Computer Science Extended Essay

Research Title: Investigating the current state of implementation of predictive algorithms in terms of fuzzy logic and Quantum Computing.

Research Question : How effective is present-day quantum algorithm compared to a simpler fuzzy logic system for designing accurate and reliable predictive analysis systems?

Word Count: 3994

Table of Contents

1 Introduction

Learning different aspects of computer architecture and Object Oriented Programming made me wonder whether there are alternatives for the traditional and accepted data types, such as Boolean.

With the world advancing with developments in Neural Networks, Machine Learning and Robotics, it’s important to understand the capabilities and limitations of these systems. Which leads me to question, if fuzzy logic based algorithms can be accurate and efficient for predictive analysis?

This essay investigates the predictive analysis capabilities of fuzzy logic systems including a comparison, between a fuzzy logic system programmed by myself to predict the tourist population for a country with a report that investigates the effects of COVID-19 and future possibilities using Quantum computing

The reasoning for this research question is to determine the possibility of predictive analysis independent of quantum computing technology, and hence a cheaper solution to predictive analysis.

2 Fuzzy Logic

The 'Fuzzy' word means the things that are not clear or are vague. It is an approach to computing based on "degrees of truth". Real life concepts like "tallness", "coldness" cannot be explained with boolean. Fuzzy logic being multi-valued logic allows a computer to interpret these vague concepts.

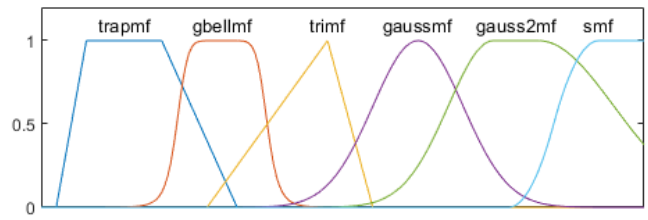
2.1 Fuzzy Sets

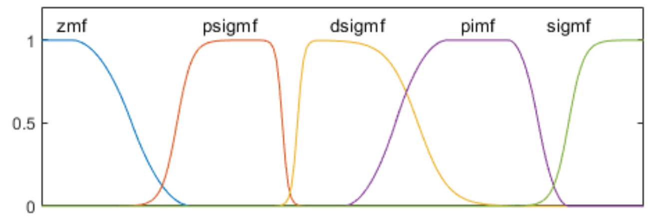
Assume that X is a collection of objects presented by x, a fuzzy set (class) A in X is characterized by a membership function f(x) which associates with each point in X a real number in the interval [0, 1], with the value of f(x) at x representing the "grade of membership" of x in A.

For example: Let X be the real line R ~ and let A be a fuzzy set of which are much greater than 1. Then, one can give a precise characterization of A by specifying fA(x) as a function on R 1. Representative values of such a function might be: fA(0) = 0; fA (1) = 0; fA(5) = 0.01;fA(10) = 0.2;fA(100) = 0.95

2.2 Membership Functions

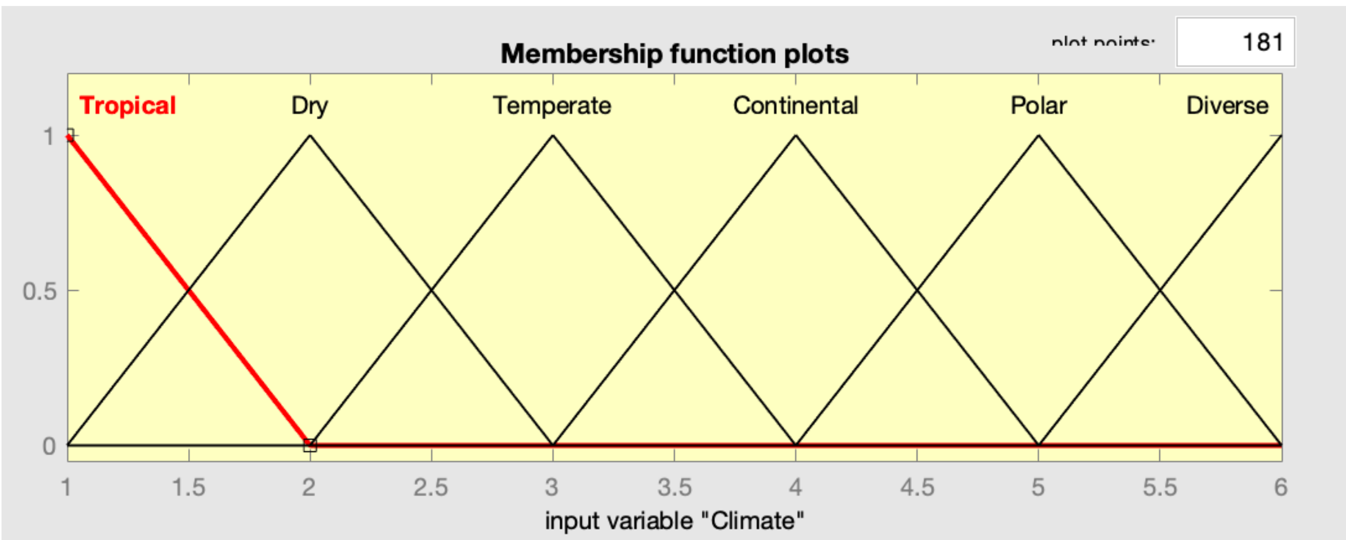
Membership functions specifies the degree to which an input belongs to a set. The membership value/degree that is mapped to the output is always between 0 and 1. These functions have predefined curves that can be used, and also allows for customised membership functions. The main membership functions types are as follows:

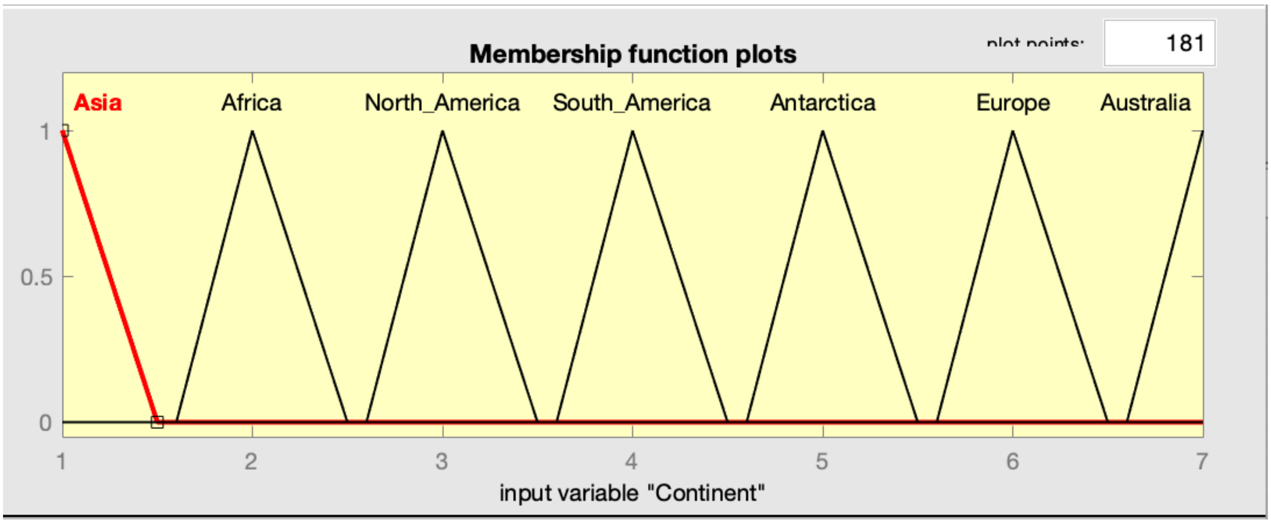




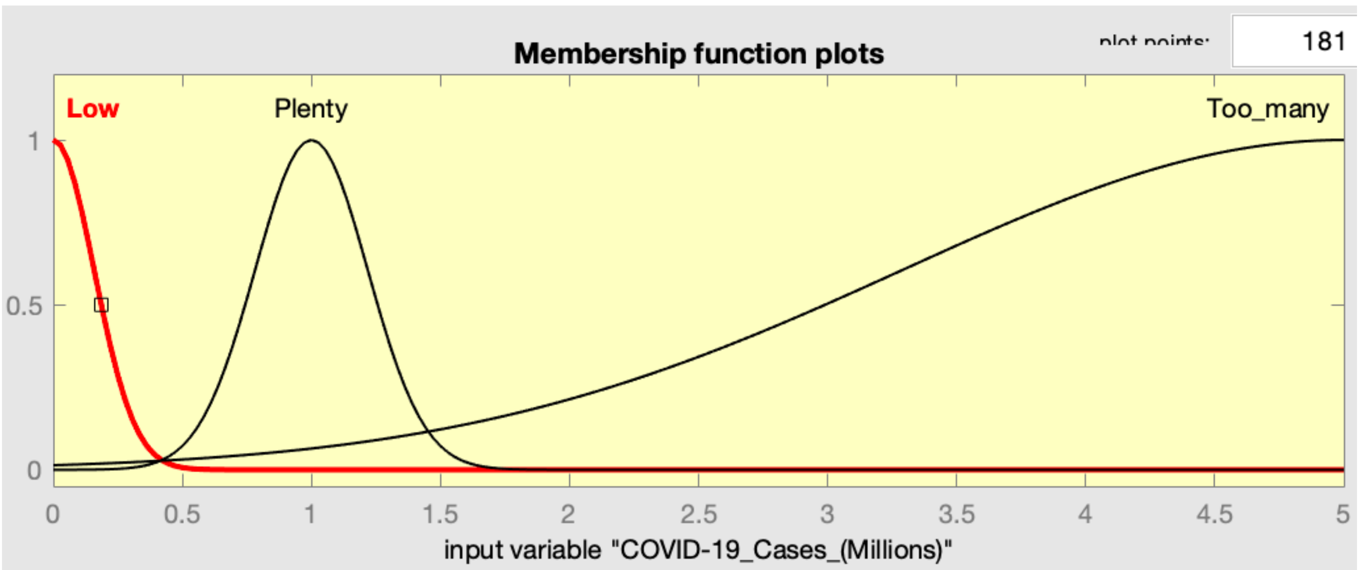
These membership functions determine how the crisp values will be converted into fuzzy values and ultimately collectively determine an output in terms of the **predicted number of tourists** for a country matching the various inputs.

The membership functions used in my predictive algorithm are:





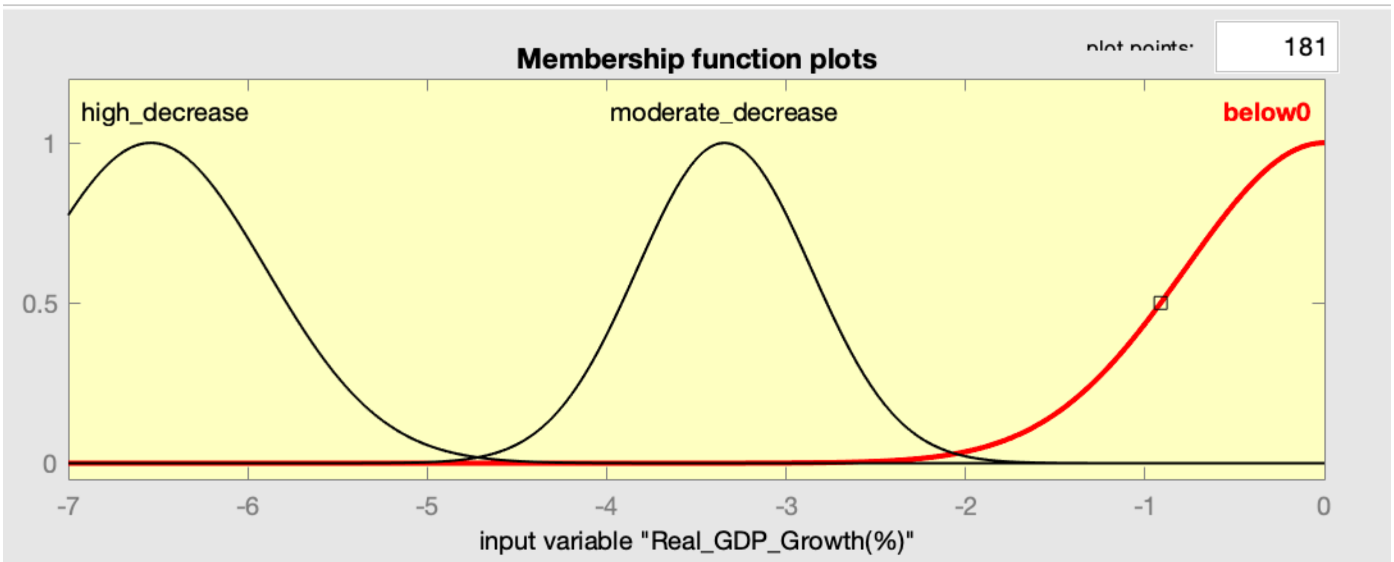
The Continent and Climate membership functions are non-fuzzy. Technically there can still be an output of anything from 0 to 1. However, to differentiate the continents and their respective climates, the user will have to input a value related to the specific continent and climate. As there needs to be some definite information that allows for classification. This displays the importance of the traditional "Boolean" data type.



COVID-19 has already caused a lot of ruckus in the world and has affected all industries of the world. Especially, the tourism industry. UNTWO (United

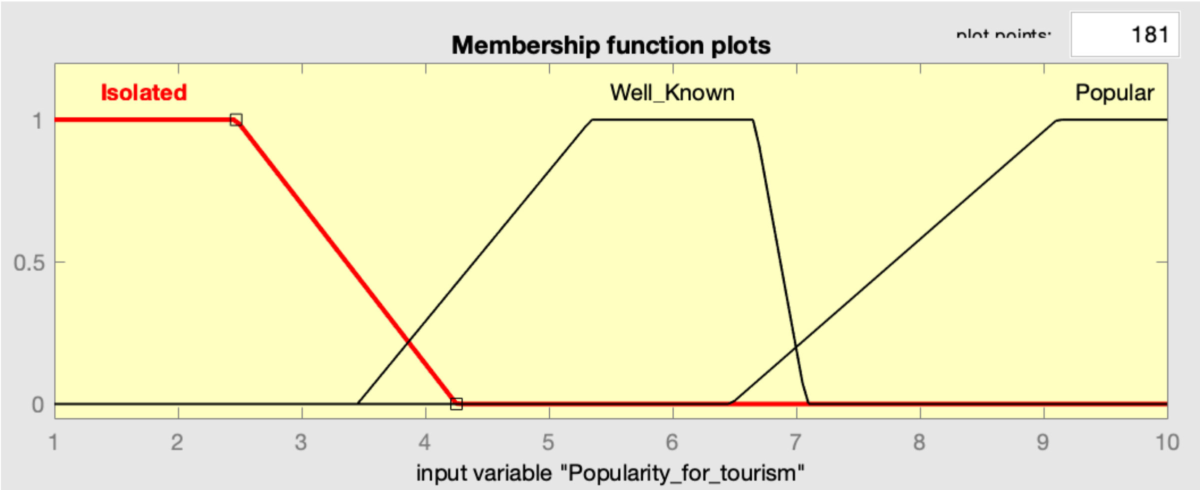
Nations Tourism World Organisation) predicted that the tourism industry will take a hit and fall by 60%-80%, 67 million less tourists and huge losses in exports due to COVID-19. Using the world data of COVID-19 cases, I categorised the cases into 3 functions : Low, Plenty and Too_many.

For example: If Continent is Asia then COVID-19 cases are “too many”, then the tourist population would be high instead very high. This would be implemented in the Rule base.



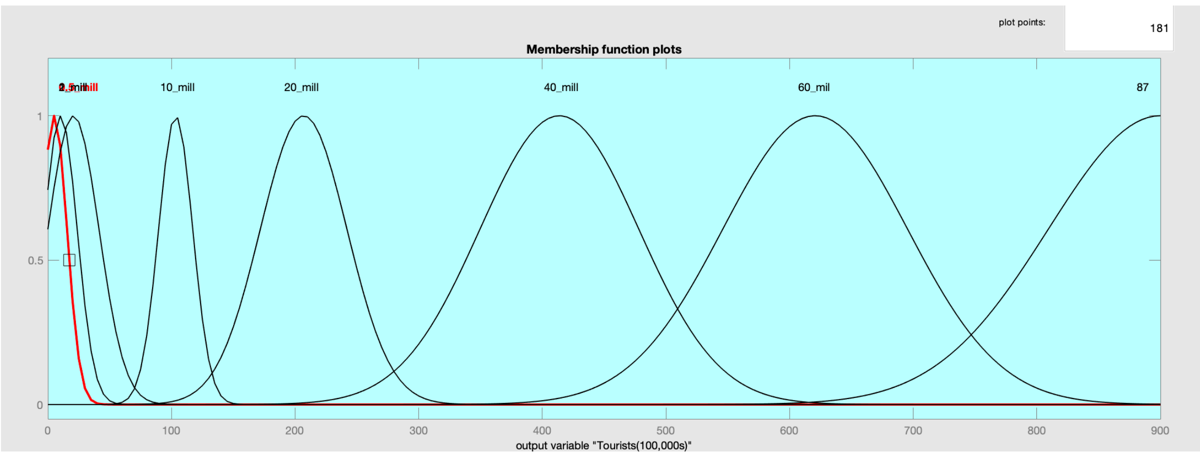
The Real gross domestic product is a measurement of economic output that accounts for the effects of inflation or deflation. It provides a more realistic assessment of growth than nominal GDP. This will tell us whether the economy of most of the countries in the continents are contracting or growing, which in turn would determine whether the costs would increase or decrease to travel in that continent.

For example: If the Real GDP Growth of X continent is approximately -6%, would fall under “high_decrease” and would have conditions set to make it more likely to have more tourists, after considering all the other rules.



Predictive analysis majorly uses historical data which is used to predict the future possible outcomes. In the same manner, the popularity of tourism would be major factor determining the number of tourists.

For example: In 2018, Europe had the most tourist population (713 million) and Africa had a tourist population of 67 million. So, even after considering all other factors, Africa cannot have a larger tourist population than Europe.

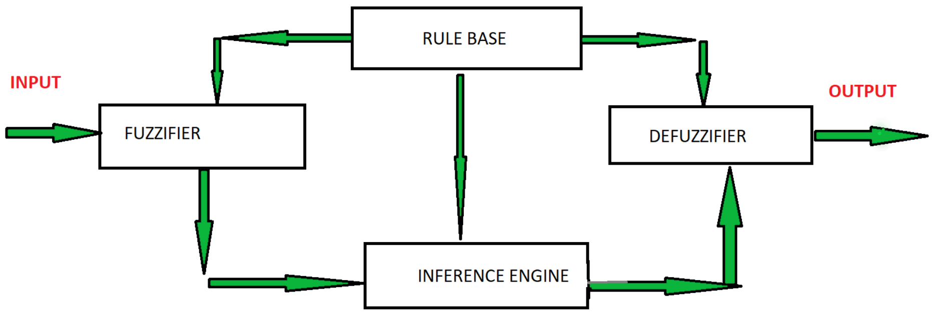


This is the output membership function, onto which all the fuzzy data is fed to and then outputs crisp values according to the parameters set for this output membership function. After entry and calculations from the input membership functions the data is mapped onto the output function and de-fuzzified into crisp data for the final output.

3 Fuzzy Logic System Architecture

A Fuzzy Logic System architecture consists of 4 parts :

1) Rule Base
2) Fuzzification
3) Inference Engine
4) Defuzzification



FUZZY LOGIC ARCHITECTURE

1) Rule Base

It contains the set of rules in the form of IF conditions with pre-determined conditions set with the appropriate linguistic options that use the membership functions to determine the output for a particular input. In fact, for the amount of membership functions I am utilising, there should be approximately 414 rules. However, as it requires too much processing power and causes the application to stop responding and even crash, I have only used approximately 50 rules which will affect its accuracy negatively.

2) Fuzzification

Fuzzification is the processing of mapping various crisp inputs to a corresponding values in a fuzzy set. This is done using different fuzzifiers – such as Gaussian fuzzifiers, trapezoidal and triangular fuzzifiers. These fuzzifiers use various membership functions to determine the values that a particular crisp value maps to in the fuzzy set.

In my algorithm the Gaussian and Triangular fuzzifiers are the most important, as most of the membership functions are represented by a Gaussian or Triangular graph.

Membership function of Gaussian fuzzifier:

$$\mu_A(x) = e^{-\left(\frac{x_1 - x_1^{\cdot}}{a_1}\right)^2} \dots e^{-\left(\frac{x_n - x_n^{\cdot}}{a_{n1}}\right)^2}$$

where $\{a_i,\ i = 1,\dots,\ n\}$ are positive parameters.

Membership function of triangular fuzzifier:

$$\mu_A(x) = \begin{cases} \left(1 - \frac{|x_1 - x_1'|}{b_1}\right)\dots\left(1 - \frac{|x_n' - x_n'|}{b_n}\right) & if\,|x_i - x_i'| \leq b_i, i = 1, \\ 0 & otherwise \end{cases}$$

where $\{b_i, i = 1,\dots,\ n\}$ are positive parameters.

3) **Inference Engine**

It determines the matching degree of the converted fuzzy input with respect to all rules in the Rule Base. There are two main Inference Engines used in Fuzzy Logic Systems :

1. Mamdani
2. Sugeno

In my algorithm, I have used the Mamdani Inference Engine, as it expects the output membership functions to be fuzzy sets. Following the aggregation process, there is a fuzzy set for each output variable, which needs defuzzification. Which allows me to implement the fuzzy logic approach using real and vague factors as membership functions.

On the other hand, Sugeno method, expects the output membership functions to be linear or constant for the Sugeno-type fuzzy inference. It would be ideal for modelling non-linear systems by using several linear relations.

4) **Defuzzification**

It is the process of converting the fuzzy data after the rules have been applied in the inference engine into crisp data which can be understood by the user. It is the opposite process of fuzzification.

Example: For a Fuzzy Logic System used to determine the % of tip that should be given, the output cannot be in fuzzy form [0,1], it has to be in crisp quantity (X %).

4 Methodology

4.1 Scripting Language

For implementing the Fuzzy Logic System, I have chosen MATLAB. It has an excellent user interface and also allows the traditional approach of coding in a scripter.

It offers a great variety of tools in its Fuzzy Logic Toolbox, the ability to plot 3 dimensional graphs to compare the input and the outputs. It allows for one to create custom membership functions and had a well-designed Rule base layout that made adding rules a bit less tedious.

4.2 Procedure

1. Determine the inputs according to the factors that affect the tourist population.
2. Determine the membership functions for each input.
3. Collect past data for each input to set appropriate range values for each membership function.
4. Add input functions in Fuzzy Logic Designer.

5. Select number of membership functions, type of curves and range in the Membership Function Editor.
6. Repeat steps 4 and 5 for each input function.
7. Open the Membership Function Editor for the output.
8. Add membership functions, select type and range for the output.
9. Determine all the necessary Rules and their respective Weights.
10. Open Rule Editor and add the rules by selecting the respective inputs, conditional statements, weights and expected outputs.
11. Analyse 3 dimensional graphs of each function with the output and compare results with predictions made by experts.

5 Analysing Fuzzy Algorithm

The algorithm is predicting the tourism populations in the fourth quarter, according to research (in Appendix) the lockdowns are opening up. So under the assumptions that there will be ***no second wave*** and that the ***decisions of opening lockdowns will be implemented***, the algorithm is created.

5.1 Relationships between each Membership Function

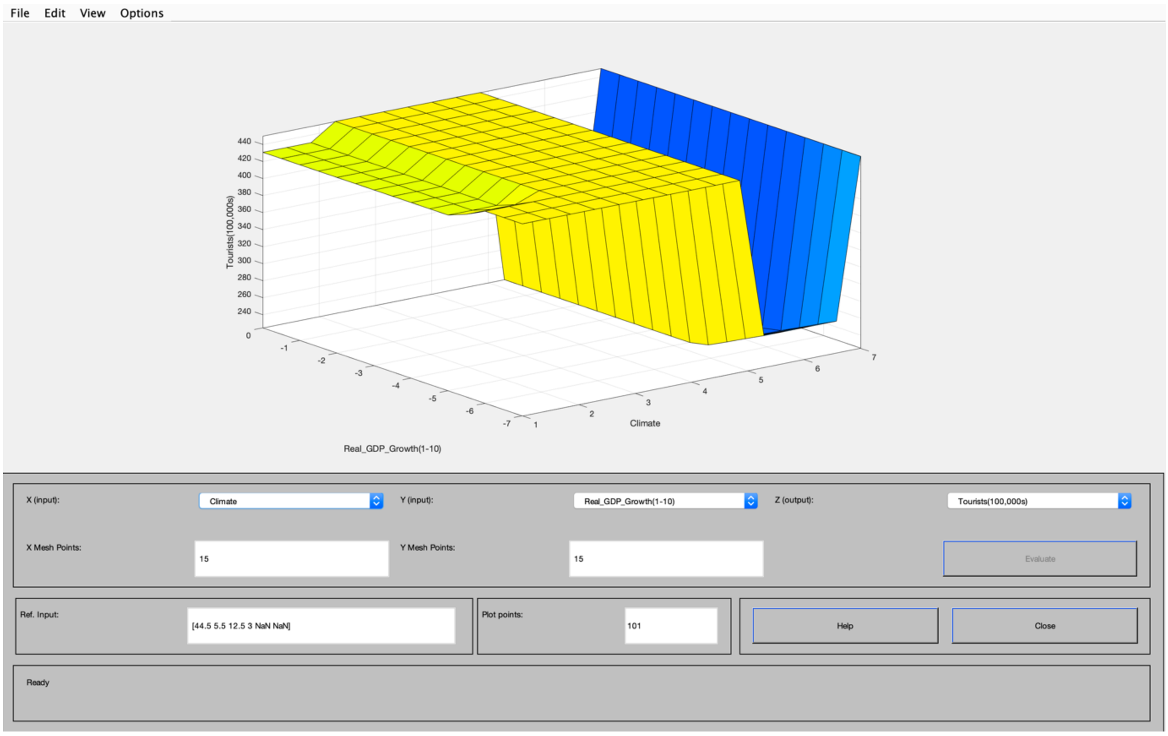


Figure 5.1

Figure 5.1 is a 3 dimensional representation of the two membership functions – Climate and Real GDP Growth (1-10). Here, climate is a specific input function with predetermined options as listed in the appendix. From this the number of tourists can be interpreted to be high in places with a climate between 2-5, which is Dry/Desert, Mediterranean, Continental and Diverse and showing a minor effect of change in Real GDP Growth for these climates. For the climates 6-7 (Temperate and Equatorial) the tourist output is extremely low.

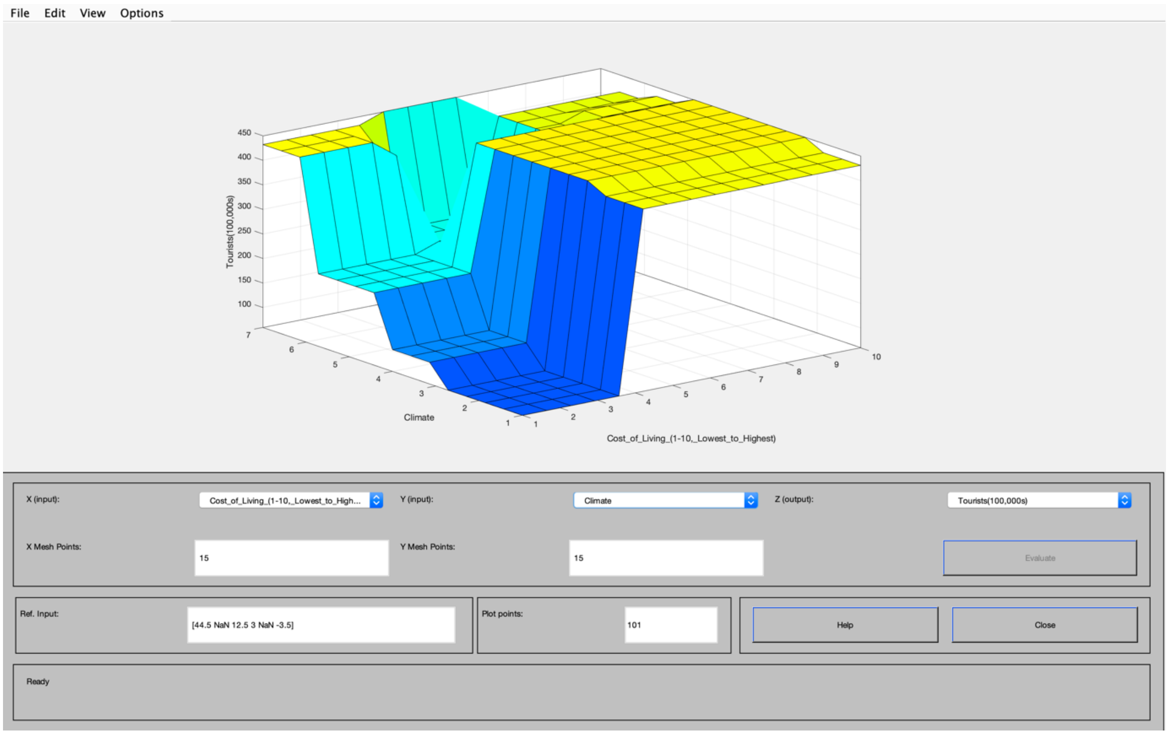


Figure 5.2

Figure 5.2 showcases the relationship between the Cost of living and Climate. For the lower cost of livings the output is low, however as the climates moves from 1 to 7, with 6 and 7 (Temperate and Equatorial) having a high output. However, for the same climate as the cost increases, the output decreases. Evidently the higher cost of livings with either Tropical, Dry/Desert, Mediterranean or Continental climates also have a high output.

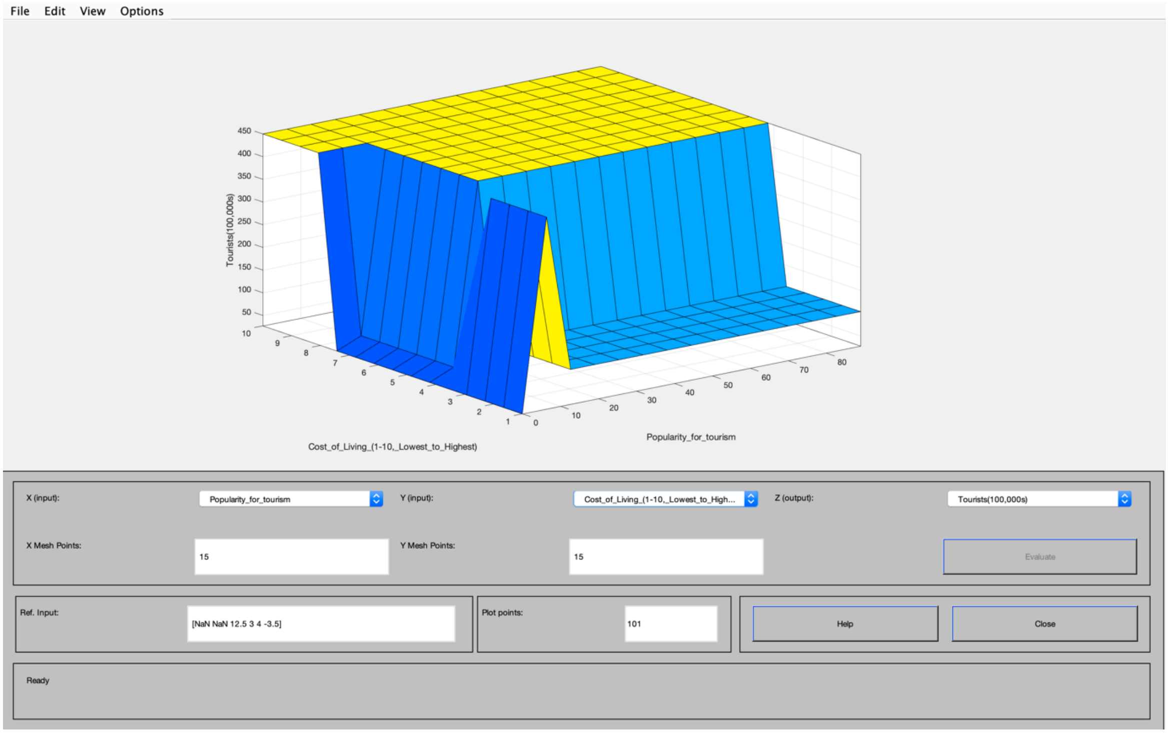


Figure 5.3

Figure 5.3 showcases the relationship between Popularity for tourism and Cost of living. Popularity uses the past tourist population number as an input. As seen here, for a moderately low popularity if the cost of living is less, then the output is high. However as the popularity increases, at a low cost of living there is barely/no output. As in the test data, there is no such country that fits the scenario. For high popularity and cost of living the output remains high.

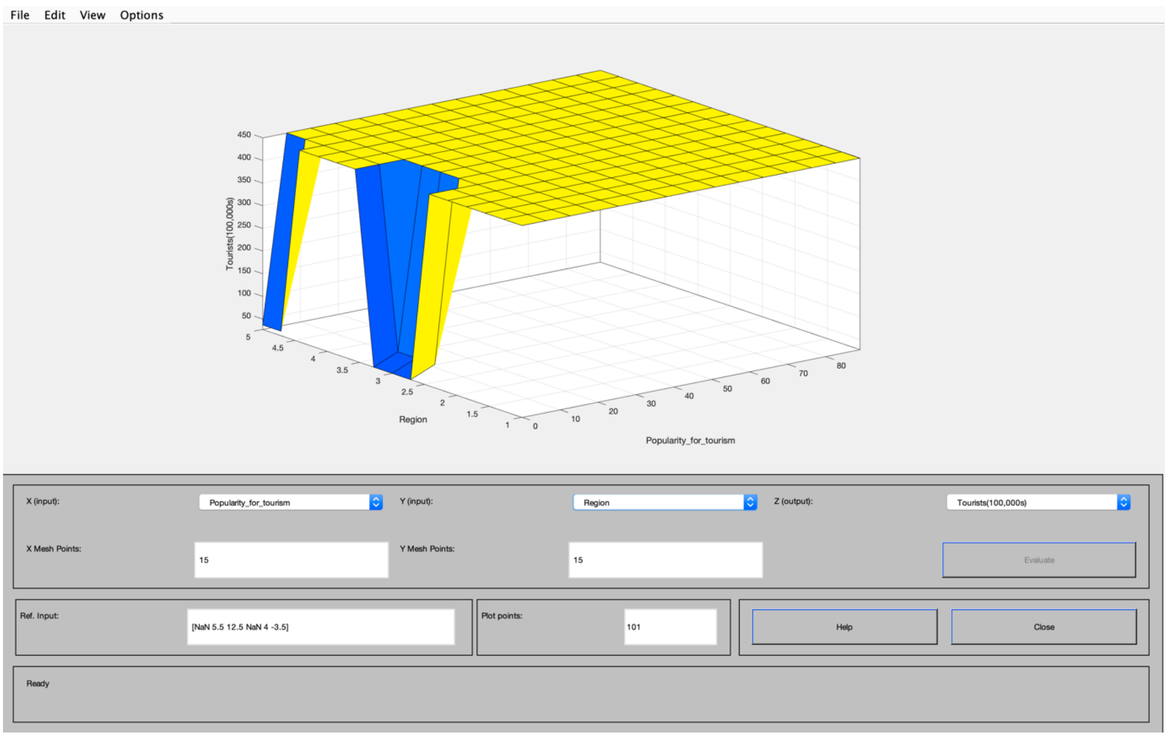


Figure 5.4

Figure 5.4 displays the relation between Popularity, Region and the number of tourists. The region is an option from pre-determined options, and these options are regions on a world-wide scale. This factor is used along with the others, to determine the specific country without adding all existing countries and searching for it. Hence, why the output is at a high for a few regions and a dip for 2 regions.

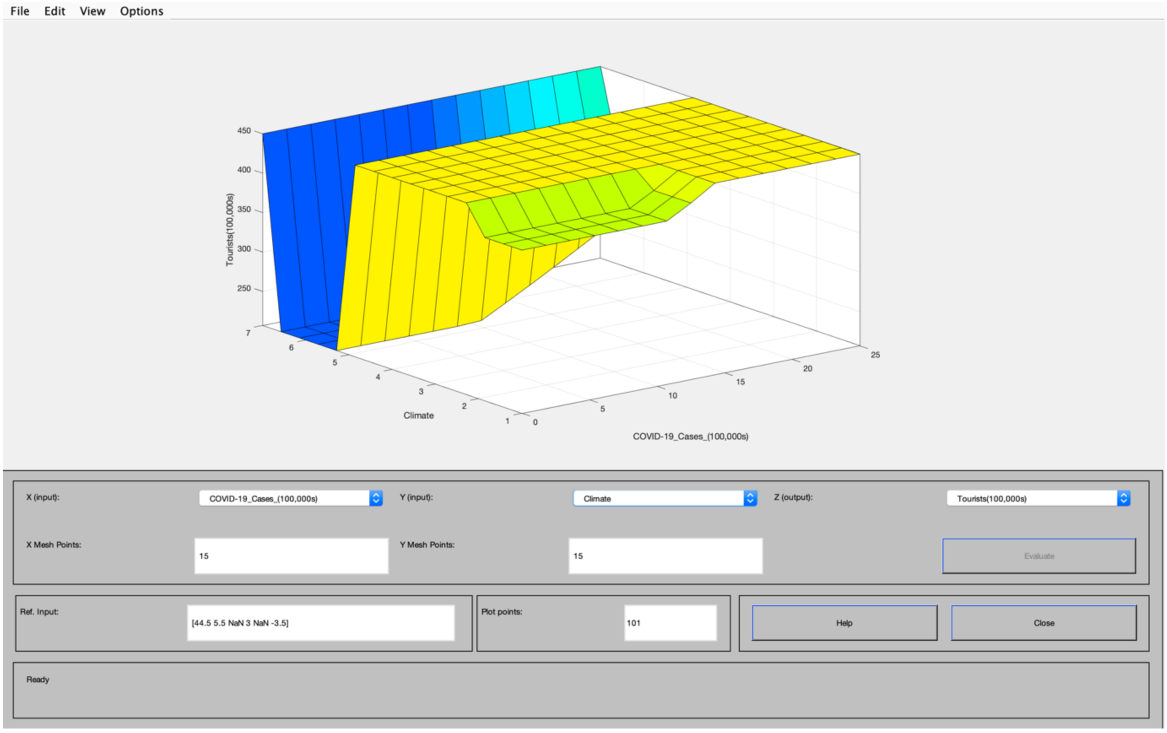


Figure 5.5

Figure 5.5 showcases the relationship between COVID-19 Cases and Climate. Now these are extremely different factors, but this is the relationship that is created based upon the rules created. For a few regions the output is basically 0, with a few showing a drop but most others showing a high output. Now, realistically this would not make sense. As for a high COVID case number the output should be, however this is taken into account with all the other relationships with COVID-19 Cases membership function.

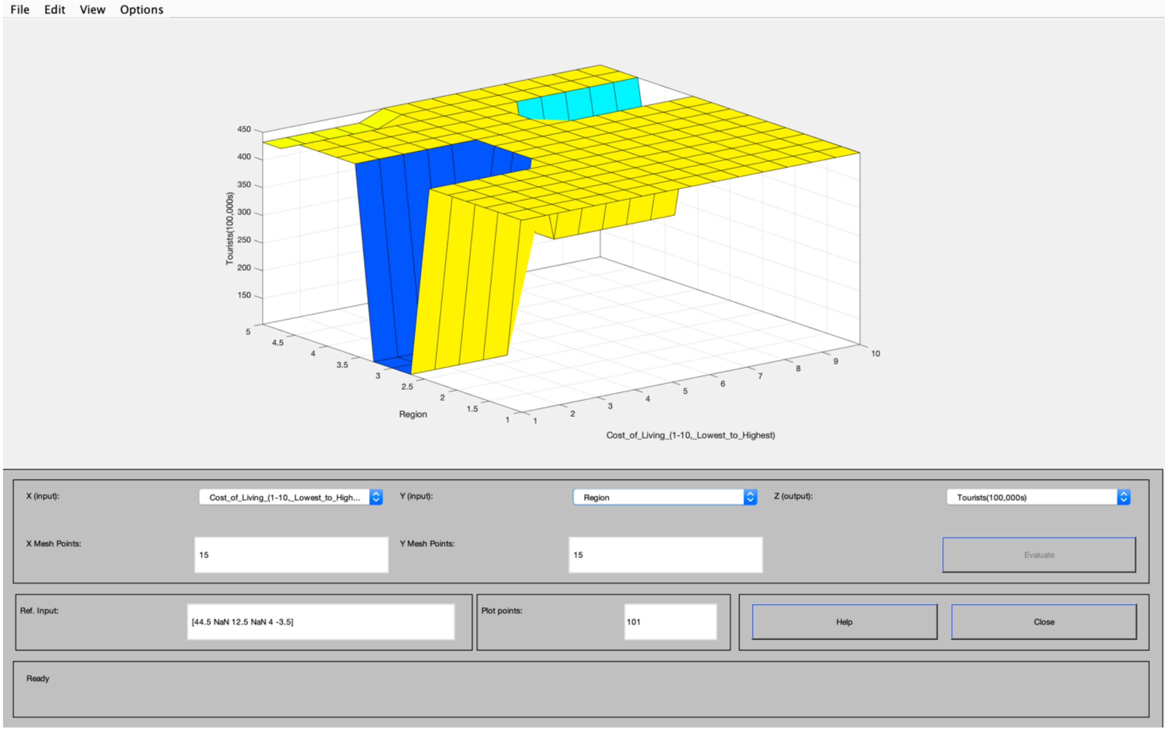


Figure 5.6

Figure 5.6 showcases the relationship between Cost of living and Region. This is an extremely important factor that helps determine a rough country and accordingly the output level is also set. For example, for 3 (Asia and Pacific) when the cost of living is low, the output is also low. However, as the cost of living increases, the output increases (possibility of countries such as Japan, Hong Kong…). However, China has a low cost of living, but according to this would have a low output, which is in fact incorrect. Which is covered up by the other factors, but this suggests that more factors are required as it is not separating and identifying countries correctly.

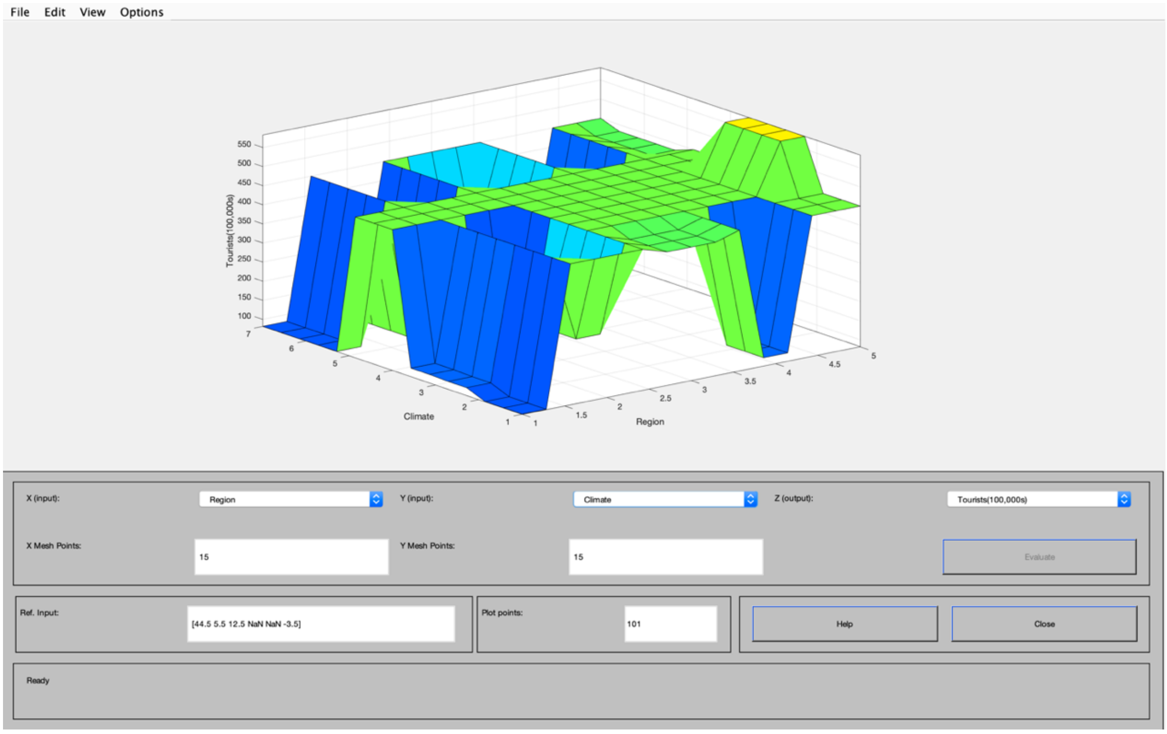


Figure 5.7

Figure 5.7 represents the relationship between Climate and the Region. As both of these functions are based upon determined inputs, the relationship between the two is extremely precise. For example the point of highest output is when region is 5 (Europe) and climate is 2-4 (Mediterranean, Continental…) Which would fall under the information of Spain, Italy, Turkey and more from the test data. Region 1 (Africa) has low output in most climates, except from 3-4 which are the Mediterranean and Continental climates. Some output levels are also 0 as no locations in the region with that specific climate even exist!

5.2 Analysing Outputs

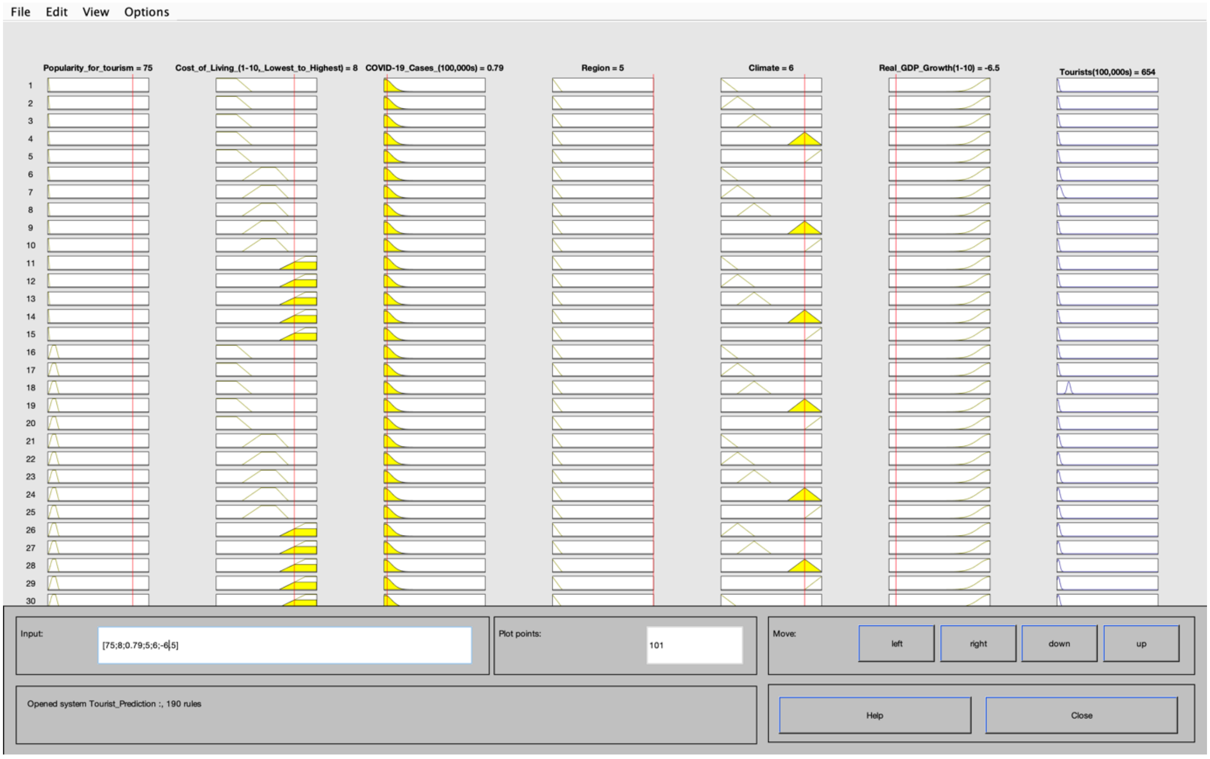


Figure 5.8

Figure 5.8 is the rule viewer, where the data can be entered and a corresponding output will be generated. Each row represents a rule and the columns correspond to the membership functions. A collated entry can be manually entered in the input box on the bottom left, otherwise for each column a value can be manually be selected. Here data has been entered considering the country “France”. Which has the highest tourist population recorded – 89 million. The output is 654 (100,000) which is approximately 65 million. That would signify a 26% decrease in its tourist population of 2018. Compared to its predictions for 2020 (before COVID-19) which was 100 million, it would suffer by a 35% loss of tourists. (Assuming the assumptions mentioned previously hold true) This is a realistic and acceptable prediction.

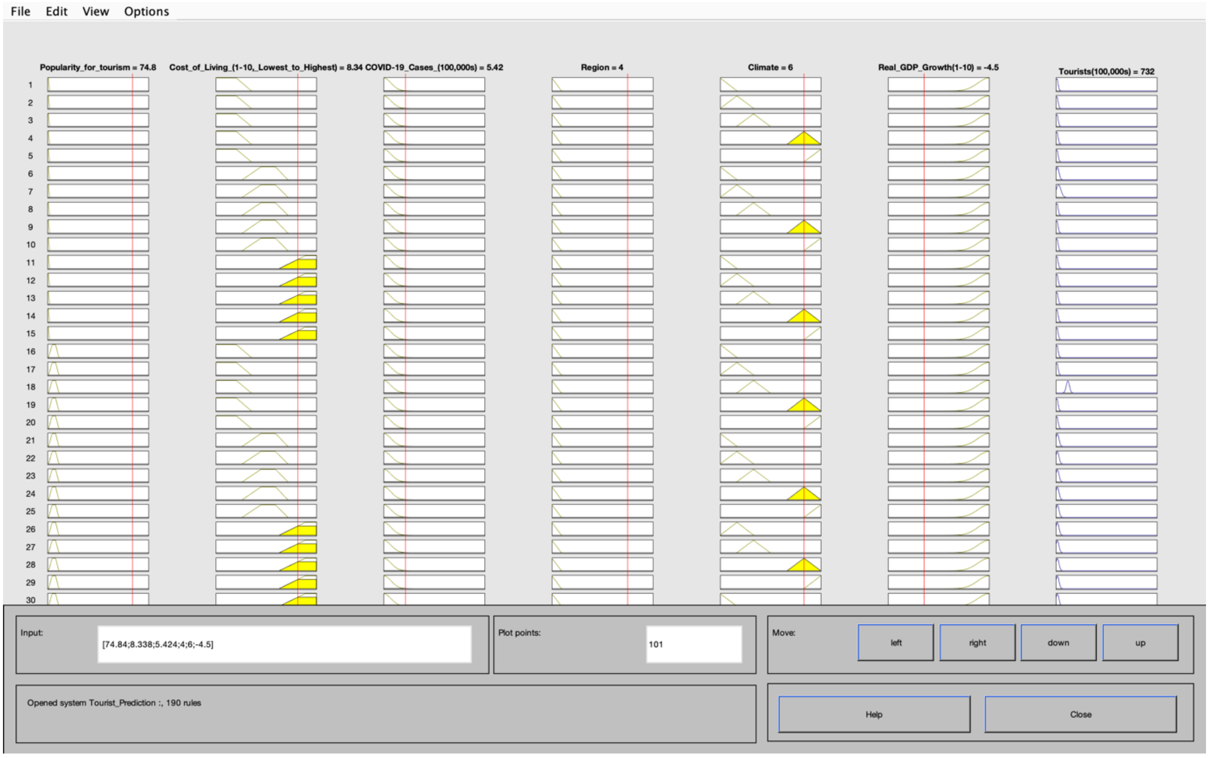


Figure 5.9

Here, the values are entered considering the country “United States of America”. According to this, the predicted value is 732 (100,000) which is 73 million. While considering the assumptions and situation, this is an unrealistic value. Which could be explained due to the lack of few factors, and hence adding more factors would improve the accuracy of the algorithm. The explanation of the result being unrealistic could be due to external factors such as the protests, the looters and increasing unemployment rates. Now, these factors are emerging instantly and are increasing in importance. Which would mean to ensure accuracy of results, each factor will have to be added; which is very tedious and inefficient. Also, these events cannot be expressed in fuzzy logic, as these are extremely controversial and subjective topics.

6 Quantum Computing

6.1 Basics

Quantum Computing utilises the intriguing complex principles of quantum physics such as quantum superposition, entanglement and tunnelling. By which it is able to reduce the number of steps to reach the final result in complex and huge data sets.

Classical bits exist as a definite value of 0 or 1. However, **Qubits** are different from the classical bits. Qubits exhibit properties of quantum mechanics such as superposition, that allows for the qubit to exists in multiple states at once, and once a result required it falls into the defined output values : 0 or 1. This means at the other times, when no result is extracted the qubits exist in a state far more complex than a simple binary value.

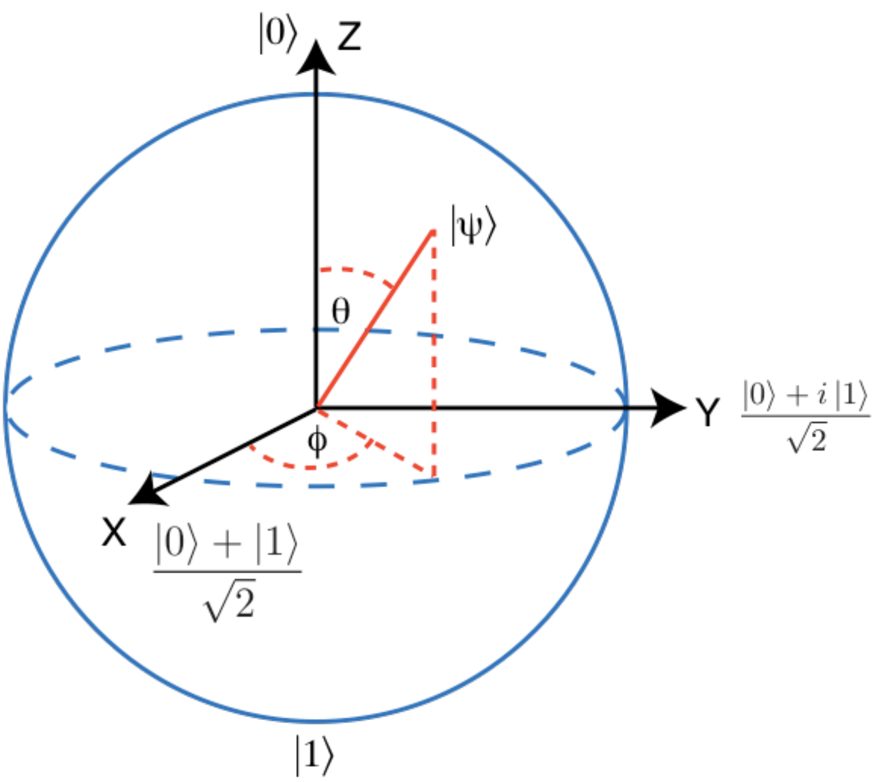
Representation of the outputs of Qubits is done using vector quantities, it helps understand its complex state.

$$|0\rangle = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \quad |1\rangle = \begin{bmatrix} 0 \\ 1 \end{bmatrix}.$$

These two vectors are orthonormal which allows us to represent any 2D vector with a combination of these two vectors.

$$|q_0\rangle = \frac{1}{\sqrt{2}}|0\rangle + \frac{i}{\sqrt{2}}|1\rangle$$

From this vector, it is clearly not an exact value of 0 or 1, and in fact a linear combination of a real and imaginary value. Which is known as superposition. Though our example state $|q_0\rangle$ can be expressed as a superposition of $|0\rangle$ and $|1\rangle$, it is no less a definite and well-defined qubit state than they are.



3D representation of a Qubit using vectors

6.2 Defining principles of Qubits

1. Superposition

It is the ability of Qubits to represent several possible outcomes or exist in multiple states at once, allowing for computation of all these possible outcomes simultaneously. A quantum computer with ‘n’ qubits, can exist in superposition in 2^n states.

2. Entanglement

Entanglement is a property of Qubits, it is a connection between 2 or more Qubits. By using logic operations (gates) and entangling two or more Qubits, the quantum state of these Qubits is described as a whole. For the extracted result it has to be 0 or 1. The special connection of the entangled qubits comes to play here, as the outcome of one qubit will always correlate to the outcome of the other correlate. The fascinating part is that this connection is irrespective of the distance between them.

In classical computing when we increase the number of bits it increases the processing power linearly. However, for Quantum Computers the processing power increases exponentially.

3. Decoherence

The quantum states of these Qubits (in the real world are created by using ions with specific magnetic properties, which are then used to manipulate the direction of the nucleus and the electrons to either represent 1 or 0 ; this is referred to as Spin) are extremely fragile. Disturbances such as temperature fluctuations and vibrations can knock Qubits out of superposition. To combat this problem, Qubits have to be kept at near-absolute 0 at all times to keep their Quantum states stable.

7 Analysing Quantum Algorithm

This research paper (check References) studies the effects of COVID-19 and uses humongous data sets for modelling and investigating the effects of COVID-19 and lockdown restrictions worldwide. It utilises SIRD Model of epidemiology, Ising model, Quantum Circuits and probabilistic plots through the Quantum Approach.

Factors Considered:

SIRD Model : It is a mathematical analytical tool to analyse disease outbreaks by breaking up the entire population into three categories – **S**usceptible, **I**nfected or **R**ecovered. Using massive data sets of the live cases, infectious rates, and incubations periods ordinary differential equations with respect to time that model the virus are created.

Ising model: It describes the 'spin' interactions of atoms (the same spin property of Qubits discussed earlier) with other atoms in a lattice structure, and how the atoms behave when they are under the influence of a magnetic field. Ising model has a more physics approach, as it relates the spin values (+½ and -½, not 0 and 1, that was for a Qubit) with the atoms respective energy levels.

Basically, the Ising model is used as a representation of the current scenario. Each atom is compared to an individual, the spin of each lattice point describes whether the individual is affected or not. The external magnetic field holds no importance in this comparison. After forming such relationships with the Ising model, the equations that fall under the Ising model are used with logical reasoning to form probability distribution equations.

These probability functions and various mathematical models are used to create multiple Quantum Circuits with different logic gates to achieve the desired output.

Here are two of the many derived quantum circuits with its respective gates utilised:

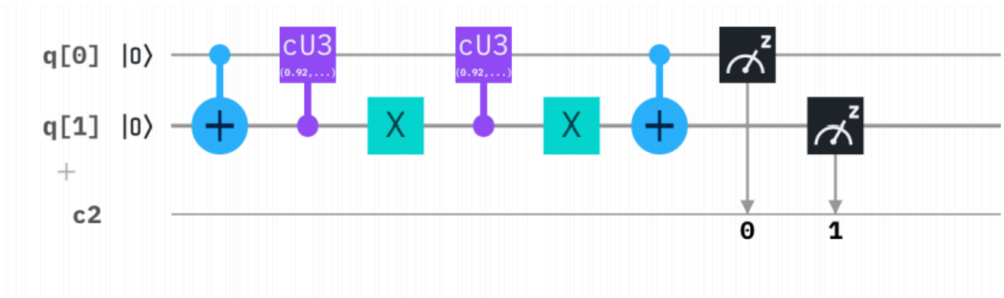


FIG. 2: **The derived circuit has a combination of a CNOT gate, control U3 gate, Anti-control U3 gate and a CNOT gate, where** $\theta_1 = 2B_n(r)t$, $\phi_1 = -\pi/2$ **and** $\lambda_1 = \pi/2$ **and** $\theta_2 = 2B_n(r)t$, $\phi_2 = \pi/2$ **and** $\lambda_2 = -\pi/2$.

Figure 7.1

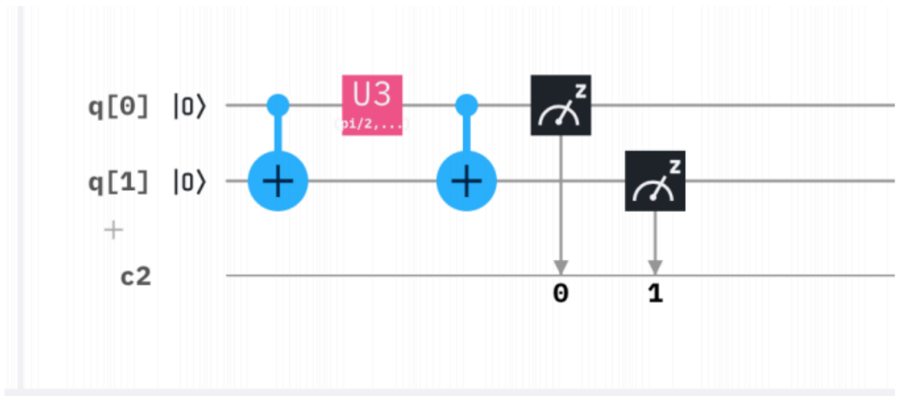


FIG. 1: **The derived circuit has a combination of a CNOT gate, U3 gate and a CNOT gate, where** $\theta = 2A_n(r)t$, $\phi = -\pi/2$ **and** $\lambda = \pi/2$.

Figure 7.2

This is where the power of Quantum computation comes into play, as it computes these specifically designed quantum circuits that have been made by using several probability functions and modelling equations and the respective data sets.

The final results were as follows:

Interval/ Leg no.	Date	Day of spread
1	4 Mar-13 Mar	33-42
2	14 Mar-23 Mar	43-52
3	24 Mar-2 Apr	53-62
4	3 Apr-12 Apr	63-72
5	13 Apr-22 Apr	73-82
6	23 Apr- 2 May	83-92
7	3 May-12 May	93-102

TABLE I: Distribution into various legs

Figure 7.3

Interval/ Leg no.	α	β
1	0.127	0.002
2	0.167	0.010
3	0.165	0.014
4	0.146	0.014
5	0.101	0.017
6	0.0825	0.020
7	0.091	0.024

TABLE II: Values of α(t) and β(t) for various intervals for making the curve fit with the respective data sets.

Figure 7.4

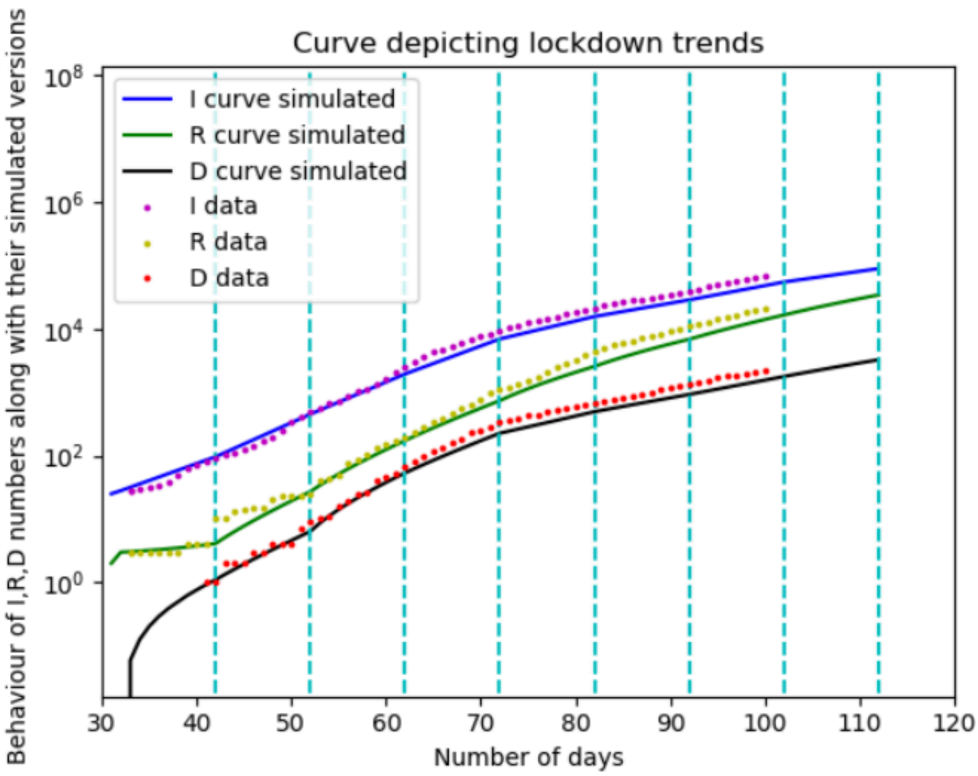


Figure 7.5

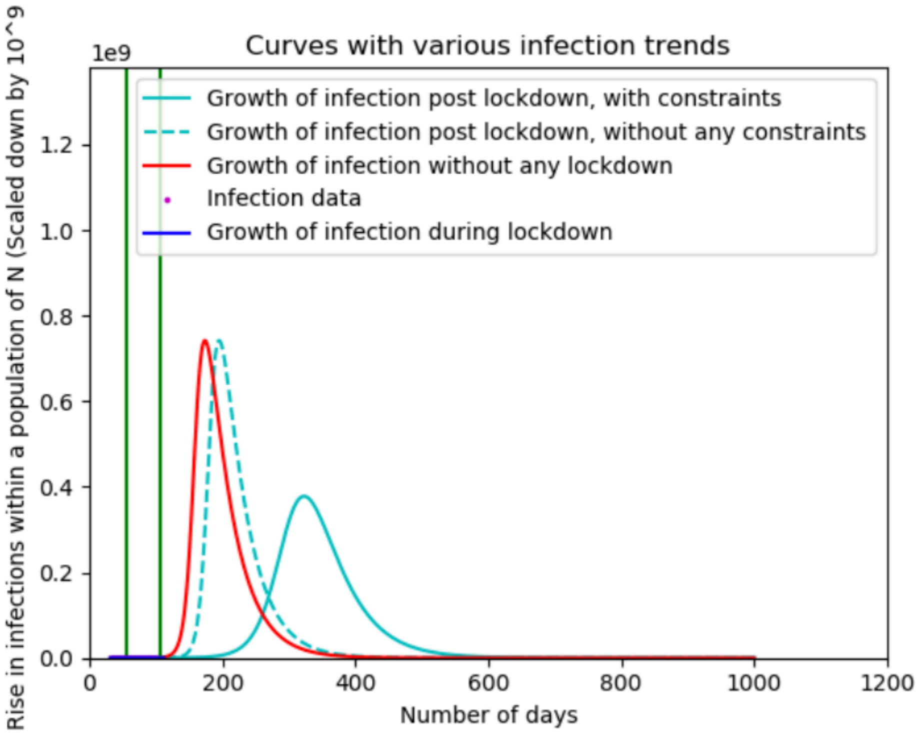


Figure 7.6

The point of all this, is to understand the variety and number of factors that have been taken into consideration for modelling the virus. In addition, each factor that has been used has a vast amount of statistical data that is fed into the computer is computed with no problem because of the capabilities of Qubits and its quantum properties.

The capability of a Qubit existing in a spectrum of values rather than 0 or 1, allows for uncertainty, and allows for the computer to compute different possibilities at once. This combined with the Entanglement property that would allow for creating quantum relationships between Qubits over an infinite distance and reduce the computational power required as they would be considered as one resource. Hence, in the case of predictive algorithms, where there are a lot of external factors that are changing with time and a lot of uncertainties, quantum computers just do a better job than the fuzzy based algorithms.

Fuzzy logic has a similar concept of functioning where the resulting value is not restricted to the certain determined values. However, it has a more focused approach, as it only refers to the application of such logic in terms of the ‘degree of truth’. The problem with this approach for creation of a prediction algorithm is that it has no relation to the computation method, and hence has no effect on the processing power required. It is a type of logic and allows for expression of vague quantities that may not exist in the strict values of “Yes” and “No” or “True” and “False”.

Hence, the approach of creation of prediction algorithms **solely** based on fuzzy logic is inefficient, as the defining factor for judging the efficiency is not considered or solved. The problem being the Computational Power required!

As the scale of the program is increased the complexity increases, and **two observations are made:**

1. Fuzzy Logic based algorithms require more data and factors to increase its accuracy. However, as the factors or data set is increased the computing power required/time required also increases; making it inefficient.

2. Compared to the linear relation of time and complexity of classical computers, as the data set and factors increase exponentially, quantum computers are able to operate more and more efficiently.

The complexity for the two systems can be understood by using the Big O Notation for a Quantum algorithm and a classical computer algorithm – that would represent the fuzzy algorithm.

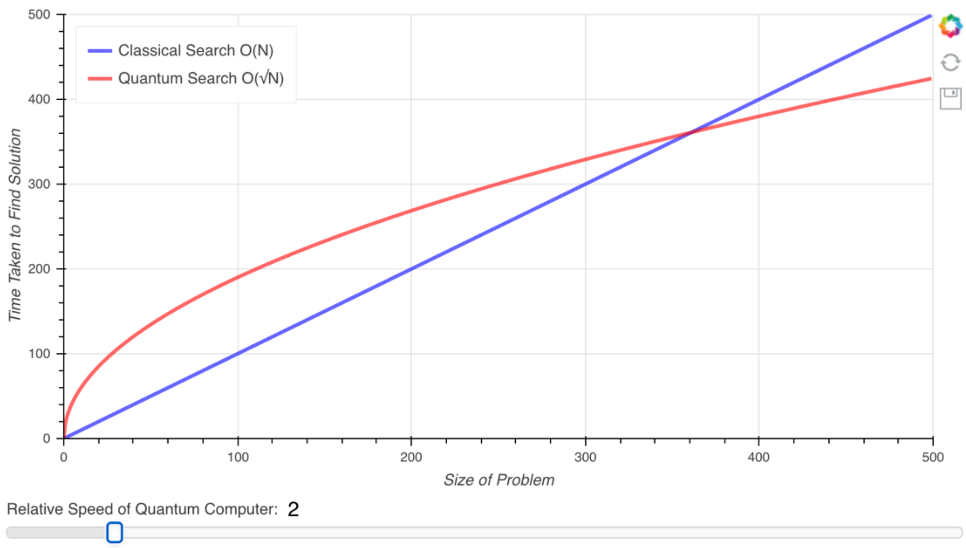


Figure 7.7

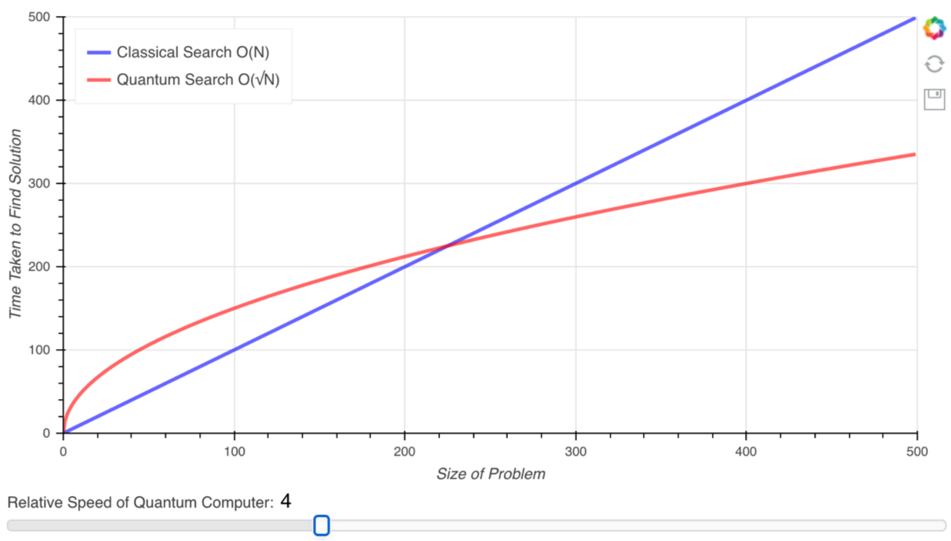


Figure 7.8

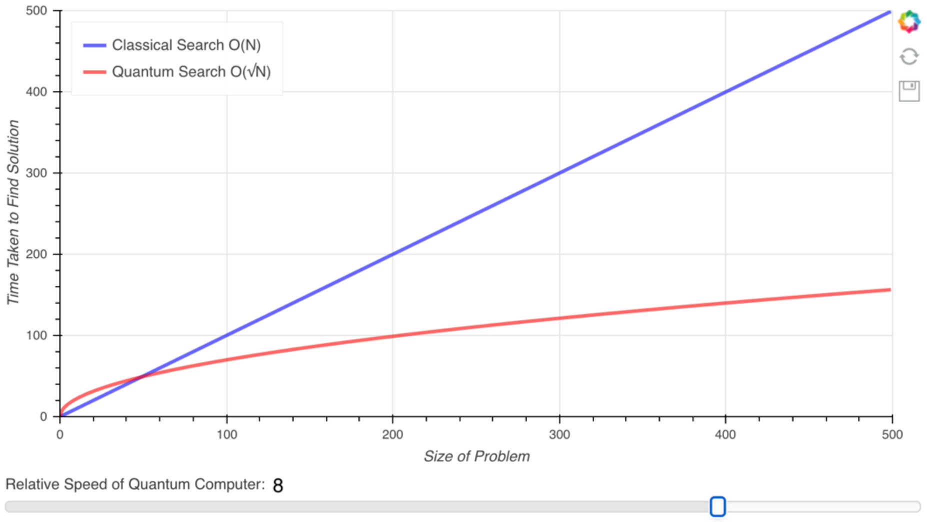


Figure 7.9

[1]Figures 7.7, 7.8 and 7.9 are graphs of the runtime vs the size of the input problem. These figures have taken searching as an example for comparison. The blue line resembles searching in a classical computer, whereas the red line resembles searching in a quantum computer. Figures 7.7, 7.8 and 7.9 consider the relative speed of the quantum computer to be 2 times, 4 times and 8 times faster respectively. However, in all three diagrams it is evident as the size of the problem increases the time taken on a Quantum computer decreases.

This doesn't only apply to searching, it applies to all algorithms such as algebraic problems or basic problem solving. As the scale increases it becomes more and more efficient to solve on a Quantum computer, Shor's algorithm is a prime example of this!

---

[1] The Big O Notation is used to quantify the rate of increase of the runtime as the size of the algorithm is increased.

O(1) resembles constant time, this would signify that it has a constant time complexity that is independent of the size of the data. Every time an operation of O(1) is run, it will take the same amount of time.

O(n) resembles linearity, as the size increases the time complexity increases linearly.

8 Conclusion

Comparing Quantum computing to classical computing is like comparing a light bulb and a candle. Candles cannot be developed into light bulbs. They both are different technologies. Quantum computing having a more scientific approach in its technology. In this case, it’s not even classical computers that it is being compared to, its fuzzy logic.

On the other hand, fuzzy logic based algorithms still require extremely powerful computers to even match the quantum computer’s speed and accuracy. Also as complexity increases, the computational power required increases along with execution time. But, for Quantum Computer’s it gets more efficient at solving the problems in the least steps as the complexity increases.

Therefore, a Quantum approach is not only more efficient, but future-proof and accurate with extensibility capabilities that the fuzzy based algorithm cannot compare to. Fuzzy logic helps in the expression of abstract data such as deliciousness or quality, it has no impact on the processing power as data sets increase in size. It is a form of multi-valued logic, whereas Quantum computing is the solution to these exponentially growing problems.

9 References

(1st reference is the chosen Research Paper for the quantum algorithm)

"Studying the Effect of Lockdown Using Epidemiological Modelling of COVID-19 and a Quantum Computational Approach Using the Ising Spin Interaction." *ResearchGate*, https://www.researchgate.net/publication/342015671_Studying_the_effect_of_lockdown_using_epidemiological_modelling_of_COVID-19_and_a_quantum_computational_approach_using_the_Ising_spin_interaction. Accessed 16 Jan. 2021.

"A Prediction System Based on Fuzzy Logic." *Researchgate*, https://www.researchgate.net/publication/44262408_A_Prediction_System_Based_on_Fuzzy_Logic. Accessed 16 Jan. 2021.

"Atmosphere | Free Full-Text | Influence of Weather on the Behaviour of Tourists in a Beach Destination | HTML." *MDPI*, Multidisciplinary Digital Publishing Institute, https://www.mdpi.com/2073-4433/11/1/121/htm. Accessed 16 Jan. 2021.

Bassan, Tanisha. *Quantum Support Vector Machine Kernel Algorithm*. YouTube, 27 Nov. 2018, https://www.youtube.com/watch?v=u0Q_NcS2a10.

"Build Fuzzy Systems Using Fuzzy Logic Designer- MATLAB & Simulink- MathWorks India." *MathWorks - Makers of MATLAB and Simulink - MATLAB & Simulink*, https://in.mathworks.com/help/fuzzy/building-systems-with-fuzzy-logic-toolbox-software.html. Accessed 16 Jan. 2021.

Coggins, Macauley. “Quantum SVM Machine Learning Tutorial — Quantum Computing UK.” *Quantum Computing UK*, Quantum Computing UK, 1 Apr. 2020, https://quantumcomputinguk.org/tutorials/how-to-implement-qsvm-algorithm-on-ibms-quantum-computers-with-qiskit.

---. “Quantum SVM Machine Learning Tutorial — Quantum Computing UK.” *Quantum Computing UK*, Quantum Computing UK, 1 Apr. 2020, https://quantumcomputinguk.org/tutorials/how-to-implement-qsvm-algorithm-on-ibms-quantum-computers-with-qiskit.

“Comparisons of Performance between Quantum and Classical Machine Learning.” *ScholarSmuEdu*, https://scholar.smu.edu/cgi/viewcontent.cgi?article=1047&context=datasciencereview. Accessed 16 Jan. 2021.

Contributors to Wikimedia projects. “World Tourism Rankings - Wikipedia.” *Wikipedia, the Free Encyclopedia*, Wikimedia Foundation, Inc., 17 Dec. 2007, https://en.wikipedia.org/wiki/World_Tourism_rankings.

“Coronavirus Update (Live): 94,333,913 Cases and 2,018,292 Deaths from COVID-19 Virus Pandemic - Worldometer.” *Worldometer - Real Time World Statistics*, https://www.worldometers.info/coronavirus/?utm_campaign=homeAdvegas1?#countries. Accessed 16 Jan. 2021.

“Cost of Living Around the World in 2020.” *MoveHub*, 5 Nov. 2020, https://www.movehub.com/blog/cost-of-living-worldwide/.

“Crisp Input - an Overview | ScienceDirect Topics.” *ScienceDirect.Com | Science, Health and Medical Journals, Full Text Articles and Books.*, https://www.sciencedirect.com/topics/engineering/crisp-input. Accessed 16 Jan. 2021.

"---." *ScienceDirect.Com | Science, Health and Medical Journals, Full Text Articles and Books.*, https://www.sciencedirect.com/topics/engineering/crisp-input. Accessed 16 Jan. 2021.

"Dynamical Behaviors of Fuzzy SIR Epidemic Model." *Researchgate.Net*, https://www.researchgate.net/publication/319404191_Dynamical_Behaviors_of_Fuzzy_SIR_Epidemic_Model. Accessed 16 Jan. 2021.

"Fuzzy Sets - ScienceDirect." *ScienceDirect.Com | Science, Health and Medical Journals, Full Text Articles and Books.*, https://www.sciencedirect.com/science/article/pii/S001999586590241X. Accessed 16 Jan. 2021.

"IBM Quantum Experience." *IBM Quantum Experience*, https://quantum-computing.ibm.com/. Accessed 16 Jan. 2021.

"International Tourist Arrivals by World Region - Our World in Data." *Our World in Data*, https://ourworldindata.org/grapher/international-tourist-arrivals-by-world-region. Accessed 16 Jan. 2021.

"International Tourist Numbers Could Fall 60-80% in 2020, UNWTO Reports | UNWTO." *Home | UNWTO*, https://www.unwto.org/news/covid-19-international-tourist-numbers-could-fall-60-80-in-2020. Accessed 16 Jan. 2021.

"Membership Function Gallery- MATLAB & Simulink- MathWorks India." *MathWorks - Makers of MATLAB and Simulink - MATLAB & Simulink*, https://in.mathworks.com/help/fuzzy/membership-function-gallery.html. Accessed 16 Jan. 2021.

"Open Rule Editor - MATLAB Ruleedit- MathWorks India." *MathWorks - Makers of MATLAB and Simulink - MATLAB & Simulink*, https://in.mathworks.com/help/fuzzy/ruleedit.html. Accessed 16 Jan. 2021.

“Proposing a New Approach to Implementing Fuzzy Systems: Using Quantum Computational Methods.” *Arxiv*, https://arxiv.org/vc/quant-ph/papers/0210/0210037v1.pdf. Accessed 16 Jan. 2021.

“Quantum Computing for the Qubit Curious - Cosmos Magazine.” *Cosmos Magazine*, https://www.facebook.com/CosmosMagazine/, 5 July 2019, https://cosmosmagazine.com/physics/quantum-computing-for-the-qubit-curious/.

“The Most Visited Country in Every Continent - MyFunkyTravel.” *MyFunkyTravel*, 16 Oct. 2018, https://myfunkytravel.com/most-visited-country-in-every-continent.html.

“The Relationship between Tourism, Financial Development and Economic Growth in India - ScienceDirect.” *ScienceDirect.Com | Science, Health and Medical Journals, Full Text Articles and Books.*, https://www.sciencedirect.com/science/article/pii/S2314721017300063. Accessed 16 Jan. 2021.

“Tourism - Our World in Data.” *Our World in Data*, https://ourworldindata.org/tourism. Accessed 16 Jan. 2021.

“TWJC Combination & Permutation Generator.” *TWJC The Royal Tunbridge Wells Juggling Club*, http://www.twjc.co.uk/combinations.html. Accessed 16 Jan. 2021.

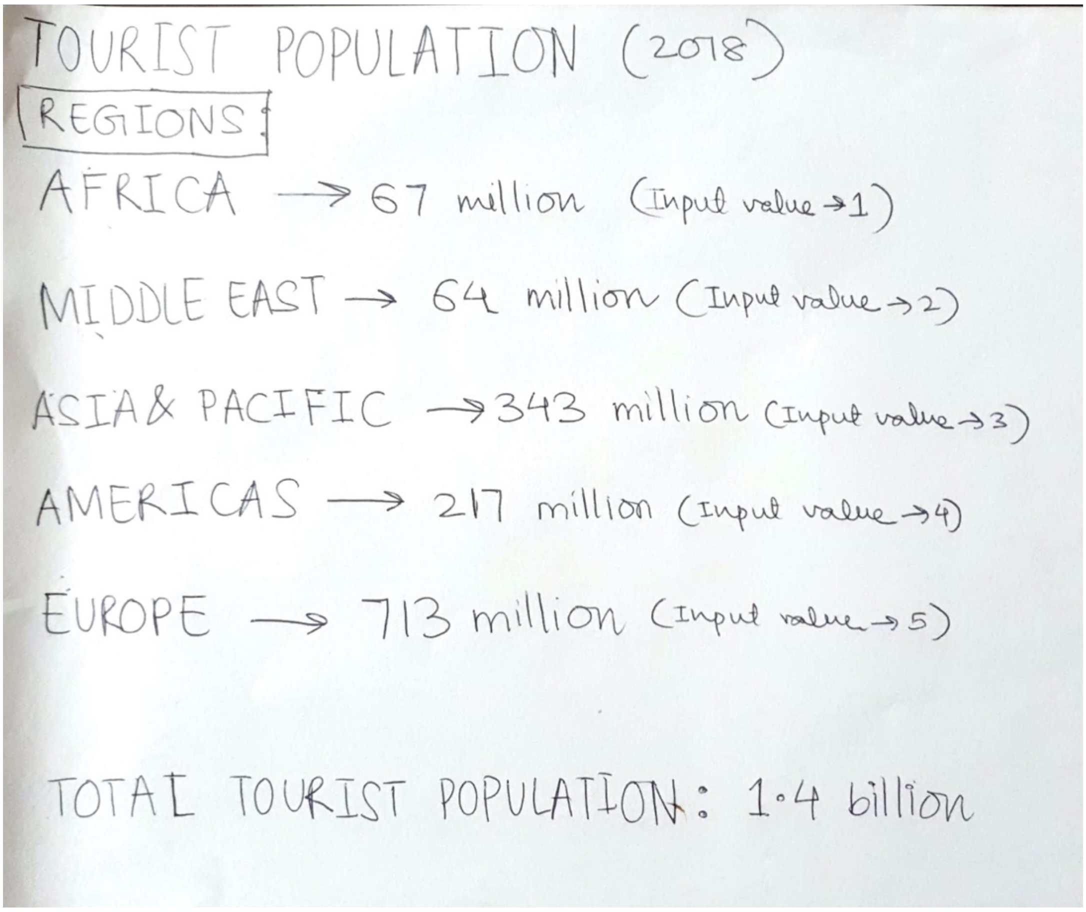
Voorhoede, De. “Superposition and Entanglement.” *Quantum Inspire*, https://www.quantum-inspire.com/kbase/superposition-and-entanglement/. Accessed 16 Jan. 2021.

---. “What Is a Qubit?” *Quantum Inspire*, https://www.quantum-inspire.com/kbase/what-is-a-qubit/. Accessed 16 Jan. 2021.

“What Is ‘Fuzzy Logic’? Are There Computers That Inherently Fuzzy and Do Not Apply the Usual Binary Logic? - Scientific American.” *Scientific American*, Scientific American, https://www.scientificamerican.com/article/what-is-fuzzy-logic-are-t/. Accessed 16 Jan. 2021.

10 Appendix

1. Planning of membership functions and Test Data



TOURIST POPULATION (2018)

REGIONS:

AFRICA → 67 million (Input value → 1)

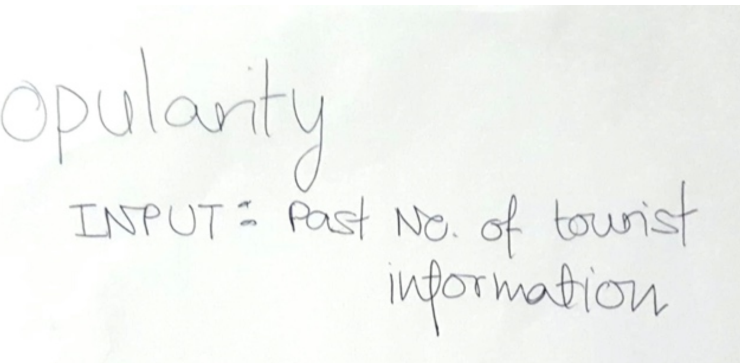
MIDDLE EAST → 64 million (Input value → 2)

ASIA & PACIFIC → 343 million (Input value → 3)

AMERICAS → 217 million (Input value → 4)

EUROPE → 713 million (Input value → 5)

TOTAL TOURIST POPULATION: 1·4 billion



Popularity

INPUT = Past No. of tourist information

CLIMATE

INPUT

1 → Tropical

2 → Dry / Desert

3 → Mediterranean

4 → Continental

5 → Diverse

6 → Temperate

7 → Equatorial

TOTAL COVID CASES (Aug 4 2020)

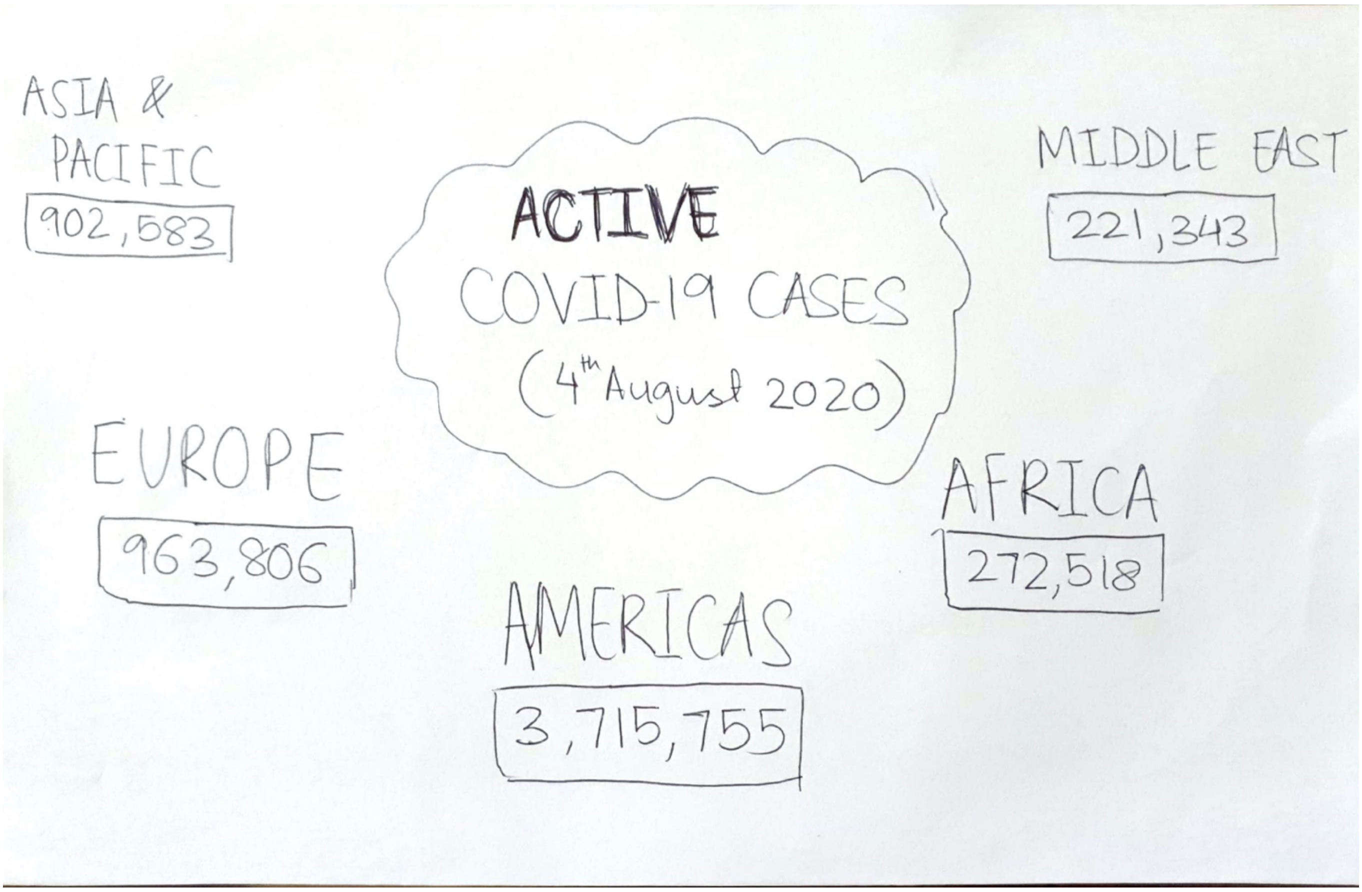
ASIA & PACIFIC → 3249981 → 3·2 million

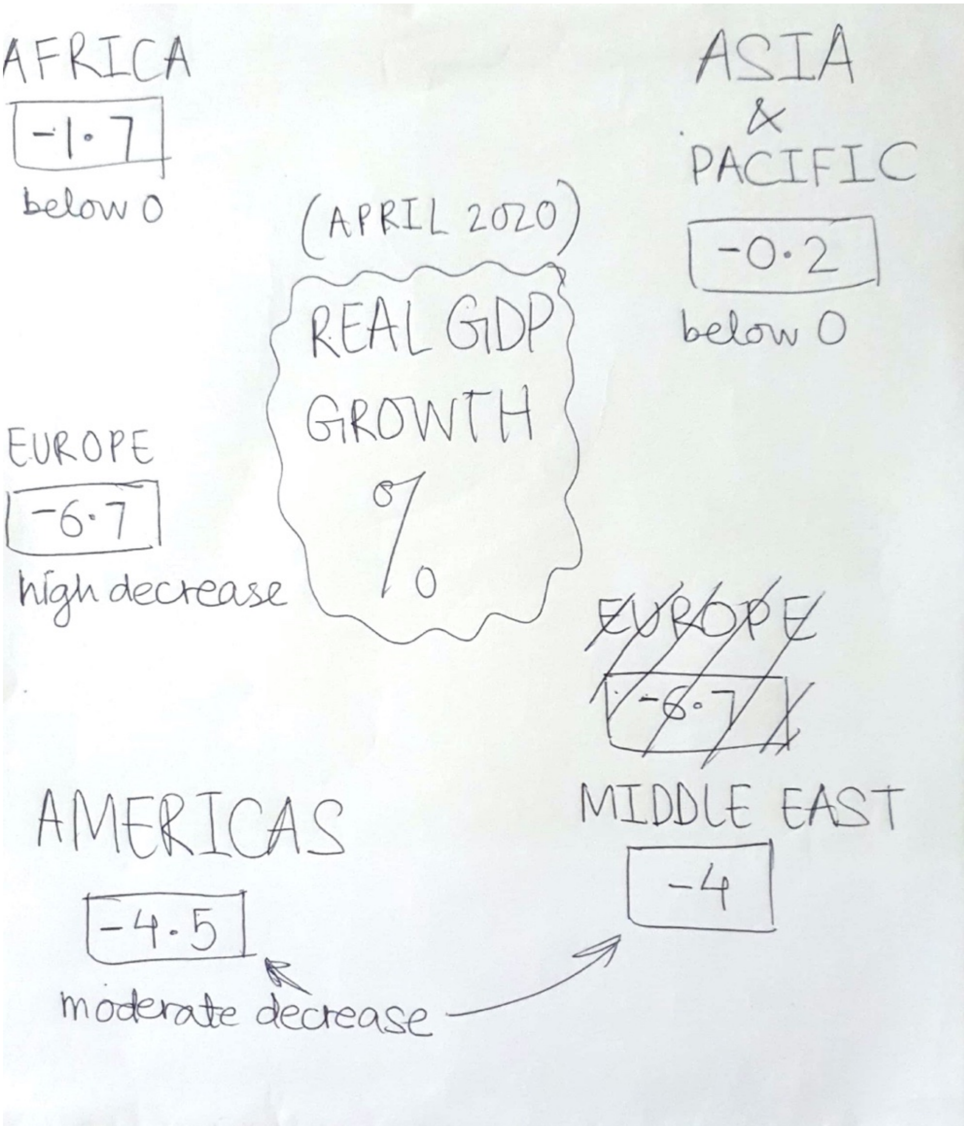
AFRICA → ~~87886~~ 878026

MIDDLE EAST → 1,415,567 → 1·4 million

AMERICAS → 10,002,822 → 10 million (USA is 4·8 million

EUROPE → 2,932,428 → 2·9 million


ACTIVE
COVID-19 CASES
(4th August 2020)
ASIA & PACIFIC
902,583
MIDDLE EAST
221,343
EUROPE
963,806
AFRICA
272,518
AMERICAS
3,715,755


(APRIL 2020)
REAL GDP GROWTH
%
AFRICA
-1.7
below 0
ASIA & PACIFIC
-0.2
below 0
EUROPE
-6.7
high decrease
~~EUROPE~~
~~-6.7~~
AMERICAS
-4.5
MIDDLE EAST
-4
moderate decrease

IN MAY, 57% decrease,

Q1
- JAN
- FEB lockdown just started,
- MAR → -55%

ESTIMATING THERE WON'T BE ANOTHER COVID-19 WAVE

Q2
- APR → -97
- MAY → -98
- June

Q3
- July
- Aug ↗
- Sept ↗ starts rising

June, July, Aug, Sept: LOCKDOWNS START OPENING

Q4
- Oct.
- Nov
- Dec

EUROPE (713 million)

France → Popular, Expensive, Temperate ; 79501

Spain → Popular, Reasonable (low) Expensive ~~Reasonable~~ ~~Expensive~~, Mediterranean;

Italy → Popular, Expensive, Mediterranean; 12474

Turkey → Popular, Cheap, Mediterranean ; 10607

Germany → Popular, Expensive, Temperate ; 8399

United Kingdom → Popular, Expensive, Temperate ;

Austria → Popular, Expensive; Temperate ; 1604

Greece → Popular; (low) Expensive ~~Cheap~~, Reasonable ~~Continental~~ Mediterranean; 3154

Russia → Popular, Cheap, continental ; 185601

Portugal → Popular, Reasonable, Temperate ; 12720

ASIA & PACIFIC (343 million)

China → Popular, Cheap, ~~Diverse Tropical~~ Diverse ; 800

Thailand → Popular, Reasonable, Tropical ; 121

Japan → Popular, Expensive, Temperate ; 11,188

Hong Kong → Popular, Expensive, Tropical ; 1,488

Malaysia → Popular, Cheap, Equatorial ; ~~123~~ 193

Macau → Popular, Expensive, Tropical ; 0

India → Popular, Cheap, ~~Trop Diverse Tropical~~ Diverse ; 589,663

Vietnam → Popular, Cheap, Tropical ; 288

South Korea → Popular, Reasonable, Temperate ; 770

Singapore → Popular, Expensive, ~~Tropical~~ Equatorial ; 6140

(Australia → Popular, Expensive, Tropical ; 7876) ~~Equatorial~~

AMERICAS (217 million)

USA → Popular, Expensive, Temperate ; 2,255,250

Mexico → Popular, Cheap, Tropical ; 100,124

Canada → Popular, Expensive, ~~Diverse~~ Continental ; 6487

Argentina → Popular, Reasonable, Temperate ; 111,628

Brazil → Popular, Reasonable, Tropical ; 744,644

Dominican Republic → well known, Reasonable, Tropical ; 33,110

Chile → well known, Reasonable, ~~Diverse~~ Mediterranean ; 17,810

Cuba → well known, Reasonable, Tropical ; 210

Peru → well known, Cheap, Dry ; 115,198

Colombia → well known, Reasonable, Tropical ; 143,106

AFRICA (67 million)

Popularity

~~POPULAR~~

Morocco → ~~low C.O.L~~ cheap ; Tropical ; 6827

~~Egypt~~ → Popular

South Africa → Reasonable ~~C.O.L~~ , Mediterranean ; 150,286

Tunisia → ~~Popular~~ well known , ~~low C.O.L~~ cheap , Mediterranean ; 289

Algeria → well known , ~~low C.O.L~~ cheap , Mediterranean ; 8832

Zimbabwe → well known , Reasonable, Temperate ; 2938

Ivory Coast → ~~Well known~~ Isolated, Dry, Cheap ; 4231

Botswana → Isolated , Reasonable, Dry ; 739

Namibia → Isolated , ~~low C.O.L~~ Cheap , Dry ; 2207

Mozambique → Isolated, Reasonable, Tropical ; 1283

MIDDLE EAST (64 million)

Saudi Arabia → Popular, Reasonable, ~~Desert~~ Dry ; 35,089

(UAE) United Arab Emirates → Popular, Expensive, ~~Dry desert~~ Dry ; 5,911

Egypt → Popular, cheap, ~~Dry Desert~~ Dry ; 45,686

Iran → Popular, ~~low C.O.L cheap~~ Cheap , Dry ; 24,634

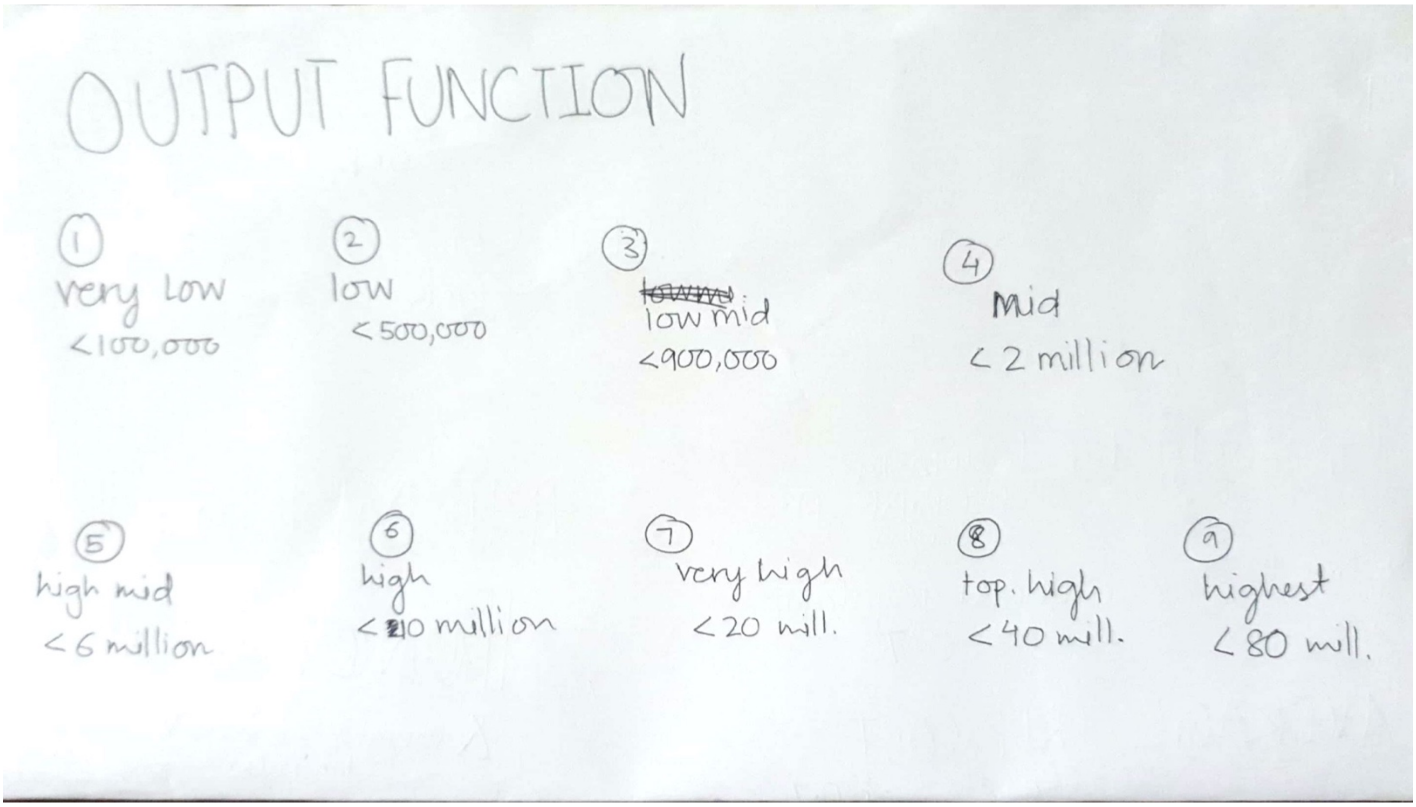
Bahrain → well known, Reasonable , Dry ; 2,678

Jordan → well known , Reasonable, Dry ; 76

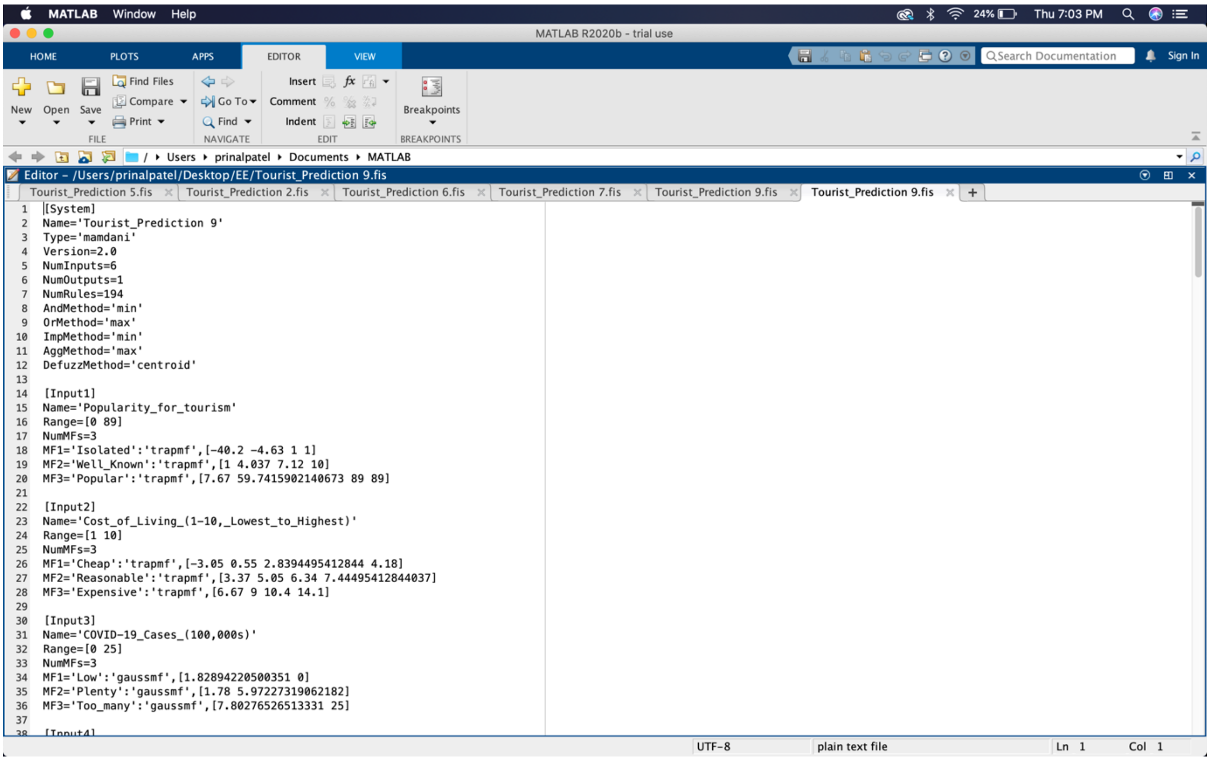
Israel → well known , Expensive, Mediterranean ; 24,766

Oman → ~~well known Isolated~~ Well know , Reasonable, Dry ; 17,317

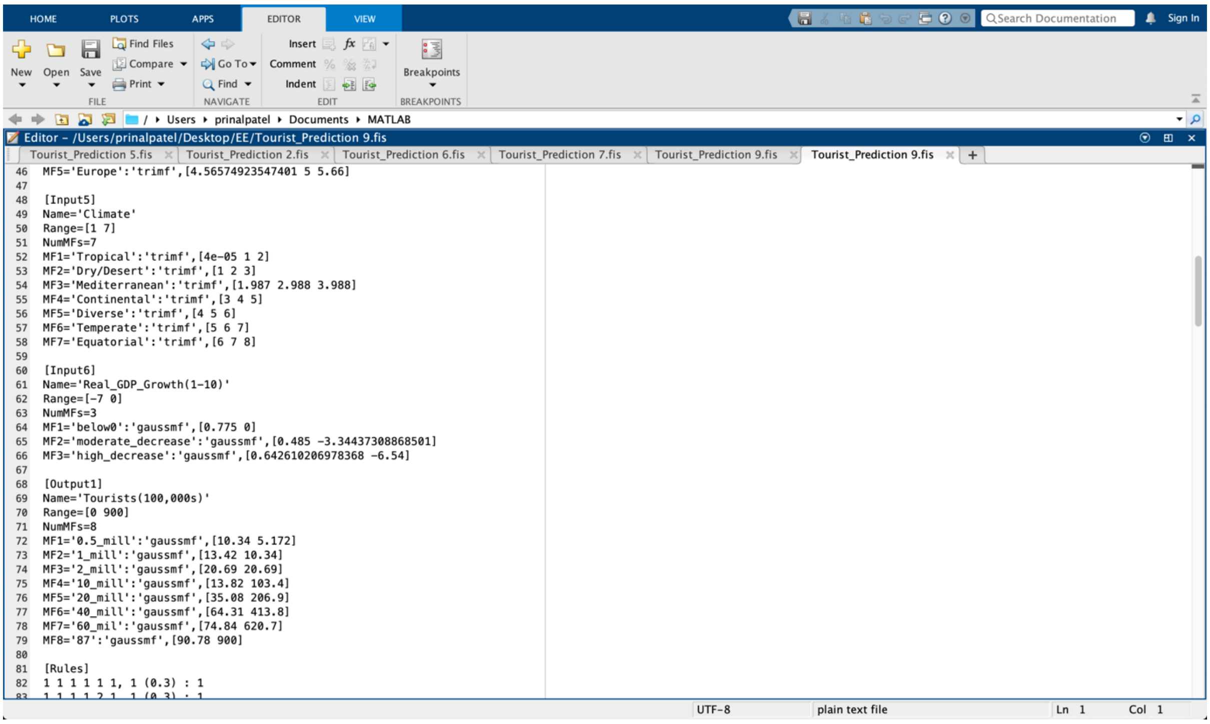
Qatar → ~~Well known Is~~ well known , Expensive , Dry ; 3143



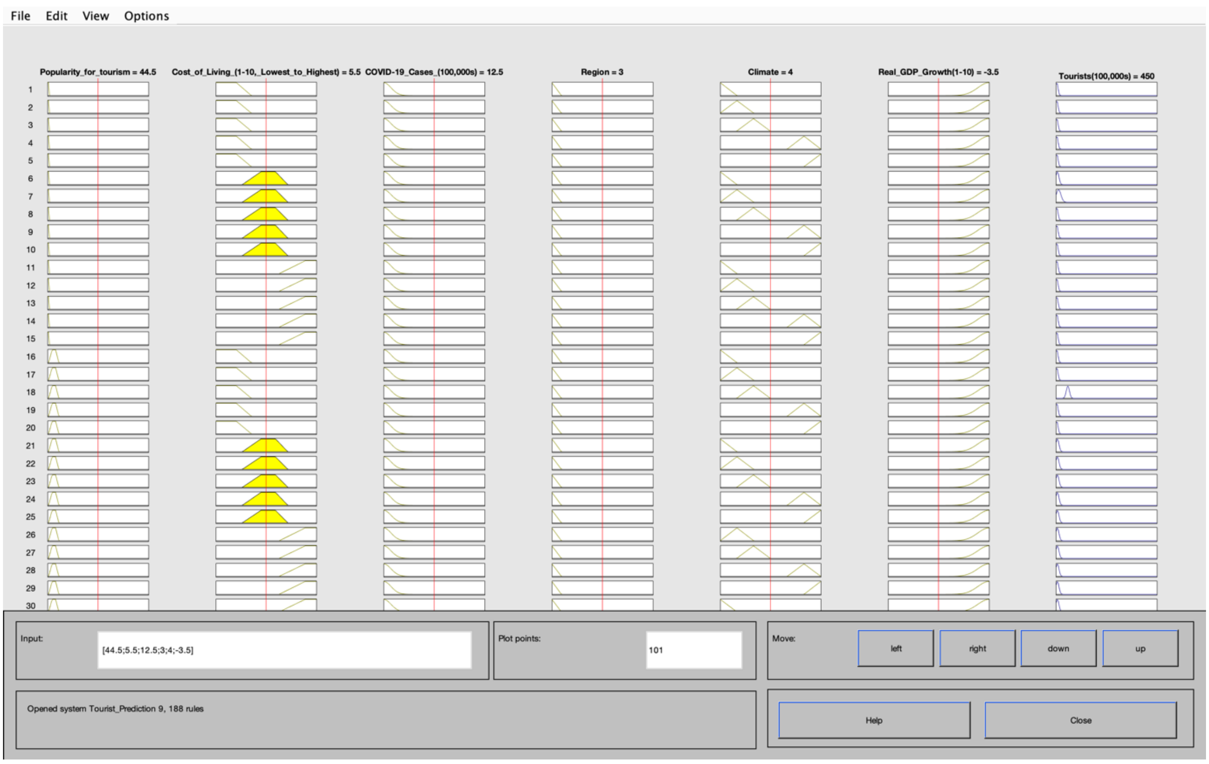
2. Preview of source code in Text Editor




```
[System]
Name='Tourist_Prediction 9'
Type='mamdani'
Version=2.0
NumInputs=6
NumOutputs=1
NumRules=194
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='centroid'

[Input1]
Name='Popularity_for_tourism'
Range=[0 89]
NumMFs=3
MF1='Isolated':'trapmf',[-40.2 -4.63 1 1]
MF2='Well_Known':'trapmf',[1 4.037 7.12 10]
MF3='Popular':'trapmf',[7.67 59.7415902140673 89 89]

[Input2]
Name='Cost_of_Living_(1-10,_Lowest_to_Highest)'
Range=[1 10]
NumMFs=3
MF1='Cheap':'trapmf',[-3.05 0.55 2.8394495412844 4.18]
MF2='Reasonable':'trapmf',[3.37 5.05 6.34 7.44495412844037]
MF3='Expensive':'trapmf',[6.67 9 10.4 14.1]

[Input3]
Name='COVID-19_Cases_(100,000s)'
Range=[0 25]
NumMFs=3
MF1='Low':'gaussmf',[1.82894220500351 0]
MF2='Plenty':'gaussmf',[1.78 5.97227319062182]
MF3='Too_many':'gaussmf',[7.80276526513331 25]

[Input4]
```



3. Rule Viewer



4. All possible rule conditions (about 50 were actually inputted with its expected output pre-determined – the highlighted ones)

AFRICA

1. Africa, Isolated, Cheap , Low , Tropical , Below 0
2. Africa, Isolated, Cheap , Low , Dry/Desert, Below 0
3. Africa, Isolated, Cheap , Low , Mediterranean, Below 0
4. Africa, Isolated, Cheap , Low , Temperate , Below 0
5. Africa, Isolated, Cheap , Low , Equatorial, Below 0
6. Africa, Isolated, Reasonable, Low , Tropical , Below 0 → 1 mill (0.75) Zimbabwe
7. Africa, Isolated, Reasonable, Low , Dry/Desert, Below 0 → 2 mill (0.5) Botswana, Namibia
8. Africa, Isolated, Reasonable, Low , Mediterranean, Below 0
9. Africa, Isolated, Reasonable, Low , Temperate , Below 0
10. Africa, Isolated, Reasonable, Low , Equatorial, Below 0
11. Africa, Isolated, Expensive, Low , Tropical , Below 0
12. Africa, Isolated, Expensive, Low , Dry/Desert, Below 0 → 0.5 mill (0.3) Djibouti
13. Africa, Isolated, Expensive, Low , Mediterranean, Below 0
14. Africa, Isolated, Expensive, Low , Temperate , Below 0
15. Africa, Isolated, Expensive, Low , Equatorial, Below 0
16. Africa, Well-Known, Cheap , Low , Tropical , Below 0
17. Africa, Well-Known, Cheap , Low , Dry/Desert, Below 0
18. Africa, Well-Known, Cheap , Low , Mediterranean, Below 0 →10 mill (0.60) Tunisia,Algeria

19. Africa, Well-Known, Cheap , Low , Temperate , Below 0
20. Africa, Well-Known, Cheap , Low , Equatorial, Below 0
21. Africa, Well-Known, Reasonable, Low , Tropical , Below 0
22. Africa, Well-Known, Reasonable, Low , Dry/Desert, Below 0
23. Africa, Well-Known, Reasonable, Low , Mediterranean, Below 0
24. Africa, Well-Known, Reasonable, Low , Temperate , Below 0
25. Africa, Well-Known, Reasonable, Low , Equatorial, Below 0
26. Africa, Well-Known, Expensive, Low , Dry/Desert, Below 0
27. Africa, Well-Known, Expensive, Low , Mediterranean, Below 0
28. Africa, Well-Known, Expensive, Low , Temperate , Below 0
29. Africa, Well-Known, Expensive, Low , Equatorial, Below 0
30. Africa, Popular , Cheap , Low , Tropical , Below 0 → 20 million (0.5) Morocco
31. Africa, Popular , Cheap , Low , Dry/Desert, Below 0
32. Africa, Popular , Cheap , Low , Mediterranean, Below 0
33. Africa, Popular , Cheap , Low , Temperate , Below 0
34. Africa, Popular , Cheap , Low , Equatorial, Below 0
35. Africa, Popular , Reasonable, Low , Tropical , Below 0
36. Africa, Popular , Reasonable, Low , Dry/Desert, Below 0
37. Africa, Popular , Reasonable, Low , Mediterranean, Below 0 → 10 mill (0.75) South Africa
38. Africa, Popular , Reasonable, Low , Temperate , Below 0
39. Africa, Popular , Reasonable, Low , Equatorial, Below 0
40. Africa, Well Known , Expensive, Low , Tropical , Below 0 → 1 mill (1) Zambia
41. Africa, Popular , Expensive, Low , Dry/Desert, Below 0
42. Africa, Popular , Expensive, Low , Mediterranean, Below 0

43. Africa, Popular , Expensive, Low , Temperate , Below 0

44. Africa, Popular , Expensive, Low , Equatorial, Below 0

Middle East

- Middle East, Isolated, Cheap , Low , Dry/Desert, Moderate decrease → 0.5 mill (0.5) Tajikistan
- Middle East, Isolated, Cheap , Low , Mediterranean, Moderate decrease
- Middle East, Isolated, Cheap , Low , Temperate , Moderate decrease
- Middle East, Isolated, Cheap , Low , Equatorial, Moderate decrease
- Middle East, Isolated, Reasonable, Low , Dry/Desert, Moderate decrease
- Middle East, Isolated, Reasonable, Low , Mediterranean, Moderate decrease
- Middle East, Isolated, Reasonable, Low , Temperate , Moderate decrease
- Middle East, Isolated, Reasonable, Low , Equatorial, Moderate decrease
- Middle East, Isolated, Expensive, Low , Dry/Desert, Moderate decrease
- Middle East, Isolated, Expensive, Low , Mediterranean, Moderate decrease
- Middle East, Isolated, Expensive, Low , Temperate , Moderate decrease
- Middle East, Isolated, Expensive, Low , Equatorial, Moderate decrease
- Middle East, Well-Known, Cheap , Low , Dry/Desert, Moderate decrease
- Middle East, Well-Known, Cheap , Low , Mediterranean, Moderate decrease
- Middle East, Well-Known, Cheap , Low , Temperate , Moderate decrease
- Middle East, Well-Known, Cheap , Low , Equatorial, Moderate decrease
- Middle East, Well-Known, Reasonable, Low , Dry/Desert, Moderate decrease → 10 mill (0.4) Bahrain, Jordan

- Middle East, Well-Known, Reasonable, Low , Mediterranean, Moderate decrease
- Middle East, Well-Known, Reasonable, Low , Temperate , Moderate decrease
- Middle East, Well-Known, Reasonable, Low , Equatorial, Moderate decrease
- Middle East, Well-Known, Expensive, Low , Dry/Desert, Moderate decrease → 2 mill (0.9) Qatar
- Middle East, Well-Known, Expensive, Low , Mediterranean, Moderate decrease → 10 mill (0.4) Israel
- Middle East, Well-Known, Expensive, Low , Temperate , Moderate decrease → 1 mill (0.8)
- Middle East, Well-Known, Expensive, Low , Equatorial, Moderate decrease
- Middle East, Popular , Cheap , Low , Dry/Desert, Moderate decrease → 10 mill (1) Egypt
- Middle East, Popular , Cheap , Low , Mediterranean, Moderate decrease
- Middle East, Popular , Cheap , Low , Temperate , Moderate decrease
- Middle East, Popular , Cheap , Low , Equatorial, Moderate decrease
- Middle East, Popular , Reasonable, Low , Dry/Desert, Moderate decrease → 20 mill (0.75) Saudi Arabia
- Middle East, Popular , Reasonable, Low , Mediterranean, Moderate decrease
- Middle East, Popular , Reasonable, Low , Temperate , Moderate decrease
- Middle East, Popular , Reasonable, Low , Equatorial, Moderate decrease
- Middle East, Popular , Expensive, Low , Dry/Desert, Moderate decrease → 20 mill (0.75) UAE
- Middle East, Popular , Expensive, Low , Mediterranean, Moderate decrease
- Middle East, Popular , Expensive, Low , Temperate , Moderate decrease

- Middle East, Popular , Expensive, Low , Equatorial, Moderate decrease

Asia & Pacific

- Asia & Pacific , Isolated, Cheap , Low , Tropical , Below 0
- Asia & Pacific , Isolated, Cheap , Low , Dry/Desert, Below 0
- Asia & Pacific , Isolated, Cheap , Low , Mediterranean, Below 0
- Asia & Pacific , Isolated, Cheap , Low , Continental, Below 0 → 0.5 mill (0.9) Mongolia
- Asia & Pacific , Isolated, Cheap , Low , Diverse, Below 0
- Asia & Pacific , Isolated, Cheap , Low , Temperate , Below 0
- Asia & Pacific , Isolated, Cheap , Low , Equatorial, Below 0
- Asia & Pacific , Isolated, Cheap , Plenty, Tropical , Below 0
- Asia & Pacific , Isolated, Cheap , Plenty, Dry/Desert, Below 0
- Asia & Pacific , Isolated, Cheap , Plenty, Mediterranean, Below 0
- Asia & Pacific , Isolated, Cheap , Plenty, Continental, Below 0
- Asia & Pacific , Isolated, Cheap , Plenty, Diverse, Below 0
- Asia & Pacific , Isolated, Cheap , Plenty, Temperate , Below 0
- Asia & Pacific , Isolated, Cheap , Plenty, Equatorial, Below 0
- Asia & Pacific , Isolated, Reasonable, Low , Tropical , Below 0
- Asia & Pacific , Isolated, Reasonable, Low , Dry/Desert, Below 0
- Asia & Pacific , Isolated, Reasonable, Low , Mediterranean, Below 0
- Asia & Pacific , Isolated, Reasonable, Low , Continental, Below 0
- Asia & Pacific , Isolated, Reasonable, Low , Diverse, Below 0
- Asia & Pacific , Isolated, Reasonable, Low , Temperate , Below 0

- Asia & Pacific , Isolated, Reasonable, Low , Equatorial, Below 0
- Asia & Pacific , Isolated, Reasonable, Plenty, Tropical , Below 0
- Asia & Pacific , Isolated, Reasonable, Plenty, Dry/Desert, Below 0
- Asia & Pacific , Isolated, Reasonable, Plenty, Mediterranean, Below 0
- Asia & Pacific , Isolated, Reasonable, Plenty, Continental, Below 0
- Asia & Pacific , Isolated, Reasonable, Plenty, Diverse, Below 0
- Asia & Pacific , Isolated, Reasonable, Plenty, Temperate , Below 0
- Asia & Pacific , Isolated, Reasonable, Plenty, Equatorial, Below 0
- Asia & Pacific , Isolated, Expensive, Low , Tropical , Below 0 → 0.5 mill (0.4) Bhutan
- Asia & Pacific , Isolated, Expensive, Low , Dry/Desert, Below 0
- Asia & Pacific , Isolated, Expensive, Low , Mediterranean, Below 0
- Asia & Pacific , Isolated, Expensive, Low , Continental, Below 0
- Asia & Pacific , Isolated, Expensive, Low , Diverse, Below 0
- Asia & Pacific , Isolated, Expensive, Low , Temperate , Below 0 → 0.5 mill (0.005) Tuvalu
- Asia & Pacific , Isolated, Expensive, Low , Equatorial, Below 0
- Asia & Pacific , Isolated, Expensive, Plenty, Tropical , Below 0
- Asia & Pacific , Isolated, Expensive, Plenty, Dry/Desert, Below 0
- Asia & Pacific , Isolated, Expensive, Plenty, Mediterranean, Below 0
- Asia & Pacific , Isolated, Expensive, Plenty, Continental, Below 0
- Asia & Pacific , Isolated, Expensive, Plenty, Diverse, Below 0
- Asia & Pacific , Isolated, Expensive, Plenty, Temperate , Below 0
- Asia & Pacific , Isolated, Expensive, Plenty, Equatorial, Below 0

- Asia & Pacific , Well-Known, Cheap , Low , Tropical , Below 0 →10 mill (0.3)

  Philippines, Laos
- Asia & Pacific , Well-Known, Cheap , Low , Dry/Desert, Below 0
- Asia & Pacific , Well-Known, Cheap , Low , Mediterranean, Below 0
- Asia & Pacific , Well-Known, Cheap , Low , Continental, Below 0
- Asia & Pacific , Well-Known, Cheap , Low , Diverse, Below 0
- Asia & Pacific , Well-Known, Cheap , Low , Temperate , Below 0
- Asia & Pacific , Well-Known, Cheap , Low , Equatorial, Below 0
- Asia & Pacific , Well-Known, Cheap , Plenty, Tropical , Below 0
- Asia & Pacific , Well-Known, Cheap , Plenty, Dry/Desert, Below 0
- Asia & Pacific , Well-Known, Cheap , Plenty, Mediterranean, Below 0
- Asia & Pacific , Well-Known, Cheap , Plenty, Continental, Below 0
- Asia & Pacific , Well-Known, Cheap , Plenty, Diverse, Below 0
- Asia & Pacific , Well-Known, Cheap , Plenty, Temperate , Below 0
- Asia & Pacific , Well-Known, Cheap , Plenty, Equatorial, Below 0
- Asia & Pacific , Well-Known, Reasonable, Low , Tropical , Below 0
- Asia & Pacific , Well-Known, Reasonable, Low , Dry/Desert, Below 0
- Asia & Pacific , Well-Known, Reasonable, Low , Mediterranean, Below 0
- Asia & Pacific , Well-Known, Reasonable, Low , Continental, Below 0
- Asia & Pacific , Well-Known, Reasonable, Low , Diverse, Below 0
- Asia & Pacific , Well-Known, Reasonable, Low , Temperate , Below 0
- Asia & Pacific , Well-Known, Reasonable, Low , Equatorial, Below 0
- Asia & Pacific , Well-Known, Reasonable, Plenty, Tropical , Below 0
- Asia & Pacific , Well-Known, Reasonable, Plenty, Dry/Desert, Below 0
- Asia & Pacific , Well-Known, Reasonable, Plenty, Mediterranean, Below 0

- Asia & Pacific , Well-Known, Reasonable, Plenty, Continental, Below 0
- Asia & Pacific , Well-Known, Reasonable, Plenty, Diverse, Below 0
- Asia & Pacific , Well-Known, Reasonable, Plenty, Temperate , Below 0
- Asia & Pacific , Well-Known, Reasonable, Plenty, Equatorial, Below 0
- Asia & Pacific , Well-Known, Expensive, Low , Tropical , Below 0 → 1 mill (0.7) Fiji
- Asia & Pacific , Well-Known, Expensive, Low , Dry/Desert, Below 0
- Asia & Pacific , Well-Known, Expensive, Low , Mediterranean, Below 0
- Asia & Pacific , Well-Known, Expensive, Low , Continental, Below 0
- Asia & Pacific , Well-Known, Expensive, Low , Diverse, Below 0
- Asia & Pacific , Well-Known, Expensive, Low , Temperate , Below 0
- Asia & Pacific , Well-Known, Expensive, Low , Equatorial, Below 0
- Asia & Pacific , Well-Known, Expensive, Plenty, Tropical , Below 0
- Asia & Pacific , Well-Known, Expensive, Plenty, Dry/Desert, Below 0
- Asia & Pacific , Well-Known, Expensive, Plenty, Mediterranean, Below 0
- Asia & Pacific , Well-Known, Expensive, Plenty, Continental, Below 0
- Asia & Pacific , Well-Known, Expensive, Plenty, Diverse, Below 0
- Asia & Pacific , Well-Known, Expensive, Plenty, Temperate , Below 0
- Asia & Pacific , Well-Known, Expensive, Plenty, Equatorial, Below 0
- Asia & Pacific , Popular , Cheap , Low , Tropical , Below 0 → 20 mill (0.7) Vietnam
- Asia & Pacific , Popular , Cheap , Low , Dry/Desert, Below 0
- Asia & Pacific , Popular , Cheap , Low , Mediterranean, Below 0
- Asia & Pacific , Popular , Cheap , Low , Continental, Below 0
- Asia & Pacific , Popular , Cheap , Low , Diverse, Below 0 →60 mill (0.7) China

- Asia & Pacific , Popular , Cheap , Low , Temperate , Below 0
- Asia & Pacific , Popular , Cheap , Low , Equatorial, Below 0 → 40 mill (0.5) Malaysia
- Asia & Pacific , Popular , Cheap , Plenty, Tropical , Below 0
- Asia & Pacific , Popular , Cheap , Plenty, Dry/Desert, Below 0
- Asia & Pacific , Popular , Cheap , Plenty, Mediterranean, Below 0
- Asia & Pacific , Popular , Cheap , Plenty, Continental, Below 0
- Asia & Pacific , Popular , Cheap , Plenty, Diverse, Below 0 → 20 mill (0.7) India
- Asia & Pacific , Popular , Cheap , Plenty, Temperate , Below 0
- Asia & Pacific , Popular , Cheap , Plenty, Equatorial, Below 0
- Asia & Pacific , Popular , Reasonable, Low , Tropical , Below 0 → 40 mill (0.7) Thailand
- Asia & Pacific , Popular , Reasonable, Low , Dry/Desert, Below 0
- Asia & Pacific , Popular , Reasonable, Low , Mediterranean, Below 0
- Asia & Pacific , Popular , Reasonable, Low , Continental, Below 0
- Asia & Pacific , Popular , Reasonable, Low , Diverse, Below 0
- Asia & Pacific , Popular , Reasonable, Low , Temperate , Below 0 → 20 mill (0.7) South Korea
- Asia & Pacific , Popular , Reasonable, Low , Equatorial, Below 0
- Asia & Pacific , Popular , Reasonable, Plenty, Tropical , Below 0
- Asia & Pacific , Popular , Reasonable, Plenty, Dry/Desert, Below 0
- Asia & Pacific , Popular , Reasonable, Plenty, Mediterranean, Below 0
- Asia & Pacific , Popular , Reasonable, Plenty, Continental, Below 0
- Asia & Pacific , Popular , Reasonable, Plenty, Diverse, Below 0

- Asia & Pacific , Popular , Reasonable, Plenty, Temperate , Below 0
- Asia & Pacific , Popular , Reasonable, Plenty, Equatorial, Below 0
- Asia & Pacific , Popular , Expensive, Low , Tropical , Below 0 → 40 mill (0.6) Hong Kong
- Asia & Pacific , Popular , Expensive, Low , Dry/Desert, Below 0
- Asia & Pacific , Popular , Expensive, Low , Mediterranean, Below 0
- Asia & Pacific , Popular , Expensive, Low , Continental, Below 0
- Asia & Pacific , Popular , Expensive, Low , Diverse, Below 0
- Asia & Pacific , Popular , Expensive, Low , Temperate , Below 0→ 40 mill (0.6) Japan
- Asia & Pacific , Popular , Expensive, Low , Equatorial, Below 0 → 20 mill (0.7) Singapore
- Asia & Pacific , Popular , Expensive, Plenty, Tropical , Below 0
- Asia & Pacific , Popular , Expensive, Plenty, Dry/Desert, Below 0
- Asia & Pacific , Popular , Expensive, Plenty, Mediterranean, Below 0
- Asia & Pacific , Popular , Expensive, Plenty, Continental, Below 0
- Asia & Pacific , Popular , Expensive, Plenty, Diverse, Below 0
- Asia & Pacific , Popular , Expensive, Plenty, Temperate , Below 0
- Asia & Pacific , Popular , Expensive, Plenty, Equatorial, Below 0

Americas

- Americas, Isolated, Cheap , Low , Tropical , Moderate decrease → 0.5 mill (0.4) Suriname
- Americas, Isolated, Cheap , Low , Dry/Desert, Moderate decrease

- Americas, Isolated, Cheap , Low , Mediterranean, Moderate decrease
- Americas, Isolated, Cheap , Low , Temperate , Moderate decrease
- Americas, Isolated, Cheap , Low , Equatorial, Moderate decrease
- Americas, Isolated, Cheap , Plenty, Tropical , Moderate decrease
- Americas, Isolated, Cheap , Plenty, Dry/Desert, Moderate decrease
- Americas, Isolated, Cheap , Plenty, Mediterranean, Moderate decrease
- Americas, Isolated, Cheap , Plenty, Temperate , Moderate decrease
- Americas, Isolated, Cheap , Plenty, Equatorial, Moderate decrease
- Americas, Isolated, Cheap , Too Many, Tropical , Moderate decrease
- Americas, Isolated, Cheap , Too Many, Dry/Desert, Moderate decrease
- Americas, Isolated, Cheap , Too Many, Mediterranean, Moderate decrease
- Americas, Isolated, Cheap , Too Many, Temperate , Moderate decrease
- Americas, Isolated, Cheap , Too Many, Equatorial, Moderate decrease
- Americas, Isolated, Reasonable, Low , Tropical , Moderate decrease
- Americas, Isolated, Reasonable, Low , Dry/Desert, Moderate decrease
- Americas, Isolated, Reasonable, Low , Mediterranean, Moderate decrease
- Americas, Isolated, Reasonable, Low , Temperate , Moderate decrease
- Americas, Isolated, Reasonable, Low , Equatorial, Moderate decrease
- Americas, Isolated, Reasonable, Plenty, Tropical , Moderate decrease
- Americas, Isolated, Reasonable, Plenty, Dry/Desert, Moderate decrease
- Americas, Isolated, Reasonable, Plenty, Mediterranean, Moderate decrease
- Americas, Isolated, Reasonable, Plenty, Temperate , Moderate decrease
- Americas, Isolated, Reasonable, Plenty, Equatorial, Moderate decrease
- Americas, Isolated, Reasonable, Too Many, Tropical , Moderate decrease
- Americas, Isolated, Reasonable, Too Many, Dry/Desert, Moderate decrease

- Americas, Isolated, Reasonable, Too Many, Mediterranean, Moderate decrease
- Americas, Isolated, Reasonable, Too Many, Temperate , Moderate decrease
- Americas, Isolated, Reasonable, Too Many, Equatorial, Moderate decrease
- Americas, Isolated, Expensive, Low , Tropical , Moderate decrease → 0.5 mill (0.5) Guyana
- Americas, Isolated, Expensive, Low , Dry/Desert, Moderate decrease
- Americas, Isolated, Expensive, Low , Mediterranean, Moderate decrease
- Americas, Isolated, Expensive, Low , Temperate , Moderate decrease
- Americas, Isolated, Expensive, Low , Equatorial, Moderate decrease
- Americas, Isolated, Expensive, Plenty, Tropical , Moderate decrease
- Americas, Isolated, Expensive, Plenty, Dry/Desert, Moderate decrease
- Americas, Isolated, Expensive, Plenty, Mediterranean, Moderate decrease
- Americas, Isolated, Expensive, Plenty, Temperate , Moderate decrease
- Americas, Isolated, Expensive, Plenty, Equatorial, Moderate decrease
- Americas, Isolated, Expensive, Too Many, Tropical , Moderate decrease
- Americas, Isolated, Expensive, Too Many, Dry/Desert, Moderate decrease
- Americas, Isolated, Expensive, Too Many, Mediterranean, Moderate decrease
- Americas, Isolated, Expensive, Too Many, Temperate , Moderate decrease
- Americas, Isolated, Expensive, Too Many, Equatorial, Moderate decrease
- Americas, Well-Known, Cheap , Low , Tropical , Moderate decrease
- Americas, Well-Known, Cheap , Low , Dry/Desert, Moderate decrease →10 mill (0.3) Peru
- Americas, Well-Known, Cheap , Low , Mediterranean, Moderate decrease
- Americas, Well-Known, Cheap , Low , Temperate , Moderate decrease

- Americas, Well-Known, Cheap , Low , Equatorial, Moderate decrease
- Americas, Well-Known, Cheap , Plenty, Tropical , Moderate decrease
- Americas, Well-Known, Cheap , Plenty, Dry/Desert, Moderate decrease
- Americas, Well-Known, Cheap , Plenty, Mediterranean, Moderate decrease
- Americas, Well-Known, Cheap , Plenty, Temperate , Moderate decrease
- Americas, Well-Known, Cheap , Plenty, Equatorial, Moderate decrease
- Americas, Well-Known, Cheap , Too Many, Tropical , Moderate decrease
- Americas, Well-Known, Cheap , Too Many, Dry/Desert, Moderate decrease
- Americas, Well-Known, Cheap , Too Many, Mediterranean, Moderate decrease
- Americas, Well-Known, Cheap , Too Many, Temperate , Moderate decrease
- Americas, Well-Known, Cheap , Too Many, Equatorial, Moderate decrease
- Americas, Well-Known, Reasonable, Low , Tropical , Moderate decrease → 10 mill (0.3) Cuba
- Americas, Well-Known, Reasonable, Low , Dry/Desert, Moderate decrease
- Americas, Well-Known, Reasonable, Low , Mediterranean, Moderate decrease → 10 mill (0.4) Chile
- Americas, Well-Known, Reasonable, Low , Temperate , Moderate decrease → 10 mill (0.4) Dominican Republic
- Americas, Well-Known, Reasonable, Low , Equatorial, Moderate decrease
- Americas, Well-Known, Reasonable, Plenty, Tropical , Moderate decrease
- Americas, Well-Known, Reasonable, Plenty, Dry/Desert, Moderate decrease
- Americas, Well-Known, Reasonable, Plenty, Mediterranean, Moderate decrease
- Americas, Well-Known, Reasonable, Plenty, Temperate , Moderate decrease

- Americas, Well-Known, Reasonable, Plenty, Equatorial, Moderate decrease
- Americas, Well-Known, Reasonable, Too Many, Tropical , Moderate decrease
- Americas, Well-Known, Reasonable, Too Many, Dry/Desert, Moderate decrease
- Americas, Well-Known, Reasonable, Too Many, Mediterranean, Moderate decrease
- Americas, Well-Known, Reasonable, Too Many, Temperate , Moderate decrease
- Americas, Well-Known, Reasonable, Too Many, Equatorial, Moderate decrease
- Americas, Well-Known, Expensive, Low , Tropical , Moderate decrease
- Americas, Well-Known, Expensive, Low , Dry/Desert, Moderate decrease
- Americas, Well-Known, Expensive, Low , Mediterranean, Moderate decrease
- Americas, Well-Known, Expensive, Low , Temperate , Moderate decrease
- Americas, Well-Known, Expensive, Low , Equatorial, Moderate decrease
- Americas, Well-Known, Expensive, Plenty, Tropical , Moderate decrease
- Americas, Well-Known, Expensive, Plenty, Dry/Desert, Moderate decrease
- Americas, Well-Known, Expensive, Plenty, Mediterranean, Moderate decrease
- Americas, Well-Known, Expensive, Plenty, Temperate , Moderate decrease
- Americas, Well-Known, Expensive, Plenty, Equatorial, Moderate decrease
- Americas, Well-Known, Expensive, Too Many, Tropical , Moderate decrease
- Americas, Well-Known, Expensive, Too Many, Dry/Desert, Moderate decrease

- Americas, Well-Known, Expensive, Too Many, Mediterranean, Moderate decrease
- Americas, Well-Known, Expensive, Too Many, Temperate , Moderate decrease
- Americas, Well-Known, Expensive, Too Many, Equatorial, Moderate decrease
- Americas, Popular , Cheap , Low , Tropical , Moderate decrease → 40 mill (0.8) Mexico
- Americas, Popular , Cheap , Low , Dry/Desert, Moderate decrease
- Americas, Popular , Cheap , Low , Mediterranean, Moderate decrease
- Americas, Popular , Cheap , Low , Temperate , Moderate decrease
- Americas, Popular , Cheap , Low , Equatorial, Moderate decrease
- Americas, Popular , Cheap , Plenty, Tropical , Moderate decrease
- Americas, Popular , Cheap , Plenty, Dry/Desert, Moderate decrease
- Americas, Popular , Cheap , Plenty, Mediterranean, Moderate decrease
- Americas, Popular , Cheap , Plenty, Temperate , Moderate decrease
- Americas, Popular , Cheap , Plenty, Equatorial, Moderate decrease
- Americas, Popular , Cheap , Too Many, Tropical , Moderate decrease
- Americas, Popular , Cheap , Too Many, Dry/Desert, Moderate decrease
- Americas, Popular , Cheap , Too Many, Mediterranean, Moderate decrease
- Americas, Popular , Cheap , Too Many, Temperate , Moderate decrease
- Americas, Popular , Cheap , Too Many, Equatorial, Moderate decrease
- Americas, Popular , Reasonable, Low , Tropical , Moderate decrease
- Americas, Popular , Reasonable, Low , Dry/Desert, Moderate decrease
- Americas, Popular , Reasonable, Low , Mediterranean, Moderate decrease

- Americas, Popular , Reasonable, Low , Temperate , Moderate decrease →10 mill (0.7) Argentina
- Americas, Popular , Reasonable, Low , Equatorial, Moderate decrease
- Americas, Popular , Reasonable, Plenty, Tropical , Moderate decrease →10 mill (0.5) Brazil
- Americas, Popular , Reasonable, Plenty, Dry/Desert, Moderate decrease
- Americas, Popular , Reasonable, Plenty, Mediterranean, Moderate decrease
- Americas, Popular , Reasonable, Plenty, Temperate , Moderate decrease
- Americas, Popular , Reasonable, Plenty, Equatorial, Moderate decrease
- Americas, Popular , Reasonable, Too Many, Tropical , Moderate decrease
- Americas, Popular , Reasonable, Too Many, Dry/Desert, Moderate decrease
- Americas, Popular , Reasonable, Too Many, Mediterranean, Moderate decrease
- Americas, Popular , Reasonable, Too Many, Temperate , Moderate decrease
- Americas, Popular , Reasonable, Too Many, Equatorial, Moderate decrease
- Americas, Popular , Expensive, Low , Tropical , Moderate decrease
- Americas, Popular , Expensive, Low , Dry/Desert, Moderate decrease
- Americas, Popular , Expensive, Low , Mediterranean, Moderate decrease
- Americas, Popular , Expensive, Low , Temperate , Moderate decrease
- Americas, Popular , Expensive, Low , Equatorial, Moderate decrease
- Americas, Popular, Expensive, Low, Continental, Moderate Decrease → 20 mill (0.8) Canada
- Americas, Popular , Expensive, Plenty, Tropical , Moderate decrease
- Americas, Popular , Expensive, Plenty, Dry/Desert, Moderate decrease
- Americas, Popular , Expensive, Plenty, Mediterranean, Moderate decrease

- Americas, Popular , Expensive, Plenty, Temperate , Moderate decrease
- Americas, Popular , Expensive, Plenty, Equatorial, Moderate decrease
- Americas, Popular , Expensive, Too Many, Tropical , Moderate decrease
- Americas, Popular , Expensive, Too Many, Dry/Desert, Moderate decrease
- Americas, Popular , Expensive, Too Many, Mediterranean, Moderate decrease
- Americas, Popular , Expensive, Too Many, Temperate , Moderate decrease →90 mill (0.6) USA
- Americas, Popular , Expensive, Too Many, Equatorial, Moderate decrease

EUROPE

- Europe, Isolated, Cheap , Low , Tropical , High decrease
- Europe, Isolated, Cheap , Low , Mediterranean, High decrease
- Europe, Isolated, Cheap , Low , Continental, High decrease
- Europe, Isolated, Cheap , Low , Temperate , High decrease
- Europe, Isolated, Cheap , Plenty, Tropical , High decrease
- Europe, Isolated, Cheap , Plenty, Mediterranean, High decrease
- Europe, Isolated, Cheap , Plenty, Continental, High decrease
- Europe, Isolated, Cheap , Plenty, Temperate , High decrease
- Europe, Isolated, Reasonable, Low , Tropical , High decrease
- Europe, Isolated, Reasonable, Low , Mediterranean, High decrease
- Europe, Isolated, Reasonable, Low , Continental, High decrease → 0.5 mill (0.2) Liechtenstein
- Europe, Isolated, Reasonable, Low , Temperate , High decrease

- Europe, Isolated, Reasonable, Plenty, Tropical , High decrease
- Europe, Isolated, Reasonable, Plenty, Mediterranean, High decrease
- Europe, Isolated, Reasonable, Plenty, Continental, High decrease
- Europe, Isolated, Reasonable, Plenty, Temperate , High decrease
- Europe, Isolated, Expensive, Low , Tropical , High decrease
- Europe, Isolated, Expensive, Low , Mediterranean, High decrease
- Europe, Isolated, Expensive, Low , Continental, High decrease
- Europe, Isolated, Expensive, Low , Temperate , High decrease
- Europe, Isolated, Expensive, Plenty, Tropical , High decrease
- Europe, Isolated, Expensive, Plenty, Mediterranean, High decrease
- Europe, Isolated, Expensive, Plenty, Continental, High decrease
- Europe, Isolated, Expensive, Plenty, Temperate , High decrease
- Europe, Well-Known, Cheap , Low , Tropical , High decrease
- Europe, Well-Known, Cheap , Low , Mediterranean, High decrease
- Europe, Well-Known, Cheap , Low , Continental, High decrease
- Europe, Well-Known, Cheap , Low , Temperate , High decrease
- Europe, Well-Known, Cheap , Plenty, Tropical , High decrease
- Europe, Well-Known, Cheap , Plenty, Mediterranean, High decrease
- Europe, Well-Known, Cheap , Plenty, Continental, High decrease
- Europe, Well-Known, Cheap , Plenty, Temperate , High decrease
- Europe, Well-Known, Reasonable, Low , Tropical , High decrease
- Europe, Well-Known, Reasonable, Low , Mediterranean, High decrease
- Europe, Well-Known, Reasonable, Low , Continental, High decrease
- Europe, Well-Known, Reasonable, Low , Temperate , High decrease → 1 million (0.8) Luxembourg

- Europe, Well-Known, Reasonable, Plenty, Tropical , High decrease
- Europe, Well-Known, Reasonable, Plenty, Mediterranean, High decrease
- Europe, Well-Known, Reasonable, Plenty, Continental, High decrease
- Europe, Well-Known, Reasonable, Plenty, Temperate , High decrease
- Europe, Well-Known, Expensive, Low , Tropical , High decrease
- Europe, Well-Known, Expensive, Low , Mediterranean, High decrease
- Europe, Well-Known, Expensive, Low , Continental, High decrease
- Europe, Well-Known, Expensive, Low , Temperate , High decrease
- Europe, Well-Known, Expensive, Plenty, Tropical , High decrease
- Europe, Well-Known, Expensive, Plenty, Mediterranean, High decrease
- Europe, Well-Known, Expensive, Plenty, Continental, High decrease
- Europe, Well-Known, Expensive, Plenty, Temperate , High decrease
- Europe, Popular , Cheap , Low , Tropical , High decrease
- Europe, Popular , Cheap , Low , Mediterranean, High decrease → 60 mill (0.7) Turkey
- Europe, Popular , Cheap , Low , Continental, High decrease → 40 mill (0.5) Russia
- Europe, Popular , Cheap , Low , Temperate , High decrease
- Europe, Popular , Cheap , Plenty, Tropical , High decrease
- Europe, Popular , Cheap , Plenty, Mediterranean, High decrease
- Europe, Popular , Cheap , Plenty, Continental, High decrease
- Europe, Popular , Cheap , Plenty, Temperate , High decrease
- Europe, Popular , Reasonable, Low , Tropical , High decrease
- Europe, Popular , Reasonable, Low , Mediterranean, High decrease → 90 million (0.6) Spain, Greece

- Europe, Popular , Reasonable, Low , Continental, High decrease
- Europe, Popular , Reasonable, Low , Temperate , High decrease →40 million (0.5)
- Europe, Popular , Reasonable, Plenty, Tropical , High decrease
- Europe, Popular , Reasonable, Plenty, Mediterranean, High decrease
- Europe, Popular , Reasonable, Plenty, Continental, High decrease
- Europe, Popular , Reasonable, Plenty, Temperate , High decrease
- Europe, Popular , Expensive, Low , Tropical , High decrease
- Europe, Popular , Expensive, Low , Mediterranean, High decrease → 60 million (0.7) Italy
- Europe, Popular , Expensive, Low , Continental, High decrease
- Europe, Popular , Expensive, Low , Temperate , High decrease → 90 million (0.7) France , UK, Germany, Austria
- Europe, Popular , Expensive, Plenty, Tropical , High decrease
- Europe, Popular , Expensive, Plenty, Mediterranean, High decrease
- Europe, Popular , Expensive, Plenty, Continental, High decrease
- Europe, Popular , Expensive, Plenty, Temperate , High decrease