 2.66 | 7.38 | 0.431 | 4.23 | 0.374 | 9.285 | 2.59 |
| Monteneg | 2014 | 132 | 0.779 | 6.31 | 1.98 | 6.1075 | 0.779 | 1.22 | 0.725 | 3.305 | 0 |
| Qatar | 2014 | 143 | 0.515 | 7.76 | 1.36 | 6.742 | 0.515 | 1.85 | 0.422 | 8.665 | 0.04 |
| Chile | 2014 | 150 | 0.394 | 5.16 | 0.92 | 5.9715 | 0.394 | 8.67 | 0.28 | 6 | 4.01 |
| Costa Rica | 2014 | 142 | 0.425 | 5.87 | 3.46 | 4.0005 | 0.425 | 7.65 | 0.457 | 3.15 | 0.41 |
| Bahamas | 2014 | 136 | 0.758 | 7.08 | 0.24 | 3.1145 | 0.758 | 2.89 | 0.723 | 5.13 | 0 |
| Panama | 2014 | 131 | 0.525 | 6.14 | 0.66 | 6.024 | 0.525 | 1.94 | 0.475 | 0.49 | 0 |
| Latvia | 2014 | 140 | 0.586 | 6.6 | 0.3 | 6.3035 | 0.586 | 2.07 | 0.59 | 0.795 | 2.11 |
| Estonia | 2014 | 146 | 0.582 | 5.76 | 1.06 | 5.5325 | 0.582 | 7.03 | 0.439 | 3.52 | 0.01 |
| Poland | 2014 | 153 | 0.678 | 7.27 | 2.78 | 5.453 | 0.678 | 6.74 | 0.655 | 2.79 | 0 |
| Argentina | 2014 | 141 | 0.784 | 7.61 | 3.24 | 3.4425 | 0.784 | 0.61 | 0.695 | 1.71 | 0.05 |
| Italy | 2014 | 147 | 0.649 | 6.94 | 2.74 | 6.9625 | 0.649 | 0.31 | 0.5 | 4.28 | 0.06 |
| Mauritius | 2014 | 145 | 0.787 | 6.28 | 1.54 | 5.4805 | 0.787 | 0.78 | 0.7 | 0 | 3.63 |
| Czech Repu | 2014 | 154 | 0.875 | 7.86 | 1.32 | 4.4875 | 0.875 | 0.29 | 0.878 | 11.125 | 0 |
| Slovak Rep | 2014 | 149 | 0.72 | 7.51 | 2.64 | 6.6485 | 0.72 | 0.87 | 0.657 | 2.62 | 0 |
| South Kore | 2014 | 156 | 0.775 | 6.65 | 4.88 | 7.3375 | 0.775 | 3.55 | 0.76 | 3.435 | 0 |
| France | 2014 | 160 | 0.734 | 7 | 4.08 | 5.2195 | 0.734 | 1.94 | 0.777 | 7.4 | 1.99 |
| Malta | 2014 | 151 | 0.511 | 8.17 | 1.18 | 5.593 | 0.511 | 4.51 | 0.492 | 0.965 | 0 |
| Lithuania | 2014 | 148 | 0.828 | 6.62 | 4.12 | 3.4165 | 0.828 | 0.72 | 0.835 | 1.8 | 0 |
| United Sta | 2014 | 158 | 0.718 | 6.82 | 1.26 | 8.3505 | 0.718 | 1.09 | 0.766 | 5.495 | 0.08 |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| Uruguay | 2014 | 155 | 0.779 | 5.97 | 1.32 | 8.2205 | 0.779 | 0.52 | 0.717 | 4.15 | 0 |
| Austria | 2014 | 167 | 0.937 | 8.24 | 0.98 | 6.0705 | 0.937 | 0.32 | 0.939 | 6.345 | 8.12 |
| Japan | 2014 | 157 | 0.898 | 8.24 | 2.38 | 6.4185 | 0.898 | 0.3 | 0.87 | 2.62 | 0 |
| Australia | 2014 | 170 | 0.741 | 7.47 | 1.12 | 2.9535 | 0.741 | 1.32 | 0.73 | 8.295 | 9.39 |
| United Kin | 2014 | 161 | 0.484 | 7.54 | 1.22 | 8.481 | 0.484 | 3.62 | 0.489 | 0.84 | 0.41 |
| Belgium | 2014 | 163 | 0.798 | 7.13 | 2.32 | 5.4395 | 0.798 | 0.35 | 0.833 | 7.72 | 1.16 |
| Singapore | 2014 | 159 | 0.735 | 7.38 | 0.56 | 6.928 | 0.735 | 3.27 | 0.677 | 1.705 | 0 |
| Denmark | 2014 | 175 | 0.466 | 5.15 | 11.14 | 3.5895 | 0.466 | 6.85 | 0.406 | 1.66 | 4.01 |
| Portugal | 2014 | 164 | 0.785 | 7.29 | 0.04 | 7.3705 | 0.785 | 1.47 | 0.691 | 3.55 | 2.58 |
| Germany | 2014 | 165 | 0.45 | 6.02 | 1.18 | 5.688 | 0.45 | 4.86 | 0.358 | 7.03 | 0.1 |
| Slovenia | 2014 | 162 | 0.702 | 7.29 | 1.94 | 7.113 | 0.702 | 1.3 | 0.702 | 1.655 | 0.29 |
| New Zeala | 2014 | 172 | 0.414 | 7.4 | 1.12 | 6.2005 | 0.414 | 2.46 | 0.366 | 11.535 | 0 |
| Netherland | 2014 | 166 | 0.645 | 7.62 | 1.16 | 6.677 | 0.645 | 0.46 | 0.503 | 3.575 | 3.04 |
| Canada | 2014 | 168 | 0.558 | 6.84 | 1.38 | 2.9955 | 0.558 | 2.63 | 0.459 | 0.815 | 5.29 |
| Finland | 2014 | 178 | 0.441 | 6.41 | 2.06 | 4.4555 | 0.441 | 4.29 | 0.315 | 8.23 | 0 |
| Norway | 2014 | 176 | 0.913 | 8.16 | 1.12 | 6.7175 | 0.913 | 3.05 | 0.917 | 0 | 0 |
| Ireland | 2014 | 169 | 0.686 | 6.89 | 1.18 | 5.7655 | 0.686 | 1.39 | 0.622 | 0.02 | 0 |
| Iceland | 2014 | 171 | 0.623 | 7.31 | 0.7 | 3.804 | 0.623 | 1.8 | 0.518 | 3.065 | 0 |
| Sweden | 2014 | 177 | 0.665 | 6.79 | 2.64 | 6.3795 | 0.665 | 0.61 | 0.705 | 1.945 | 0 |
| Switzerlan | 2014 | 173 | 0.421 | 5.54 | 2.18 | 6.72 | 0.421 | 0.22 | 0.297 | 0.825 | 0 |
| Luxembou | 2014 | 174 | 0.763 | 7.42 | 2.14 | 4.8025 | 0.763 | 0.73 | 0.656 | 2.1 | 0 |
| Sudan | 2015 | 4 | 0.842 | 8.3 | 5.22 | 8.435 | 0.842 | 1.19 | 0.82 | 10.53 | 1.84 |
| Somalia | 2015 | 2 | 0.845 | 6.65 | 1.5 | 8.1625 | 0.845 | 1.54 | 0.768 | 6.345 | 0.16 |
| Congo Den | 2015 | 5 | 0.498 | 6.33 | 0.76 | 6.378 | 0.498 | 5.66 | 0.469 | 0.04 | 6.5 |
| South Suda | 2015 | 1 | 0.781 | 7.49 | 0.86 | 7.9935 | 0.781 | 1.29 | 0.706 | 1.11 | 0 |
| Syria | 2015 | 9 | 0.882 | 5.74 | 0.62 | 7.647 | 0.882 | 2.42 | 0.818 | 7.875 | 0.01 |
| Yemen | 2015 | 7 | 0.488 | 7.53 | 0.38 | 8.247 | 0.488 | 1.87 | 0.462 | 3.605 | 3.57 |
| Central Afr | 2015 | 3 | 0.919 | 8.2 | 1.12 | 3.369 | 0.919 | 0.44 | 0.89 | 1.715 | 5.25 |
| Chad | 2015 | 6 | 0.347 | 5.07 | 1.28 | 4.95 | 0.347 | 9.35 | 0.338 | 0.55 | 1.59 |
| Afghanista | 2015 | 8 | 0.479 | 6.04 | 1.82 | 2.7165 | 0.479 | 6.81 | 0.398 | 0.115 | 5.6 |
| Liberia | 2015 | 21 | 0.662 | 7.44 | 5.28 | 7.39 | 0.662 | 2.01 | 0.721 | 9.745 | 0.58 |
| Guinea | 2015 | 10 | 0.751 | 7.34 | 2.24 | 6.018 | 0.751 | 1.11 | 0.725 | 1.42 | 5.52 |
| Haiti | 2015 | 11 | 0.421 | 5.52 | 0.66 | 5.6095 | 0.421 | 6.24 | 0.353 | 1.445 | 2.58 |
| Guinea Bis | 2015 | 17 | 0.637 | 7.18 | 1.38 | 4.2405 | 0.637 | 2.51 | 0.508 | 0.79 | 7.86 |
| Nigeria | 2015 | 14 | 0.555 | 6.48 | 0.7 | 6.095 | 0.555 | 3.34 | 0.475 | 0.61 | 4.41 |
| Zimbabwe | 2015 | 16 | 0.836 | 5.85 | 1.92 | 8.32 | 0.836 | 1.23 | 0.681 | 5.69 | 0 |
| Iraq | 2015 | 12 | 0.615 | 6.8 | 2.26 | 6.0785 | 0.615 | 2.36 | 0.525 | 0 | 0.24 |
| Pakistan | 2015 | 13 | 0.351 | 7.49 | 0.96 | 6.5935 | 0.351 | 0.48 | 0.206 | 2.395 | 1.72 |
| Burundi | 2015 | 18 | 0.399 | 5.87 | 2.14 | 3.821 | 0.399 | 6.22 | 0.261 | 1.17 | 4.24 |
| Banglades | 2015 | 32 | 0.823 | 7.66 | 2.46 | 4.3 | 0.823 | 0.56 | 0.717 | 2.99 | 9.37 |
| Niger | 2015 | 19 | 0.637 | 6.59 | 0.96 | 6.4215 | 0.637 | 4.07 | 0.546 | 2.365 | 1.45 |
| Mali | 2015 | 30 | 0.896 | 7.33 | 1.64 | 6.7645 | 0.896 | 3.7 | 0.783 | 3.535 | 2.71 |
| Tajikistan | 2015 | 57 | 0.764 | 5.57 | 0.16 | 7.612 | 0.764 | 8.74 | 0.752 | 8.8 | 4.71 |
| Rwanda | 2015 | 37 | 0.679 | 7.46 | 4.16 | 7.9545 | 0.679 | 1.81 | 0.637 | 2.4 | 4.73 |
| Kenya | 2015 | 21 | 0.902 | 8.35 | 1.34 | 6.256 | 0.902 | 1.58 | 0.842 | 1.755 | 1.18 |
| Uzbekistar | 2015 | 52 | 0.723 | 7.28 | 2.04 | 8.73 | 0.723 | 4.61 | 0.641 | 8.435 | 1.34 |
| Cote dIvoir | 2015 | 15 | 0.775 | 7.94 | 0.54 | 3.6905 | 0.775 | 0.86 | 0.684 | 4.5 | 0 |
| Jordan | 2015 | 81 | 0.881 | 8.31 | 1.02 | 5.405 | 0.881 | 1.39 | 0.804 | 18.85 | 5.21 |
| Myanmar | 2015 | 27 | 0.701 | 6.91 | 5.38 | 6.7055 | 0.701 | 1.39 | 0.725 | 1.75 | 0 |
| Uganda | 2015 | 23 | 0.738 | 6.94 | 0.76 | 8.248 | 0.738 | 0.35 | 0.641 | 1.455 | 0.24 |
| Iran | 2015 | 44 | 0.919 | 8.26 | 3.2 | 5.9255 | 0.919 | 3.93 | 0.906 | 2.17 | 2.38 |
| Nepal | 2015 | 35 | 0.804 | 6.94 | 1.36 | 7.3235 | 0.804 | 1.99 | 0.797 | 2.765 | 2.3 |
| Mauritania | 2015 | 26 | 0.473 | 6.51 | 6.18 | 5.6985 | 0.473 | 0.62 | 0.445 | 0 | 0 |
| Togo | 2015 | 47 | 0.909 | 7.11 | 1.06 | 8.2705 | 0.909 | 0.86 | 0.852 | 8.44 | 0 |
| Venezuela | 2015 | 74 | 0.764 | 7.04 | 0.9 | 8.4935 | 0.764 | 5.36 | 0.666 | 12.59 | 0 |
| TimorLeste | 2015 | 35 | 0.541 | 6.35 | 1.54 | 8.2365 | 0.541 | 0.36 | 0.545 | 1.01 | 5.17 |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| Ethiopia | 2015 | 20 | 0.418 | 6.37 | 1.66 | 4.533 | 0.418 | 3.5 | 0.267 | 0 | 0.08 |
| Eritrea | 2015 | 24 | 0.678 | 7.3 | 1.48 | 5.389 | 0.678 | 1.49 | 0.584 | 0 | 0 |
| Kyrgyz Rep | 2015 | 62 | 0.793 | 6.94 | 0.7 | 7.4995 | 0.793 | 3.66 | 0.805 | 8.115 | 2.85 |
| North Kore | 2015 | 29 | 0.923 | 6.96 | 1.26 | 4.926 | 0.923 | 2.97 | 0.897 | 1.09 | 0 |
| Libya | 2015 | 25 | 0.582 | 7.06 | 0.8 | 2.414 | 0.582 | 5.23 | 0.474 | 0.035 | 0 |
| Lebanon | 2015 | 40 | 0.899 | 7.03 | 2.16 | 6.1295 | 0.899 | 0.3 | 0.867 | 0 | 5.98 |
| Cameroon | 2015 | 28 | 0.646 | 7.33 | 0.88 | 3.1654 | 0.646 | 2.13 | 0.531 | 2.36 | 0 |
| Egypt | 2015 | 38 | 0.718 | 7.35 | 1.24 | 3.9275 | 0.718 | 2.62 | 0.622 | 4.41 | 0 |
| Laos | 2015 | 55 | 0.55 | 6.16 | 1.64 | 5.5105 | 0.55 | 4.46 | 0.518 | 3.035 | 4.67 |
| Cambodia | 2015 | 42 | 0.406 | 5.67 | 0.08 | 4.6905 | 0.406 | 5.58 | 0.395 | 4.23 | 1.45 |
| Angola | 2015 | 42 | 0.857 | 8.13 | 1.52 | 3.3445 | 0.857 | 0.21 | 0.718 | 1.21 | 5.77 |
| Gambia | 2015 | 51 | 0.894 | 8.22 | 2.48 | 5.228 | 0.894 | 0.36 | 0.832 | 2.685 | 3.55 |
| Solomon Is | 2015 | 50 | 0.565 | 7.34 | 6.78 | 6.447 | 0.565 | 1.7 | 0.489 | 0.715 | 0 |
| Sierra Leor | 2015 | 31 | 0.762 | 6.42 | 0.68 | 6.4695 | 0.762 | 0.85 | 0.659 | 0.09 | 1.73 |
| Madagasca | 2015 | 56 | 0.427 | 4.98 | 0.36 | 4.8335 | 0.427 | 5.47 | 0.423 | 9.725 | 0 |
| Colombia | 2015 | 61 | 0.734 | 7.58 | 3.88 | 4.3605 | 0.734 | 0.98 | 0.631 | 3.545 | 5.23 |
| Mozambiq | 2015 | 46 | 0.637 | 7.68 | 0.92 | 3.51 | 0.637 | 2.94 | 0.649 | 5.59 | 0 |
| Congo Rep | 2015 | 33 | 0.59 | 6.23 | 1.92 | 4.2115 | 0.59 | 3.44 | 0.52 | 0.435 | 0.7 |
| Sri Lanka | 2015 | 34 | 0.924 | 5.09 | 1.38 | 7.795 | 0.924 | 0.6 | 0.814 | 1.13 | 0 |
| Papua Nev | 2015 | 57 | 0.948 | 5.28 | 1.2 | 6.4555 | 0.948 | 5.84 | 0.916 | 3.93 | 0.19 |
| Israel and \ | 2015 | 68 | 0.774 | 7.54 | 2.54 | 5.4535 | 0.774 | 2.72 | 0.704 | 8.28 | 0.76 |
| Djibouti | 2015 | 41 | 0.923 | 8.02 | 2.9 | 3.7005 | 0.923 | 0.3 | 0.923 | 3 | 0 |
| Zambia | 2015 | 53 | 0.748 | 6.56 | 3.28 | 8.426 | 0.748 | 1.26 | 0.803 | 0 | 1.07 |
| Tanzania | 2015 | 63 | 0.488 | 8.26 | 5.6 | 8.441 | 0.488 | 3.44 | 0.318 | 0 | 0 |
| Honduras | 2015 | 76 | 0.638 | 6.64 | 1.54 | 6.1185 | 0.638 | 3.26 | 0.572 | 3.015 | 7.19 |
| Bosnia anc | 2015 | 78 | 0.671 | 6.83 | 3.58 | 4.974 | 0.671 | 3.17 | 0.656 | 2.935 | 6.58 |
| Georgia | 2015 | 70 | 0.694 | 6.44 | 1 | 6.335 | 0.694 | 3.7 | 0.618 | 2.43 | 6.24 |
| Thailand | 2015 | 71 | 0.723 | 7.49 | 0.88 | 7.9625 | 0.723 | 6.2 | 0.63 | 0.975 | 2.67 |
| Swaziland | 2015 | 48 | 0.514 | 8.04 | 0.9 | 8.307 | 0.514 | 0.22 | 0.445 | 1.045 | 0.81 |
| Bolivia | 2015 | 76 | 0.604 | 6.95 | 6.24 | 4.263 | 0.604 | 2.83 | 0.452 | 2.76 | 3.7 |
| Burkina Fa | 2015 | 39 | 0.792 | 7.42 | 0.32 | 3.675 | 0.792 | 0.97 | 0.778 | 1.44 | 0.56 |
| Philippines | 2015 | 48 | 0.783 | 6.62 | 1.8 | 6.4175 | 0.783 | 1 | 0.808 | 1.235 | 0.04 |
| Comoros | 2015 | 59 | 0.724 | 7.4 | 1.44 | 4.2875 | 0.724 | 1.41 | 0.63 | 1.46 | 4 |
| Maldives | 2015 | 91 | 0.846 | 8 | 2.32 | 6.431 | 0.846 | 0.16 | 0.882 | 7.025 | 4.66 |
| Algeria | 2015 | 67 | 0.743 | 7.48 | 2.12 | 4.47 | 0.743 | 2.2 | 0.658 | 0.9 | 5.19 |
| India | 2015 | 69 | 0.916 | 8.4 | 1.18 | 5.5925 | 0.916 | 0.53 | 0.822 | 5.805 | 0.16 |
| Equatorial | 2015 | 54 | 0.688 | 7.11 | 1.66 | 5.345 | 0.688 | 2.1 | 0.597 | 0.235 | 0.14 |
| Russia | 2015 | 65 | 0.737 | 7.29 | 0.54 | 6.688 | 0.737 | 4.57 | 0.671 | 1.9 | 0 |
| Malawi | 2015 | 44 | 0.719 | 6.09 | 1.32 | 4.548 | 0.719 | 1.19 | 0.616 | 0.81 | 0 |
| China | 2015 | 83 | 0.845 | 8.17 | 1.82 | 4.76 | 0.845 | 0.72 | 0.784 | 8.47 | 0 |
| Senegal | 2015 | 60 | 0.798 | 7.82 | 1.18 | 5.023 | 0.798 | 0.3 | 0.764 | 2.89 | 0 |
| Turkey | 2015 | 89 | 0.625 | 8.3 | 1.98 | 8.2365 | 0.625 | 4.58 | 0.658 | 2 | 1.02 |
| Mexico | 2015 | 99 | 0.701 | 7.47 | 0.98 | 6.428 | 0.701 | 7.59 | 0.561 | 5.785 | 0.47 |
| Bhutan | 2015 | 74 | 0.481 | 5.96 | 0.64 | 3.688 | 0.481 | 6.57 | 0.408 | 2.365 | 2.59 |
| Morocco | 2015 | 89 | 0.758 | 7.44 | 4.46 | 6.218 | 0.758 | 1.19 | 0.649 | 2.895 | 2.37 |
| Ukraine | 2015 | 84 | 0.746 | 6.5 | 1.86 | 7.91 | 0.746 | 1.17 | 0.673 | 4.32 | 0.95 |
| Dominican | 2015 | 104 | 0.47 | 6.2 | 0.76 | 5.886 | 0.47 | 5.58 | 0.31 | 2.52 | 7.29 |
| Paraguay | 2015 | 103 | 0.795 | 8.16 | 0.66 | 6.331 | 0.795 | 7.15 | 0.648 | 2.55 | 1.54 |
| Suriname | 2015 | 109 | 0.888 | 7.63 | 1.6 | 7.5395 | 0.888 | 9.02 | 0.886 | 3.02 | 0 |
| Guyana | 2015 | 107 | 0.414 | 5.88 | 0.78 | 7.196 | 0.414 | 6.28 | 0.33 | 3.04 | 4.66 |
| Belarus | 2015 | 87 | 0.794 | 7.56 | 1.7 | 4.9805 | 0.794 | 1.23 | 0.773 | 2.14 | 3.76 |
| Nicaragua | 2015 | 72 | 0.552 | 5.51 | 0.54 | 6.764 | 0.552 | 5.85 | 0.41 | 0 | 0 |
| Fiji | 2015 | 82 | 0.863 | 7.68 | 1.74 | 3.19 | 0.863 | 0.25 | 0.876 | 5.655 | 1.26 |
| Tunisia | 2015 | 86 | 0.553 | 8.22 | 3.06 | 8.2215 | 0.553 | 1.95 | 0.436 | 0.055 | 0.23 |
| Ghana | 2015 | 100 | 0.768 | 7.49 | 5.3 | 4.7265 | 0.768 | 1.13 | 0.794 | 1.91 | 3.71 |
| Guatemala | 2015 | 64 | 0.865 | 8.09 | 1.52 | 3.399 | 0.865 | 0.37 | 0.83 | 2.09 | 0.01 |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| Saudi Arab | 2015 | 101 | 0.855 | 8.09 | 2.78 | 7.4605 | 0.855 | 0.45 | 0.698 | 5.41 | 0.23 |
| Azerbaijan | 2015 | 80 | 0.892 | 8.14 | 3.02 | 4.1715 | 0.892 | 0.3 | 0.82 | 1.69 | 1.12 |
| Benin | 2015 | 73 | 0.706 | 7 | 0.52 | 3.4575 | 0.706 | 1.46 | 0.704 | 1.02 | 3.97 |
| Indonesia | 2015 | 88 | 0.834 | 7.52 | 2.12 | 6.7015 | 0.834 | 0.16 | 0.835 | 3.79 | 0.54 |
| Turkmenis | 2015 | 78 | 0.519 | 6.96 | 2.02 | 7.989 | 0.519 | 0.24 | 0.42 | 1.475 | 0.58 |
| Serbia | 2015 | 92 | 0.805 | 7.47 | 1.94 | 7.744 | 0.805 | 0.7 | 0.816 | 3.87 | 0.07 |
| Lesotho | 2015 | 66 | 0.799 | 8.19 | 1.34 | 2.855 | 0.799 | 0.77 | 0.611 | 2.7 | 0 |
| Sao Tome | 2015 | 93 | 0.841 | 7.74 | 1.32 | 5.796 | 0.841 | 2.28 | 0.756 | 4 | 0 |
| Ecuador | 2015 | 85 | 0.724 | 7.78 | 2.6 | 4.899 | 0.724 | 1.95 | 0.615 | 1.585 | 0 |
| Armenia | 2015 | 108 | 0.826 | 7.63 | 1.22 | 3.9975 | 0.826 | 1.15 | 0.807 | 2.555 | 7.31 |
| Vietnam | 2015 | 97 | 0.688 | 7.48 | 1.4 | 8.3065 | 0.688 | 1.47 | 0.629 | 1.78 | 0.19 |
| South Afric | 2015 | 113 | 0.491 | 7.43 | 4.98 | 7.942 | 0.491 | 0.27 | 0.355 | 3.285 | 2.55 |
| Kazakhstar | 2015 | 110 | 0.729 | 7.57 | 1.84 | 6.435 | 0.729 | 0.21 | 0.677 | 5.31 | 2.95 |
| Bahrain | 2015 | 119 | 0.79 | 7.54 | 0.88 | 4.868 | 0.79 | 1.02 | 0.713 | 3.755 | 10 |
| Jamaica | 2015 | 117 | 0.92 | 8.09 | 0.7 | 6.401 | 0.92 | 0.33 | 0.91 | 8.66 | 1.76 |
| Grenada | 2015 | 120 | 0.575 | 6.14 | 0.34 | 6.8485 | 0.575 | 4.42 | 0.546 | 3.42 | 6.76 |
| Gabon | 2015 | 104 | 0.893 | 8.08 | 6.04 | 4.0295 | 0.893 | 0.2 | 0.847 | 0.69 | 0 |
| Croatia | 2015 | 137 | 0.823 | 7.73 | 3.22 | 5.9645 | 0.823 | 0.38 | 0.795 | 15.39 | 6.4 |
| El Salvador | 2015 | 102 | 0.739 | 7.59 | 1.72 | 4.0695 | 0.739 | 1.9 | 0.665 | 3.685 | 0 |
| Micronesia | 2015 | 94 | 0.438 | 7.68 | 0.78 | 5.7275 | 0.438 | 0.52 | 0.312 | 2.505 | 0 |
| Namibia | 2015 | 106 | 0.733 | 7.16 | 0.62 | 6.2015 | 0.733 | 0.29 | 0.738 | 1.49 | 3.04 |
| Cape Verd | 2015 | 94 | 0.514 | 5.55 | 1.52 | 3.386 | 0.514 | 5.86 | 0.493 | 0 | 0 |
| Macedonia | 2015 | 118 | 0.495 | 7.93 | 1.18 | 6.5025 | 0.495 | 7.05 | 0.503 | 2.275 | 0.28 |
| Cyprus | 2015 | 114 | 0.854 | 8.02 | 1.88 | 5.87 | 0.854 | 0.26 | 0.786 | 1.46 | 4.9 |
| Peru | 2015 | 98 | 0.548 | 7.68 | 1.32 | 5.572 | 0.548 | 0.22 | 0.395 | 2.04 | 0 |
| Moldova | 2015 | 96 | 0.853 | 5.8 | 1.46 | 5.4605 | 0.853 | 3.02 | 0.781 | 1.31 | 0 |
| Albania | 2015 | 125 | 0.762 | 7.78 | 3.5 | 2.1565 | 0.762 | 1.29 | 0.715 | 3.385 | 7.41 |
| Antigua an | 2015 | 127 | 0.531 | 5.23 | 1.46 | 3.353 | 0.531 | 9.88 | 0.48 | 4.23 | 5.9 |
| Samoa | 2015 | 111 | 0.852 | 6.82 | 3.94 | 5.394 | 0.852 | 1.36 | 0.852 | 0 | 0 |
| Brazil | 2015 | 123 | 0.698 | 6.45 | 0.32 | 4.837 | 0.698 | 3.56 | 0.658 | 5.255 | 2.93 |
| Cuba | 2015 | 112 | 0.773 | 7.94 | 1.22 | 4.334 | 0.773 | 0.41 | 0.779 | 3.67 | 0.31 |
| Malaysia | 2015 | 115 | 0.911 | 7.16 | 0.58 | 5.9 | 0.911 | 0.36 | 0.818 | 0.755 | 2.96 |
| Mongolia | 2015 | 129 | 0.513 | 8.06 | 3.6 | 7.1635 | 0.513 | 6.61 | 0.377 | 1.94 | 0.27 |
| Seychelles | 2015 | 124 | 0.493 | 7.01 | 3.78 | 7.488 | 0.493 | 1.01 | 0.426 | 1.31 | 0 |
| Belize | 2015 | 116 | 0.895 | 8.08 | 0.22 | 4.209 | 0.895 | 0.34 | 0.841 | 2.85 | 0.35 |
| Brunei Dar | 2015 | 121 | 0.754 | 7.45 | 2.28 | 3.1245 | 0.754 | 1.44 | 0.677 | 1.275 | 2.45 |
| Trinidad ar | 2015 | 126 | 0.938 | 4.9 | 0.66 | 7.338 | 0.938 | 4.88 | 0.892 | 2.735 | 0.53 |
| Bulgaria | 2015 | 130 | 0.864 | 7.88 | 0.6 | 5.3005 | 0.864 | 0.85 | 0.714 | 3.125 | 6.25 |
| Kuwait | 2015 | 128 | 0.741 | 7.4 | 0.7 | 6.8135 | 0.741 | 1.35 | 0.701 | 2.215 | 3.29 |
| Hungary | 2015 | 139 | 0.49 | 6.28 | 0.98 | 5.7255 | 0.49 | 5.35 | 0.422 | 11.81 | 0 |
| Greece | 2015 | 134 | 0.924 | 8.09 | 0.56 | 5.885 | 0.924 | 0.32 | 0.914 | 6.93 | 2.61 |
| Botswana | 2015 | 122 | 0.747 | 7.65 | 1.36 | 3.3685 | 0.747 | 0.54 | 0.694 | 0.425 | 0.08 |
| Romania | 2015 | 132 | 0.692 | 6.26 | 1.04 | 6.7205 | 0.692 | 1.51 | 0.613 | 4.02 | 0.7 |
| Barbados | 2015 | 138 | 0.575 | 7.16 | 1.18 | 4.8735 | 0.575 | 3.21 | 0.457 | 0 | 8.58 |
| Oman | 2015 | 135 | 0.642 | 8.18 | 5.38 | 5.916 | 0.642 | 0.33 | 0.542 | 2.06 | 0 |
| United Ara | 2015 | 144 | 0.603 | 7.44 | 0.76 | 8.0635 | 0.603 | 3.97 | 0.494 | 4.405 | 3.09 |
| Spain | 2015 | 151 | 0.431 | 7.31 | 2.66 | 7.38 | 0.431 | 4.23 | 0.374 | 9.285 | 2.59 |
| Monteneg | 2015 | 132 | 0.779 | 6.31 | 1.98 | 6.1075 | 0.779 | 1.22 | 0.725 | 3.305 | 0 |
| Qatar | 2015 | 143 | 0.515 | 7.76 | 1.36 | 6.742 | 0.515 | 1.85 | 0.422 | 8.665 | 0.04 |
| Chile | 2015 | 150 | 0.394 | 5.16 | 0.92 | 5.9715 | 0.394 | 8.67 | 0.28 | 6 | 4.01 |
| Costa Rica | 2015 | 142 | 0.425 | 5.87 | 3.46 | 4.0005 | 0.425 | 7.65 | 0.457 | 3.15 | 0.41 |
| Bahamas | 2015 | 136 | 0.758 | 7.08 | 0.24 | 3.1145 | 0.758 | 2.89 | 0.723 | 5.13 | 0 |
| Panama | 2015 | 131 | 0.525 | 6.14 | 0.66 | 6.024 | 0.525 | 1.94 | 0.475 | 0.49 | 0 |
| Latvia | 2015 | 140 | 0.586 | 6.6 | 0.3 | 6.3035 | 0.586 | 2.07 | 0.59 | 0.795 | 2.11 |
| Estonia | 2015 | 146 | 0.582 | 5.76 | 1.06 | 5.5325 | 0.582 | 7.03 | 0.439 | 3.52 | 0.01 |
| Poland | 2015 | 153 | 0.678 | 7.27 | 2.78 | 5.453 | 0.678 | 6.74 | 0.655 | 2.79 | 0 |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| Argentina | 2015 | 141 | 0.784 | 7.61 | 3.24 | 3.4425 | 0.784 | 0.61 | 0.695 | 1.71 | 0.05 |
| Italy | 2015 | 147 | 0.649 | 6.94 | 2.74 | 6.9625 | 0.649 | 0.31 | 0.5 | 4.28 | 0.06 |
| Mauritius | 2015 | 145 | 0.787 | 6.28 | 1.54 | 5.4805 | 0.787 | 0.78 | 0.7 | 0 | 3.63 |
| Czech Repu | 2015 | 154 | 0.875 | 7.86 | 1.32 | 4.4875 | 0.875 | 0.29 | 0.878 | 11.125 | 0 |
| Slovak Rep | 2015 | 149 | 0.72 | 7.51 | 2.64 | 6.6485 | 0.72 | 0.87 | 0.657 | 2.62 | 0 |
| South Kore | 2015 | 156 | 0.775 | 6.65 | 4.88 | 7.3375 | 0.775 | 3.55 | 0.76 | 3.435 | 0 |
| France | 2015 | 160 | 0.734 | 7 | 4.08 | 5.2195 | 0.734 | 1.94 | 0.777 | 7.4 | 1.99 |
| Malta | 2015 | 151 | 0.511 | 8.17 | 1.18 | 5.593 | 0.511 | 4.51 | 0.492 | 0.965 | 0 |
| Lithuania | 2015 | 148 | 0.828 | 6.62 | 4.12 | 3.4165 | 0.828 | 0.72 | 0.835 | 1.8 | 0 |
| United Sta | 2015 | 158 | 0.718 | 6.82 | 1.26 | 8.3505 | 0.718 | 1.09 | 0.766 | 5.495 | 0.08 |
| Uruguay | 2015 | 155 | 0.779 | 5.97 | 1.32 | 8.2205 | 0.779 | 0.52 | 0.717 | 4.15 | 0 |
| Austria | 2015 | 167 | 0.937 | 8.24 | 0.98 | 6.0705 | 0.937 | 0.32 | 0.939 | 6.345 | 8.12 |
| Japan | 2015 | 157 | 0.898 | 8.24 | 2.38 | 6.4185 | 0.898 | 0.3 | 0.87 | 2.62 | 0 |
| Australia | 2015 | 170 | 0.741 | 7.47 | 1.12 | 2.9535 | 0.741 | 1.32 | 0.73 | 8.295 | 9.39 |
| United King | 2015 | 161 | 0.484 | 7.54 | 1.22 | 8.481 | 0.484 | 3.62 | 0.489 | 0.84 | 0.41 |
| Belgium | 2015 | 163 | 0.798 | 7.13 | 2.32 | 5.4395 | 0.798 | 0.35 | 0.833 | 7.72 | 1.16 |
| Singapore | 2015 | 159 | 0.735 | 7.38 | 0.56 | 6.928 | 0.735 | 3.27 | 0.677 | 1.705 | 0 |
| Denmark | 2015 | 175 | 0.466 | 5.15 | 11.14 | 3.5895 | 0.466 | 6.85 | 0.406 | 1.66 | 4.01 |
| Portugal | 2015 | 164 | 0.785 | 7.29 | 0.04 | 7.3705 | 0.785 | 1.47 | 0.691 | 3.55 | 2.58 |
| Germany | 2015 | 165 | 0.45 | 6.02 | 1.18 | 5.688 | 0.45 | 4.86 | 0.358 | 7.03 | 0.1 |
| Slovenia | 2015 | 162 | 0.702 | 7.29 | 1.94 | 7.113 | 0.702 | 1.3 | 0.702 | 1.655 | 0.29 |
| New Zeala | 2015 | 172 | 0.414 | 7.4 | 1.12 | 6.2005 | 0.414 | 2.46 | 0.366 | 11.535 | 0 |
| Netherland | 2015 | 166 | 0.645 | 7.62 | 1.16 | 6.677 | 0.645 | 0.46 | 0.503 | 3.575 | 3.04 |
| Canada | 2015 | 168 | 0.558 | 6.84 | 1.38 | 2.9955 | 0.558 | 2.63 | 0.459 | 0.815 | 5.29 |
| Finland | 2015 | 178 | 0.441 | 6.41 | 2.06 | 4.4555 | 0.441 | 4.29 | 0.315 | 8.23 | 0 |
| Norway | 2015 | 176 | 0.913 | 8.16 | 1.12 | 6.7175 | 0.913 | 3.05 | 0.917 | 0 | 0 |
| Ireland | 2015 | 169 | 0.686 | 6.89 | 1.18 | 5.7655 | 0.686 | 1.39 | 0.622 | 0.02 | 0 |
| Iceland | 2015 | 171 | 0.623 | 7.31 | 0.7 | 3.804 | 0.623 | 1.8 | 0.518 | 3.065 | 0 |
| Sweden | 2015 | 177 | 0.665 | 6.79 | 2.64 | 6.3795 | 0.665 | 0.61 | 0.705 | 1.945 | 0 |
| Switzerlan | 2015 | 173 | 0.421 | 5.54 | 2.18 | 6.72 | 0.421 | 0.22 | 0.297 | 0.825 | 0 |
| Luxembou | 2015 | 174 | 0.763 | 7.42 | 2.14 | 4.8025 | 0.763 | 0.73 | 0.656 | 2.1 | 0 |
| Sudan | 2016 | 4 | 8.47 | 6.66 | 1.5 | 7.669 | 8.47 | 1.5 | 7.68 | 6.055 | 0.038 |
| Somalia | 2016 | 1 | 7.82 | 7.5 | 0.94 | 7.084 | 7.82 | 1.25 | 7.06 | 1.215 | 0 |
| Syria | 2016 | 6 | 9.2 | 8.22 | 1.12 | 0 | 9.2 | 0.43 | 8.9 | 1.74 | 6.712 |
| Central Afr | 2016 | 3 | 8.45 | 8.32 | 5.12 | 7.036 | 8.45 | 1.17 | 8.23 | 9.68 | 4.094 |
| South Suda | 2016 | 2 | 4.93 | 7.55 | 0.42 | 7.623 | 4.93 | 3.38 | 4.67 | 0 | 2.139 |
| Liberia | 2016 | 27 | 8.84 | 5.77 | 0.64 | 4.828 | 8.84 | 2.36 | 8.18 | 7.62 | 0 |
| Afghanista | 2016 | 9 | 3.52 | 5.15 | 1.28 | 4.225 | 3.52 | 9.15 | 3.38 | 0.89 | 7.686 |
| Chad | 2016 | 7 | 4.98 | 6.36 | 0.76 | 5.925 | 4.98 | 5.51 | 4.69 | 1.075 | 1.71 |
| Yemen | 2016 | 4 | 4.79 | 6.07 | 1.92 | 3.75 | 4.79 | 6.63 | 3.98 | 0.02 | 9.065 |
| Guinea | 2016 | 12 | 4.24 | 5.55 | 0.66 | 8.891 | 4.24 | 6.03 | 3.53 | 1.58 | 2.622 |
| Kenya | 2016 | 20 | 6.24 | 6.83 | 1.9 | 8.664 | 6.24 | 2.28 | 5.35 | 0 | 2.088 |
| Congo Dem | 2016 | 8 | 7.54 | 7.36 | 2.24 | 8.542 | 7.54 | 1.08 | 7.25 | 1.715 | 0 |
| Mali | 2016 | 29 | 5.58 | 6.51 | 0.82 | 7.529 | 5.58 | 3.28 | 4.75 | 0.815 | 0 |
| Iraq | 2016 | 11 | 3.53 | 7.52 | 1.04 | 5.889 | 3.53 | 0.47 | 2.06 | 2.44 | 1.381 |
| Iran | 2016 | 47 | 4.02 | 5.9 | 2.16 | 0 | 4.02 | 6.09 | 2.62 | 1.425 | 0 |
| Jordan | 2016 | 77 | 8.4 | 5.92 | 2.14 | 6.606 | 8.4 | 4.66 | 6.87 | 0 | 0 |
| Zimbabwe | 2016 | 16 | 6.4 | 7.21 | 1.38 | 8.898 | 6.4 | 2.43 | 5.08 | 0.995 | 0 |
| Haiti | 2016 | 10 | 6.8 | 7.33 | 1.18 | 8.059 | 6.8 | 1.44 | 5.84 | 0 | 0 |
| Djibouti | 2016 | 39 | 6.4 | 6.61 | 1.16 | 6.959 | 6.4 | 3.95 | 5.46 | 2.41 | 0 |
| Cote dvoir | 2016 | 21 | 9.03 | 8.37 | 1.34 | 8.658 | 9.03 | 1.54 | 8.42 | 2.245 | 0 |
| Myanmar | 2016 | 26 | 7.76 | 7.96 | 0.6 | 6.934 | 7.76 | 0.85 | 6.84 | 4.435 | 0 |
| Tajikistan | 2016 | 57 | 6.48 | 7.35 | 0.92 | 5.034 | 6.48 | 2.07 | 5.34 | 2.695 | 3.334 |
| Egypt | 2016 | 38 | 7.4 | 6.96 | 0.72 | 7.305 | 7.4 | 0.77 | 6.41 | 1.675 | 1.869 |
| Venezuela | 2016 | 63 | 4.2 | 6.42 | 1.54 | 8.571 | 4.2 | 3.41 | 2.67 | 0 | 0 |
| Papua New | 2016 | 50 | 5.86 | 7.08 | 0.84 | 7.028 | 5.86 | 5.07 | 4.74 | 0 | 4.75 |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| North Kore | 2016 | 30 | 6.99 | 6.93 | 5.1 | 7.904 | 6.99 | 1.36 | 7.25 | 2.175 | 0 |
| Guinea Bis | 2016 | 17 | 6.64 | 7.45 | 5.5 | 7.438 | 6.64 | 1.9 | 7.21 | 10.3 | 2.116 |
| Nigeria | 2016 | 13 | 4.76 | 6.55 | 6.22 | 7.072 | 4.76 | 0.6 | 4.45 | 0 | 0 |
| Uganda | 2016 | 23 | 8.98 | 7.35 | 1.7 | 7.109 | 8.98 | 3.59 | 7.83 | 4.005 | 0.076 |
| Niger | 2016 | 19 | 9.24 | 7 | 1.26 | 6.737 | 9.24 | 2.91 | 8.97 | 0 | 0 |
| Lebanon | 2016 | 40 | 5.92 | 6.29 | 1.72 | 6.255 | 5.92 | 3.32 | 5.2 | 0.485 | 0 |
| Libya | 2016 | 25 | 6.82 | 7.48 | 4.02 | 7.329 | 6.82 | 1.75 | 6.37 | 2.725 | 1.881 |
| Cameroon | 2016 | 22 | 8.07 | 6.98 | 1.22 | 4.529 | 8.07 | 1.9 | 7.97 | 2.83 | 2.567 |
| Burkina Fa | 2016 | 41 | 7.65 | 6.47 | 0.68 | 4.969 | 7.65 | 0.82 | 6.59 | 1.04 | 0 |
| Rwanda | 2016 | 32 | 5.41 | 6.37 | 1.54 | 6.492 | 5.41 | 0.35 | 5.45 | 1.14 | 0 |
| Bangladesl | 2016 | 36 | 8.24 | 7.67 | 2.46 | 4.583 | 8.24 | 0.53 | 7.17 | 2.985 | 3.544 |
| Eritrea | 2016 | 18 | 8.58 | 8.15 | 1.52 | 4.337 | 8.58 | 0.21 | 7.18 | 1.55 | 3.342 |
| Nepal | 2016 | 33 | 7.22 | 7.37 | 1.28 | 8.581 | 7.22 | 2.57 | 6.22 | 4.79 | 4.976 |
| India | 2016 | 70 | 9.25 | 8.04 | 2.88 | 8.467 | 9.25 | 0.29 | 9.23 | 2.58 | 2.484 |
| Kyrgyz Rep | 2016 | 64 | 9.01 | 7.05 | 1.96 | 9.043 | 9.01 | 0.29 | 8.67 | 0 | 3.083 |
| Togo | 2016 | 51 | 7.94 | 7.43 | 0.3 | 5.827 | 7.94 | 0.93 | 7.78 | 1.465 | 8.108 |
| Angola | 2016 | 37 | 6.38 | 7.7 | 0.94 | 4.92 | 6.38 | 2.86 | 6.49 | 5.37 | 0 |
| Gambia | 2016 | 48 | 9.25 | 5.13 | 1.56 | 4.802 | 9.25 | 0.59 | 8.14 | 1.975 | 0 |
| Israel and \ | 2016 | 69 | 5.15 | 8.06 | 0.86 | 7.37 | 5.15 | 0.21 | 4.45 | 1.045 | 7.27 |
| Uzbekistar | 2016 | 60 | 7.16 | 6.12 | 1.34 | 7.355 | 7.16 | 1.14 | 6.16 | 0.9 | 0 |
| Philippines | 2016 | 54 | 4.04 | 5.71 | 0.1 | 5.142 | 4.04 | 5.41 | 3.95 | 4.14 | 9.233 |
| Mauritania | 2016 | 28 | 9.21 | 8.27 | 3.38 | 8.722 | 9.21 | 3.79 | 9.06 | 2.335 | 3.114 |
| Guatemala | 2016 | 61 | 8.97 | 8.24 | 2.46 | 7.889 | 8.97 | 0.35 | 8.39 | 0 | 0.659 |
| Pakistan | 2016 | 14 | 7.43 | 6.57 | 3.18 | 5.85 | 7.43 | 4.33 | 8.03 | 0 | 0 |
| Cambodia | 2016 | 46 | 9.49 | 5.31 | 0.98 | 6.964 | 9.49 | 5.71 | 9.16 | 4.12 | 2.009 |
| Zambia | 2016 | 49 | 9.13 | 7.13 | 1.04 | 4.692 | 9.13 | 0 | 8.55 | 8.67 | 0 |
| Mozambiq | 2016 | 42 | 5.74 | 7.37 | 6.96 | 0 | 5.74 | 1.66 | 5.09 | 0.86 | 0 |
| Laos | 2016 | 55 | 6.91 | 7.13 | 1.68 | 8.448 | 6.91 | 2.03 | 6.01 | 0.845 | 3.364 |
| Equatorial | 2016 | 53 | 7.88 | 6.64 | 1.48 | 5.358 | 7.88 | 0.99 | 8.08 | 1.38 | 6.667 |
| Sri Lanka | 2016 | 43 | 5.55 | 6.22 | 1.64 | 8.69 | 5.55 | 4.36 | 5.18 | 4.4 | 2.738 |
| Ethiopia | 2016 | 24 | 4.27 | 5.01 | 0.44 | 8.23 | 4.27 | 5.28 | 4.23 | 9.56 | 2.125 |
| Bolivia | 2016 | 75 | 7.66 | 5.61 | 0.22 | 6.863 | 7.66 | 8.5 | 7.52 | 8.94 | 4.006 |
| Madagasca | 2016 | 56 | 7.27 | 7.42 | 1.44 | 4.979 | 7.27 | 1.36 | 6.3 | 0 | 7.642 |
| Comoros | 2016 | 57 | 8.02 | 7.83 | 1.16 | 4.717 | 8.02 | 0.3 | 7.69 | 2.92 | 0 |
| Congo Rep | 2016 | 31 | 7.25 | 7.3 | 2.02 | 7.024 | 7.25 | 2.31 | 6.43 | 8.16 | 0 |
| Swaziland | 2016 | 44 | 8.66 | 8.11 | 1.52 | 8.704 | 8.66 | 0.36 | 8.3 | 2.14 | 0 |
| Colombia | 2016 | 67 | 4.9 | 8.28 | 5.38 | 6.373 | 4.9 | 3.36 | 3.18 | 0 | 3.467 |
| Burundi | 2016 | 15 | 7.67 | 7.05 | 0.86 | 7.969 | 7.67 | 1.29 | 6.68 | 11.915 | 7.2 |
| Sierra Leor | 2016 | 34 | 7.94 | 6.96 | 0.7 | 8.8 | 7.94 | 3.55 | 8.05 | 8.325 | 1.187 |
| Fiji | 2016 | 82 | 7.4 | 7.3 | 0.48 | 7.224 | 7.4 | 4.45 | 6.72 | 1.875 | 1.751 |
| Lesotho | 2016 | 66 | 8 | 8.21 | 1.42 | 8.693 | 8 | 0.73 | 6.11 | 2.9 | 1.349 |
| Morocco | 2016 | 89 | 7.38 | 7.6 | 3.92 | 5.756 | 7.38 | 0.92 | 6.31 | 2.63 | 4.894 |
| China | 2016 | 86 | 6.38 | 6.65 | 1.4 | 7.434 | 6.38 | 3.2 | 5.68 | 2.985 | 1.583 |
| Saudi Arab | 2016 | 97 | 7.74 | 7.56 | 2.42 | 8.506 | 7.74 | 2.65 | 7.04 | 6.525 | 2.297 |
| Russia | 2016 | 65 | 9.17 | 8.42 | 1.16 | 8.472 | 9.17 | 0.53 | 8.22 | 5.4 | 4.613 |
| Azerbaijan | 2016 | 81 | 5.56 | 5.55 | 0.56 | 6.807 | 5.56 | 5.67 | 4.1 | 0 | 0 |
| Suriname | 2016 | 112 | 7.06 | 7.01 | 0.52 | 6.249 | 7.06 | 1.42 | 7.04 | 0.98 | 6.66 |
| Malawi | 2016 | 44 | 6.97 | 6.49 | 0.92 | 6.013 | 6.97 | 3.61 | 6.18 | 2.63 | 0 |
| Maldives | 2016 | 91 | 7.25 | 7.5 | 1 | 7.867 | 7.25 | 6.03 | 6.3 | 1.01 | 0.41 |
| Senegal | 2016 | 59 | 6.07 | 6.99 | 6.06 | 6.329 | 6.07 | 2.72 | 4.52 | 3.335 | 7.29 |
| Thailand | 2016 | 74 | 7.45 | 7.5 | 2.1 | 4.177 | 7.45 | 2.19 | 6.58 | 1.99 | 0 |
| Ecuador | 2016 | 84 | 8.87 | 8.33 | 1.12 | 9.051 | 8.87 | 1.35 | 8.14 | 18.83 | 1.219 |
| TimorLeste | 2016 | 35 | 4.85 | 5.98 | 0.72 | 4.342 | 4.85 | 6.42 | 4.14 | 2.715 | 1.219 |
| Benin | 2016 | 72 | 6.27 | 8.31 | 2.06 | 6.858 | 6.27 | 2.28 | 6.58 | 2.1 | 0 |
| Tanzania | 2016 | 62 | 4.42 | 7.7 | 1 | 4.371 | 4.42 | 0.51 | 3.12 | 2.685 | 0.305 |
| Honduras | 2016 | 68 | 8.93 | 8.16 | 2.88 | 5.989 | 8.93 | 0.29 | 8.2 | 1.77 | 3.76 |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| Bosnia and | 2016 | 88 | 8.65 | 7.7 | 1.92 | 8.549 | 8.65 | 0.23 | 8.77 | 5.995 | 0 |
| Indonesia | 2016 | 86 | 5.31 | 6.97 | 2 | 6.063 | 5.31 | 3.77 | 4.41 | 0 | 0 |
| Belize | 2016 | 116 | 7.26 | 7.79 | 2.42 | 8.82 | 7.26 | 1.96 | 6.18 | 1.545 | 4.553 |
| Ukraine | 2016 | 85 | 7.48 | 6.55 | 1.98 | 5.834 | 7.48 | 0.59 | 6.73 | 4.51 | 3.979 |
| Serbia | 2016 | 98 | 8.47 | 8.2 | 2 | 5.579 | 8.47 | 0.7 | 7.84 | 9.845 | 0 |
| Gabon | 2016 | 98 | 8.36 | 7.53 | 2.1 | 7.398 | 8.36 | 0.16 | 8.34 | 3.84 | 0 |
| Jamaica | 2016 | 118 | 6.74 | 6.87 | 3.72 | 4.148 | 6.74 | 3.06 | 6.56 | 2.925 | 6.032 |
| El Salvador | 2016 | 96 | 5.36 | 8.23 | 2.96 | 6.555 | 5.36 | 4.37 | 4.17 | 0.45 | 4.077 |
| Solomon Is | 2016 | 52 | 7.62 | 7.46 | 4.46 | 7.593 | 7.62 | 1.13 | 6.55 | 2.995 | 6.662 |
| Georgia | 2016 | 72 | 8.48 | 8.02 | 2.36 | 6.499 | 8.48 | 0.15 | 8.82 | 7.24 | 0.305 |
| Mexico | 2016 | 107 | 7.95 | 7.58 | 1.74 | 4.82 | 7.95 | 1.2 | 7.73 | 2.575 | 0.153 |
| Turkey | 2016 | 79 | 8.56 | 5.85 | 1.42 | 5.124 | 8.56 | 2.96 | 7.81 | 0 | 0.153 |
| Paraguay | 2016 | 95 | 8.43 | 7.76 | 1.16 | 5.029 | 8.43 | 2.22 | 7.56 | 3.95 | 0.038 |
| Ghana | 2016 | 102 | 7.96 | 8.17 | 0.7 | 7.114 | 7.96 | 6.94 | 6.52 | 0 | 0 |
| Algeria | 2016 | 76 | 7.39 | 7.61 | 1.88 | 8.46 | 7.39 | 1.84 | 6.65 | 3.89 | 1.187 |
| Sao Tome | 2016 | 94 | 8.56 | 8.12 | 2.8 | 6.914 | 8.56 | 0.45 | 6.98 | 4.87 | 6.376 |
| Belarus | 2016 | 92 | 8.04 | 7.48 | 1.86 | 7.802 | 8.04 | 0.68 | 8.16 | 3.805 | 2.252 |
| Tunisia | 2016 | 88 | 8.95 | 8.1 | 6.02 | 6.439 | 8.95 | 0.19 | 8.47 | 0.845 | 0 |
| Kazakhstan | 2016 | 113 | 5.5 | 7.7 | 1.34 | 6.964 | 5.5 | 0.2 | 3.95 | 2.435 | 2.077 |
| Vietnam | 2016 | 106 | 5.18 | 5.6 | 1.52 | 2.766 | 5.18 | 5.71 | 4.93 | 0 | 7.6 |
| Samoa | 2016 | 110 | 7.69 | 7.5 | 4.98 | 8.126 | 7.69 | 1.06 | 7.94 | 1.755 | 0 |
| Namibia | 2016 | 103 | 7.35 | 7.17 | 0.62 | 8.024 | 7.35 | 0.28 | 7.37 | 1.605 | 3.08 |
| Moldova | 2016 | 93 | 4.14 | 5.92 | 0.78 | 7.061 | 4.14 | 6.1 | 3.3 | 2.84 | 0 |
| Cuba | 2016 | 114 | 4.73 | 6.23 | 0.86 | 8.859 | 4.73 | 5.42 | 3.1 | 2.74 | 0.076 |
| Bhutan | 2016 | 78 | 6.92 | 7.5 | 1.6 | 6.367 | 6.92 | 1.73 | 6.29 | 6.415 | 0 |
| Nicaragua | 2016 | 71 | 7.01 | 7.49 | 0.86 | 6.786 | 7.01 | 7.45 | 5.61 | 5.905 | 0 |
| Armenia | 2016 | 109 | 4.94 | 7.44 | 5.02 | 7.418 | 4.94 | 0.26 | 3.55 | 3.72 | 1.446 |
| Cyprus | 2016 | 119 | 8.27 | 7.65 | 1.26 | 3.783 | 8.27 | 1.11 | 8.08 | 2.41 | 2.142 |
| Macedonia | 2016 | 111 | 8.55 | 6.83 | 4 | 7.313 | 8.55 | 1.31 | 8.52 | 0 | 1.722 |
| Brazil | 2016 | 117 | 4.97 | 7.95 | 1.18 | 7.007 | 4.97 | 6.92 | 5.03 | 2.375 | 4.871 |
| Cape Verde | 2016 | 101 | 8.9 | 7.64 | 1.48 | 7.295 | 8.9 | 8.71 | 8.86 | 3.345 | 3.316 |
| Turkmenis | 2016 | 83 | 7.3 | 7.58 | 1.84 | 8.66 | 7.3 | 0.2 | 6.78 | 5.275 | 3.663 |
| Croatia | 2016 | 136 | 7.75 | 7.96 | 1.04 | 8.34 | 7.75 | 0.4 | 7.79 | 3.54 | 2.421 |
| South Afric | 2016 | 108 | 9.12 | 7.18 | 0.58 | 4.366 | 9.12 | 0.33 | 8.18 | 0 | 0 |
| Peru | 2016 | 98 | 8.96 | 8.1 | 0.22 | 6.397 | 8.96 | 0.33 | 8.41 | 3.33 | 10 |
| Dominican | 2016 | 105 | 6.98 | 6.45 | 0.38 | 4.898 | 6.98 | 3.48 | 6.58 | 5.435 | 4.08 |
| Trinidad ar | 2016 | 127 | 9.23 | 8.11 | 0.66 | 9.068 | 9.23 | 0.32 | 9.1 | 8.57 | 0 |
| Greece | 2016 | 130 | 8.56 | 8.03 | 1.9 | 7.767 | 8.56 | 0.25 | 7.86 | 1.575 | 3.969 |
| Brunei Dar | 2016 | 123 | 7.5 | 7.66 | 1.44 | 4.631 | 7.5 | 0.51 | 6.94 | 0.62 | 0.305 |
| Micronesia | 2016 | 80 | 7.92 | 7.56 | 0.88 | 3.673 | 7.92 | 0.99 | 7.15 | 4.39 | 1.636 |
| Bahrain | 2016 | 121 | 5.79 | 6.15 | 0.36 | 8.324 | 5.79 | 4.28 | 5.51 | 2.9 | 0 |
| Guyana | 2016 | 104 | 7.54 | 7.47 | 1.96 | 5.021 | 7.54 | 1.46 | 6.81 | 1.67 | 4.791 |
| Malaysia | 2016 | 115 | 7.64 | 7.8 | 3.46 | 5.132 | 7.64 | 1.25 | 7.15 | 3.13 | 0.243 |
| Albania | 2016 | 124 | 4.98 | 7.03 | 3.8 | 3.71 | 4.98 | 0.97 | 4.26 | 0 | 2.444 |
| Monteneg | 2016 | 131 | 7.42 | 7.42 | 0.74 | 8.203 | 7.42 | 1.26 | 7.01 | 2.26 | 0.429 |
| Antigua an | 2016 | 129 | 9.39 | 4.89 | 0.76 | 7.052 | 9.39 | 1.16 | 8.91 | 2.98 | 4.231 |
| Bahamas | 2016 | 137 | 5.13 | 8.07 | 3.64 | 5.198 | 5.13 | 6.51 | 3.77 | 1.86 | 0 |
| Grenada | 2016 | 122 | 5.33 | 5.27 | 1.34 | 5.713 | 5.33 | 9.6 | 4.82 | 3.4 | 6.466 |
| Kuwait | 2016 | 126 | 9.26 | 8.11 | 0.54 | 6.994 | 9.26 | 0.31 | 9.14 | 6.77 | 0 |
| Botswana | 2016 | 120 | 7.81 | 6.32 | 1.92 | 6.51 | 7.81 | 1.18 | 7.25 | 3.465 | 6.294 |
| Bulgaria | 2016 | 132 | 8.65 | 7.9 | 0.58 | 3.748 | 8.65 | 0.86 | 7.16 | 3.09 | 3.485 |
| Hungary | 2016 | 135 | 5.27 | 6.19 | 0.62 | 6.328 | 5.27 | 1.88 | 4.77 | 0.56 | 0 |
| Argentina | 2016 | 140 | 6.93 | 6.28 | 1.16 | 7.702 | 6.93 | 1.46 | 6.13 | 6.01 | 0.229 |
| Mongolia | 2016 | 128 | 4.93 | 6.31 | 0.88 | 6.935 | 4.93 | 5.22 | 4.25 | 10.575 | 1.045 |
| Romania | 2016 | 134 | 8.27 | 7.75 | 3.12 | 5.496 | 8.27 | 0.36 | 7.98 | 15.71 | 0 |
| Oman | 2016 | 137 | 7.59 | 7.09 | 0.24 | 6.645 | 7.59 | 2.79 | 7.23 | 4.97 | 6.813 |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| Czech Rep | 2016 | 151 | 6.45 | 8.2 | 5.18 | 6.496 | 6.45 | 0.32 | 5.42 | 3.21 | 2.373 |
| Qatar | 2016 | 142 | 5.79 | 7.2 | 1.22 | 5.54 | 5.79 | 3.07 | 4.57 | 0 | 1.187 |
| Seychelles | 2016 | 125 | 7.86 | 7.62 | 3.26 | 4.646 | 7.86 | 0.58 | 6.94 | 2.06 | 6.721 |
| Poland | 2016 | 152 | 5.88 | 6.62 | 0.32 | 8.863 | 5.88 | 1.97 | 5.9 | 0.95 | 0.267 |
| Chile | 2016 | 150 | 5.16 | 7.78 | 1.38 | 7.814 | 5.16 | 1.8 | 4.19 | 8.35 | 6.034 |
| United Ara | 2016 | 145 | 4.35 | 5.91 | 3.22 | 7.984 | 4.35 | 7.45 | 4.75 | 3.495 | 1.674 |
| Lithuania | 2016 | 149 | 7.22 | 7.52 | 2.26 | 5.71 | 7.22 | 0.84 | 6.57 | 2.775 | 0 |
| Costa Rica | 2016 | 142 | 6.06 | 7.46 | 0.74 | 6.954 | 6.06 | 0.35 | 4.94 | 4.64 | 7.279 |
| Uruguay | 2016 | 155 | 5.92 | 5.79 | 1.1 | 6.441 | 5.92 | 6.82 | 4.39 | 3.825 | 0.019 |
| Japan | 2016 | 157 | 7.89 | 6.39 | 1.58 | 7.89 | 7.89 | 0.74 | 7 | 0 | 2.207 |
| South Kore | 2016 | 156 | 6.49 | 6.96 | 2.74 | 8.921 | 6.49 | 0.3 | 5 | 4.16 | 0.091 |
| Slovak Rep | 2016 | 144 | 8.3 | 6.66 | 4.12 | 8.16 | 8.3 | 0.69 | 8.35 | 1.81 | 0.115 |
| Mauritius | 2016 | 147 | 3.96 | 5.19 | 0.92 | 6.691 | 3.96 | 8.5 | 2.8 | 6.18 | 9.213 |
| France | 2016 | 158 | 8.78 | 7.88 | 1.26 | 8.003 | 8.78 | 0.28 | 8.78 | 10.95 | 0 |
| Spain | 2016 | 153 | 6.84 | 7.29 | 2.42 | 6.585 | 6.84 | 6.58 | 6.55 | 2.96 | 4.755 |
| Italy | 2016 | 148 | 4.2 | 7.33 | 2.72 | 6.419 | 4.2 | 4.17 | 3.74 | 9.005 | 2.928 |
| Panama | 2016 | 133 | 5.12 | 8.19 | 1.08 | 6.328 | 5.12 | 4.34 | 4.92 | 1.095 | 1.516 |
| Latvia | 2016 | 141 | 7.8 | 6.02 | 1.46 | 6.768 | 7.8 | 3.39 | 7.17 | 5.005 | 5.98 |
| Austria | 2016 | 167 | 7.76 | 6.69 | 4.48 | 4.182 | 7.76 | 3.46 | 7.6 | 3.565 | 4.386 |
| Estonia | 2016 | 146 | 8.99 | 8.26 | 2.56 | 8.426 | 8.99 | 0.29 | 8.7 | 2.52 | 3.442 |
| Barbados | 2016 | 139 | 7.36 | 7.02 | 4.1 | 7.085 | 7.36 | 1.91 | 7.77 | 7.42 | 0 |
| United Sta | 2016 | 159 | 7.21 | 6.85 | 1.06 | 7.728 | 7.21 | 0.87 | 7.66 | 4.28 | 3.697 |
| Slovenia | 2016 | 160 | 7.04 | 7.3 | 1.86 | 7.359 | 7.04 | 1.27 | 7.02 | 1.685 | 3.985 |
| Singapore | 2016 | 161 | 7.35 | 7.4 | 0.66 | 7.423 | 7.35 | 3.11 | 6.77 | 1.8 | 3.579 |
| Malta | 2016 | 154 | 4.87 | 7.55 | 1.1 | 4.61 | 4.87 | 0.56 | 4.89 | 0.895 | 0 |
| Portugal | 2016 | 163 | 7.88 | 7.31 | 0.04 | 6.632 | 7.88 | 1.42 | 6.91 | 3.68 | 4.222 |
| Belgium | 2016 | 164 | 7.96 | 7.15 | 2.36 | 4.328 | 7.96 | 0.34 | 8.34 | 7.415 | 0 |
| Sweden | 2016 | 171 | 4.52 | 6.05 | 1.26 | 7.8 | 4.52 | 4.79 | 3.58 | 6.755 | 0 |
| Netherlan | 2016 | 166 | 6.47 | 7.64 | 1.18 | 7.532 | 6.47 | 0.43 | 5.03 | 3.76 | 2.581 |
| Australia | 2016 | 172 | 9.39 | 8.25 | 0.94 | 5.956 | 9.39 | 0.3 | 9.39 | 6.305 | 6.487 |
| Iceland | 2016 | 170 | 7.63 | 7.43 | 1.9 | 8.378 | 7.63 | 0.71 | 6.56 | 0.135 | 1.381 |
| Germany | 2016 | 165 | 5.63 | 6.88 | 1.38 | 4.598 | 5.63 | 2.46 | 4.59 | 0.74 | 0 |
| Denmark | 2016 | 175 | 6.25 | 7.33 | 0.7 | 8.738 | 6.25 | 1.74 | 5.18 | 2.97 | 6 |
| Norway | 2016 | 177 | 6.66 | 6.81 | 2.46 | 8.352 | 6.66 | 0.58 | 7.05 | 2.67 | 6.207 |
| Luxembou | 2016 | 168 | 7.43 | 7.49 | 1.14 | 4.205 | 7.43 | 1.26 | 7.3 | 8.86 | 0.823 |
| New Zeala | 2016 | 176 | 6.89 | 6.91 | 1 | 8.015 | 6.89 | 1.34 | 6.22 | 0.465 | 1.977 |
| Ireland | 2016 | 172 | 4.18 | 5.57 | 2.18 | 7.02 | 4.18 | 0.21 | 2.97 | 0.84 | 0 |
| United Kin | 2016 | 162 | 4.74 | 5.19 | 10.78 | 8.698 | 4.74 | 6.66 | 4.15 | 0 | 0.115 |
| Finland | 2016 | 178 | 4.18 | 7.43 | 1.2 | 6.658 | 4.18 | 2.37 | 3.69 | 10.945 | 0.577 |
| Canada | 2016 | 169 | 9.15 | 8.17 | 1.08 | 5.209 | 9.15 | 2.94 | 9.17 | 0 | 0 |
| Switzerlan | 2016 | 174 | 4.48 | 6.46 | 2.12 | 8.848 | 4.48 | 4.14 | 3.18 | 7.93 | 0 |

# **Appendix 11** Parameters *W* and *b* trained by model

**Shape:** *W1*: (20,21) *W2*: (7,20) *W3*: (5,7) *W4*: (1,5)

*b1*: (20,1) *b2*: (7,1) *b3*: (5,1) *b4*: (1,1)

| | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| W1 | 0.28875 | 0.099403 | -0.07575 | -0.07184 | -0.1803 | -0.37185 | -0.02211 | -0.26232 | -0.07046 | -0.16045 | 0.037922 | 0.03146 | -0.29512 | 0.071894 | -0.11184 | 0.049276 |
| | -0.23193 | 0.350886 | 0.31019 | 0.007748 | 0.596562 | 0.326704 | -0.05568 | 0.378343 | -0.02743 | -0.15257 | 0.037091 | 0.049743 | 0.169579 | -0.05012 | -0.04015 | -0.00511 |
| | 0.039378 | 0.01313 | 0.130368 | -0.16951 | -0.0956 | -0.16744 | -0.16495 | -0.07214 | 0.072956 | -0.31727 | 0.175886 | -0.39764 | -0.09047 | 0.040739 | 0.11883 | 0.017287 |
| | 0.490597 | -0.03263 | -0.0287 | -0.02689 | 0.003336 | -0.06373 | 0.087835 | 0.195669 | 0.316351 | 0.291533 | 0.126086 | 0.077017 | -0.06729 | -0.04719 | -0.18092 | -0.16917 |
| | -0.07407 | -0.2449 | 0.057878 | -0.16644 | 0.31014 | -0.15346 | -0.1857 | 0.111855 | 0.033978 | 0.0779 | 0.146795 | 0.124562 | -0.41358 | -0.25789 | 0.107902 | -0.19804 |
| | -0.13163 | -0.3082 | 0.023774 | -0.12885 | 0.071758 | 0.128509 | -0.22063 | -0.26247 | 0.136131 | -0.22663 | -0.10629 | 0.509487 | 0.38462 | 0.545132 | 0.164891 | 0.03525 |
| | 0.451425 | 0.39798 | 0.248442 | 0.316258 | 0.210423 | 0.316095 | -0.17129 | -0.01311 | 0.178634 | -0.1894 | 0.488769 | -0.26923 | -0.01592 | 0.249292 | -0.06312 | -0.02926 |
| | -0.07004 | -0.22795 | -0.01148 | -0.17716 | 0.102383 | -0.15117 | 0.243935 | -0.27775 | -0.23864 | 0.017579 | -0.19954 | -0.31379 | 0.35228 | -0.1445 | 0.114632 | 0.248616 |
| | 0.059332 | 0.087443 | 0.033585 | -0.08818 | -0.21369 | -0.18196 | -0.35072 | -0.08481 | -0.04355 | 0.22858 | -0.12512 | -0.06325 | -0.32164 | 0.229991 | -0.36156 | -0.02648 |
| | -0.23872 | -0.20473 | 0.133348 | -0.00479 | 0.318411 | 0.376001 | -0.01423 | -0.19355 | 0.347827 | -0.06725 | 0.235797 | -0.17996 | 0.143564 | 0.102838 | -0.16843 | 0.008634 |
| | -0.15686 | -0.12899 | 0.310067 | -0.22481 | 0.239788 | -0.23562 | 0.053061 | 0.103876 | 0.08602 | 0.338246 | -0.10519 | -0.52264 | 0.286879 | -0.06128 | 0.16954 | -0.11688 |
| | -0.11054 | -0.38273 | -0.29366 | 0.218253 | -0.2451 | 0.060848 | 0.140008 | -0.07745 | 0.134891 | -0.02123 | -0.28403 | 0.101078 | 0.372858 | -0.04976 | -0.2084 | 0.039399 |
| | 0.025964 | 0.252406 | 0.379644 | 0.223734 | 0.564269 | 0.349078 | 0.372451 | -0.0048 | 0.553447 | -0.063 | 0.125925 | 0.411261 | -0.37133 | -0.06897 | -0.00398 | 0.057732 |
| | 0.136651 | 0.094833 | -0.40645 | 0.100502 | 0.30658 | -0.23753 | -0.11962 | -0.30132 | -0.1345 | 0.062994 | -0.0111 | 0.024138 | 0.307463 | 0.115473 | 0.197441 | 0.391979 |
| | -0.40851 | 0.350102 | -0.02945 | -0.30473 | 0.163495 | 0.30414 | -0.01066 | 0.466713 | -0.23389 | 0.185028 | 0.336512 | -0.34798 | -0.05585 | 0.341724 | -0.07202 | 0.363106 |
| | -0.32266 | -0.07127 | -0.01301 | -0.20198 | -0.20113 | -0.07632 | 0.405613 | -0.22371 | -0.08687 | 0.02107 | -0.07382 | 0.13437 | 0.15719 | -0.03737 | -0.02693 | -0.11799 |
| | 0.156306 | -0.08088 | 0.097639 | 0.174482 | -0.218 | -0.3518 | -0.15538 | -0.07285 | 0.046221 | -0.49755 | 0.120205 | 0.242509 | -0.00399 | 0.105053 | 0.060946 | -0.14467 |
| | 0.125359 | 0.158973 | 0.170934 | -0.65338 | 0.272112 | 0.118574 | 0.310124 | -0.36699 | 0.028458 | -0.20136 | -0.31355 | -0.18816 | -0.51144 | -0.21625 | 0.106845 | -0.30003 |
| | -0.2484 | -0.05596 | -0.46543 | -0.13282 | 0.220027 | 0.795718 | 0.09252 | -0.09936 | 0.29377 | -0.11731 | 0.463509 | -0.18176 | 0.153544 | -0.10924 | -0.1962 | -0.22264 |

| | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| W2 | -0.07287 | 0.744742 | 0.175554 | 0.3862 | -0.03273 | 0.077156 | 0.491639 | 0.008675 | 0.295362 | 0.335166 | 0.345559 | -0.07422 | 1.1322 | -0.46364 | 0.046385 | -0.10825 | 0.494348 | -0.97924 | -0.44753 | 0.102858 |
| | -0.12235 | 0.194537 | 0.261416 | 0.13698 | 0.017803 | -0.23103 | 0.120439 | 0.415747 | 0.061632 | -0.16026 | -0.12063 | 0.241874 | 0.660192 | -0.03779 | -0.15094 | -0.16343 | 0.231767 | -0.2389 | 0.20836 | 0.230624 |
| | -0.20584 | -0.29861 | -0.14813 | -0.00498 | -0.13183 | -0.01408 | 0.151937 | 0.06422 | 0.239179 | 0.13527 | 0.105798 | 0.143484 | 0.018045 | -0.07658 | -0.38864 | 0.275546 | 0.137676 | -0.0403 | 0.215095 | -0.11906 |
| | -0.3115 | 0.077679 | -0.07905 | -0.45066 | 0.007173 | -0.32987 | -0.02398 | 0.156674 | -0.08179 | 0.160483 | 0.212231 | 0.086982 | 0.104704 | 0.322837 | -0.31042 | 0.238077 | 0.196489 | -0.19134 | 0.028353 | -0.31832 |
| | 0.311219 | -0.17328 | -0.26483 | -0.36254 | -0.10245 | 0.187814 | -0.02741 | 0.175182 | 0.23752 | -0.07492 | 0.205011 | 0.232234 | -0.18967 | -0.10109 | -0.25631 | 0.338374 | 0.178629 | 0.193786 | -0.36996 | -0.2378 |
| | -0.18057 | -0.51216 | -0.00858 | 0.14718 | 0.500268 | 0.716301 | 0.324107 | -0.21905 | 0.120968 | 0.084398 | -0.36729 | -0.03957 | -1.25359 | 0.611628 | 0.364155 | 0.025198 | 0.211373 | 1.01013 | 0.291897 | -0.41701 |
| | 0.066514 | -0.09459 | 0.014328 | 0.149895 | -0.05478 | -0.08308 | 0.22917 | 0.322282 | 0.023289 | 0.182745 | -0.41887 | -0.12629 | 0.322606 | 0.385099 | -0.14655 | -0.27184 | 0.190688 | -0.29656 | 0.259562 | 0.15259 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| W3 | 0.80746 | 0.529912 | -0.21549 | 0.773023 | 0.349319 | -0.76721 | 0.101194 |
| | -0.04587 | -0.16334 | -0.02901 | -0.09512 | -0.19545 | -0.10611 | -0.43345 |
| | 0.078308 | 0.016769 | 0.578446 | 0.359889 | 0.013804 | -0.36935 | -0.34023 |
| | 1.52684 | 0.401932 | 0.120999 | 0.190786 | -0.20842 | -1.73915 | 0.126714 |
| | -0.9477 | -0.15641 | 0.434039 | 0.354094 | 0.21694 | 1.46374 | 0.007695 |

| | | | | | |
|---|---|---|---|---|---|
| W4 | -1.29092 | -1.38548 | 0.399931 | -2.08041 | 1.74925 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| b1 | -0.04527 | b2 | -0.57783 | b3 | -0.4559 | b4 | 2.89334 |
| | -0.48347 | | -0.16406 | | 0 | | |
| | 0 | | 0.000766 | | 0 | | |
| | -0.12051 | | 0 | | -0.13255 | | |
| | -0.01086 | | 0.000749 | | 0.590006 | | |
| | 0.605688 | | 0.991231 | | | | |
| | -0.02425 | | -0.01636 | | | | |
| | -0.03428 | | | | | | |
| | -0.00311 | | | | | | |
| | 0.095201 | | | | | | |
| | 0.00602 | | | | | | |
| | 0 | | | | | | |
| | -1.12934 | | | | | | |
| | 0.613876 | | | | | | |
| | 0.151704 | | | | | | |
| | 0.004285 | | | | | | |
| | -0.00082 | | | | | | |
| | 0.594132 | | | | | | |
| | 0.099076 | | | | | | |
| | -0.42977 | | | | | | |