Clustering the Planet
CS451 HW5 Fall 2017
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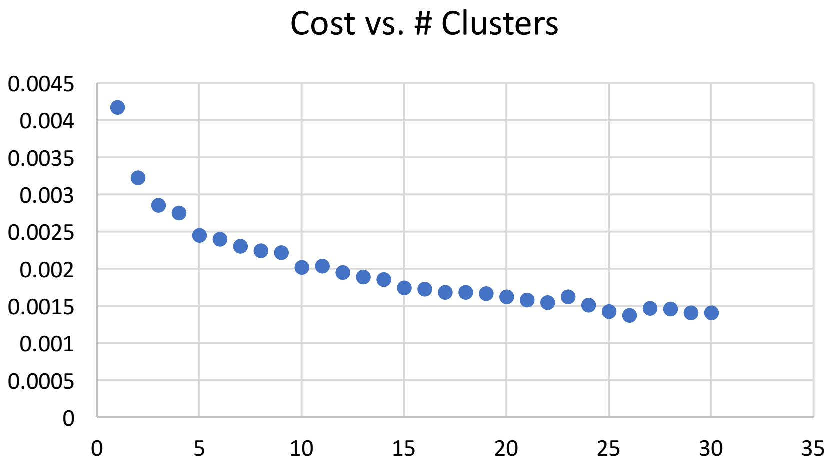
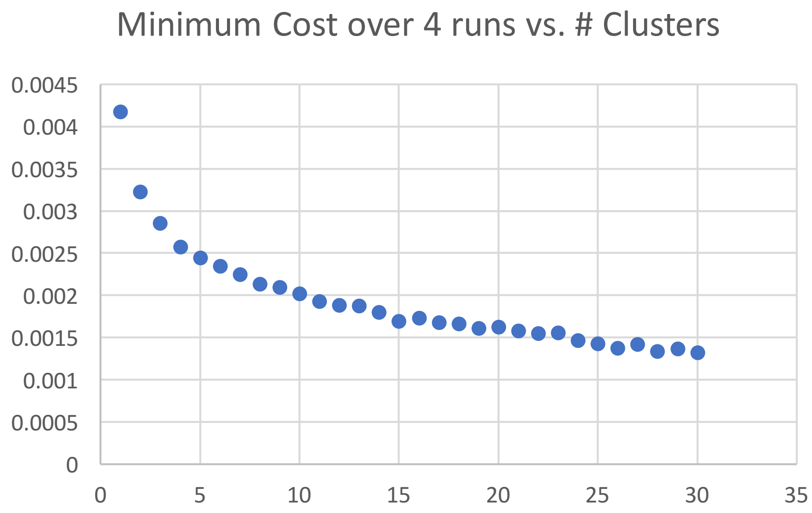
The goal of this project was to apply the k-means algorithm, an unsupervised clustering algorithm, in an attempt to group countries by their cultural priorities, using UN survey data. For the first phase of the project, we implemented the k-means algorithm in Python and made preliminary visualizations using matplotlib. We also experimented by looping through various k values. We then exported our data and processed it in Excel, where we produced the following visualizations. The first question considered was to determine an "ideal" number of clusters, and following that is a description of the clusters resulting from that k value.

This is a plot of the k-means algorithm cost function and how it relates to the number of clusters (x-axis represents k, y-axis represents the cost function, the average squared distance of each point to its centroid). There isn't a clear elbow where the cost starts decreasing less, and there is a fair amount of noise in the data, because the algorithm didn't necessarily reach the global minimum for that cluster number, especially for larger values of k.



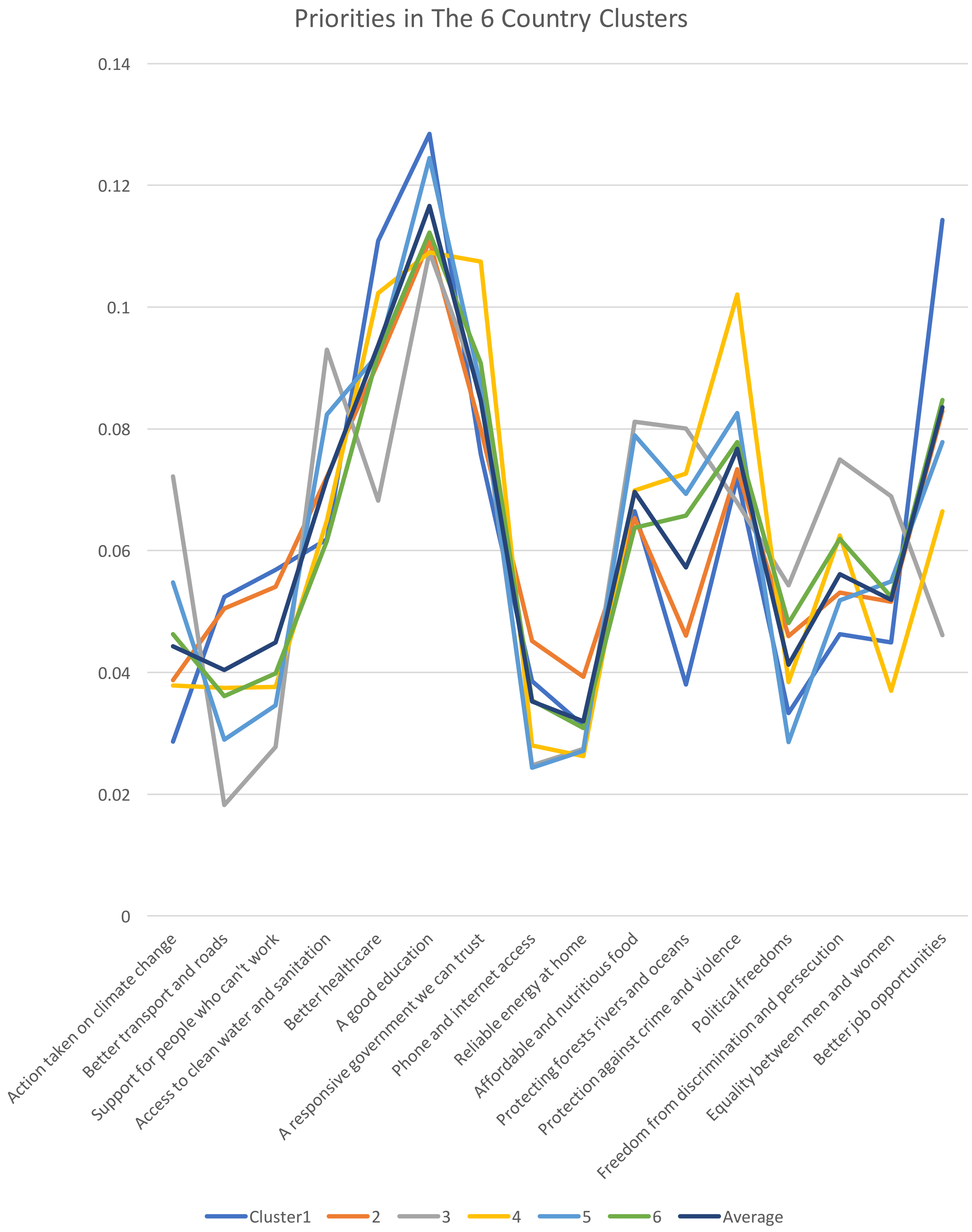
Because of this noise we decided to run the algorithm multiple times. This allows us to take away some of the per-run variation by just keeping track of the minimum over all of the runs. For smaller centroid numbers, this means that we have likely found the global minimum from the algorithm, but for larger centroid numbers it becomes increasingly less likely that we have found the global minimum. By using the minimum over 4 runs, we have effectively used 400 iterations of the k-means algorithm.

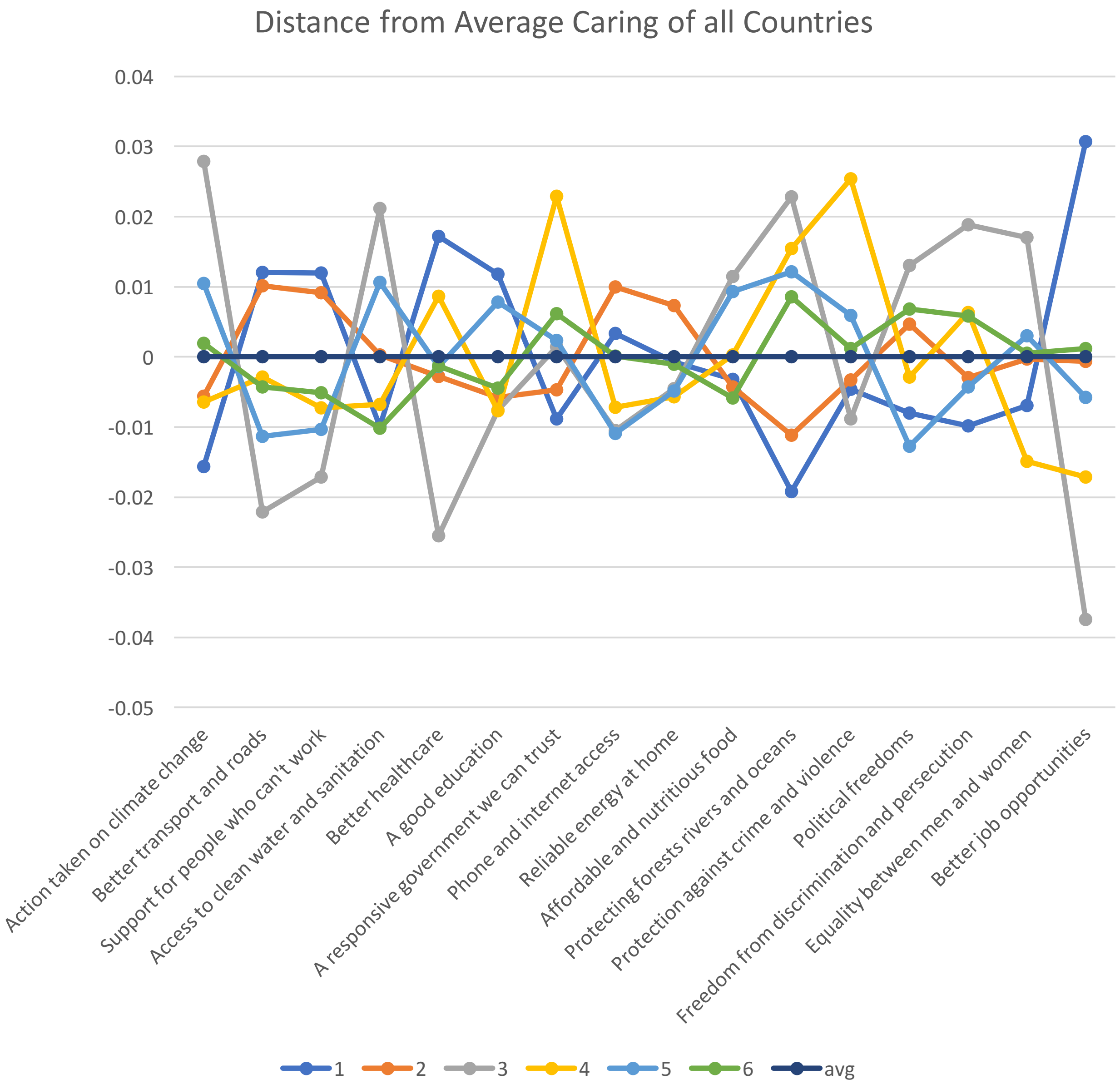


There's still no precise elbow, so the choice of cluster number remains somewhat arbitrary. It looks like the rate of decrease of cost lowers at around 4 to 6 clusters. We decided to use 6 clusters so that each cluster was smaller and hopefully more meaningful.

The goal of the k-means algorithm changes as you increase the number of clusters. The question changes from "How can these countries be categorized?" to "What are a few countries similar to this country?" as the number of clusters increases from 2 to 97.

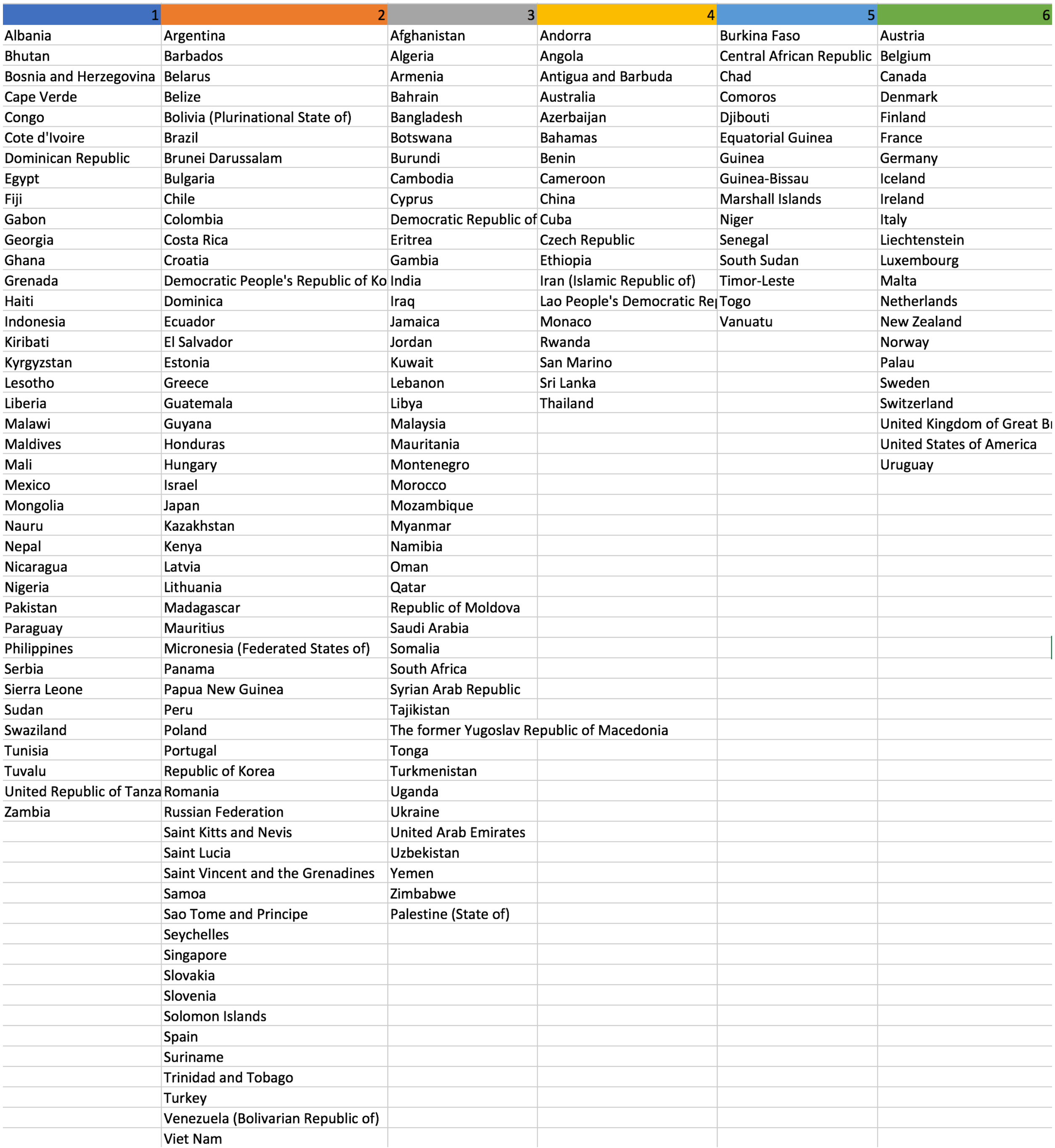
At first, we plotted the priorities of the clusters without a reference to the average. This plot shows that in general, humans across the globe tend to prioritize categories similarly (x-axis represents the issue being considered, y-axis represents the relative importance of that issue). For example, all clusters tend to prioritize education over phone and internet access.


Priorities in The 6 Country Clusters
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
Action taken on climate change
Better transport and roads
Support for people who can't work
Access to clean water and sanitation
Better healthcare
A good education
A responsive government we can trust
Phone and internet access
Reliable energy at home
Affordable and nutritious food
Protecting forests rivers and oceans
Protection against crime and violence
Political freedoms
Freedom from discrimination and persecution
Equality between men and women
Better job opportunities
Cluster1
2
3
4
5
6
Average

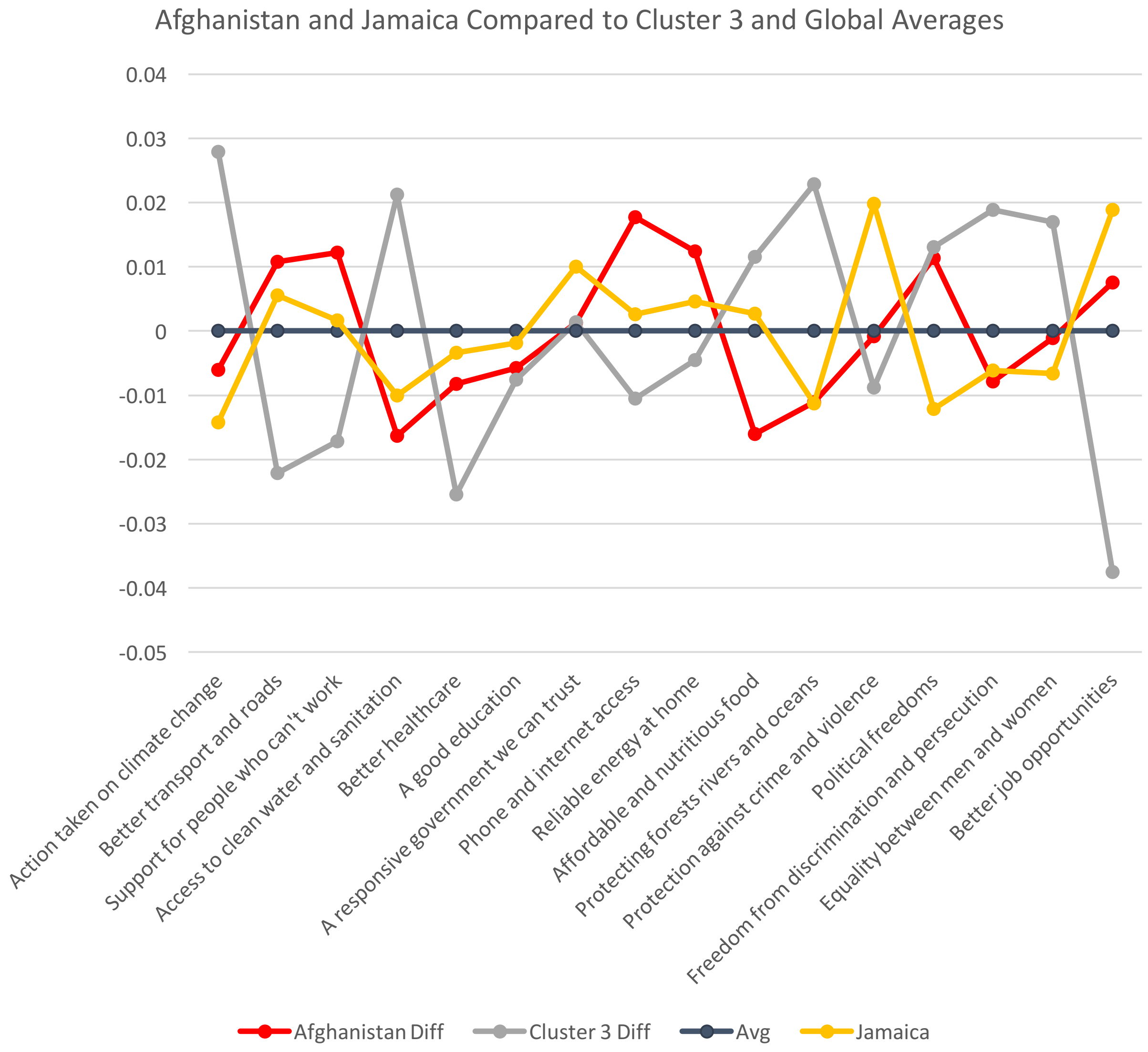


That said, there is still a lot of variation when considering particular categories. To show this, we instead plotted the difference between each cluster's opinions on the categories and the global average opinion on that category (x-axis represents issue, y-axis represents cluster centroid relative importance – global average). Each data point measures the difference between that cluster's opinion about the category and the average opinion from all countries. Here we see that the opinions of the different clusters change a lot in certain categories and less in others.

We can see the abundance of North African, South Asian, and Middle Eastern countries in cluster 3, and that most rich western countries have been grouped in a separate category, cluster 6. Category 4 primarily consists of sub-Saharan African countries. The other categories are harder to generalize, but the algorithm has found some similarities.



1	2	3	4	5	6
Albania	Argentina	Afghanistan	Andorra	Burkina Faso	Austria
Bhutan	Barbados	Algeria	Angola	Central African Republic	Belgium
Bosnia and Herzegovina	Belarus	Armenia	Antigua and Barbuda	Chad	Canada
Cape Verde	Belize	Bahrain	Australia	Comoros	Denmark
Congo	Bolivia (Plurinational State of)	Bangladesh	Azerbaijan	Djibouti	Finland
Cote d'Ivoire	Brazil	Botswana	Bahamas	Equatorial Guinea	France
Dominican Republic	Brunei Darussalam	Burundi	Benin	Guinea	Germany
Egypt	Bulgaria	Cambodia	Cameroon	Guinea-Bissau	Iceland
Fiji	Chile	Cyprus	China	Marshall Islands	Ireland
Gabon	Colombia	Democratic Republic of	Cuba	Niger	Italy
Georgia	Costa Rica	Eritrea	Czech Republic	Senegal	Liechtenstein
Ghana	Croatia	Gambia	Ethiopia	South Sudan	Luxembourg
Grenada	Democratic People's Republic of Ko	India	Iran (Islamic Republic of)	Timor-Leste	Malta
Haiti	Dominica	Iraq	Lao People's Democratic Re	Togo	Netherlands
Indonesia	Ecuador	Jamaica	Monaco	Vanuatu	New Zealand
Kiribati	El Salvador	Jordan	Rwanda		Norway
Kyrgyzstan	Estonia	Kuwait	San Marino		Palau
Lesotho	Greece	Lebanon	Sri Lanka		Sweden
Liberia	Guatemala	Libya	Thailand		Switzerland
Malawi	Guyana	Malaysia			United Kingdom of Great B
Maldives	Honduras	Mauritania			United States of America
Mali	Hungary	Montenegro			Uruguay
Mexico	Israel	Morocco			
Mongolia	Japan	Mozambique			
Nauru	Kazakhstan	Myanmar			
Nepal	Kenya	Namibia			
Nicaragua	Latvia	Oman			
Nigeria	Lithuania	Qatar			
Pakistan	Madagascar	Republic of Moldova			
Paraguay	Mauritius	Saudi Arabia			
Philippines	Micronesia (Federated States of)	Somalia			
Serbia	Panama	South Africa			
Sierra Leone	Papua New Guinea	Syrian Arab Republic			
Sudan	Peru	Tajikistan			
Swaziland	Poland	The former Yugoslav Republic of Macedonia			
Tunisia	Portugal	Tonga			
Tuvalu	Republic of Korea	Turkmenistan			
United Republic of Tanza	Romania	Uganda			
Zambia	Russian Federation	Ukraine			
	Saint Kitts and Nevis	United Arab Emirates			
	Saint Lucia	Uzbekistan			
	Saint Vincent and the Grenadines	Yemen			
	Samoa	Zimbabwe			
	Sao Tome and Principe	Palestine (State of)			
	Seychelles				
	Singapore				
	Slovakia				
	Slovenia				
	Solomon Islands				
	Spain				
	Suriname				
	Trinidad and Tobago				
	Turkey				
	Venezuela (Bolivarian Republic of)				
	Viet Nam				



We chose to look more closely at Afghanistan because it was part of cluster 3 which was one of the clusters that was a bit harder to explain than the others, as it seems to consistently have the most extreme opinions. The third cluster was wildly different in many of the categories compared to the other clusters, particularly cluster 1. Even with such consistently strong views there is still much variation within cluster 3. As an example, the way Afghanistan compares to cluster 3 is not quite obvious. The prioritization for some of the categories is very similar to the cluster, but for other clusters it is totally different. Cluster 3 contains mostly Middle Eastern, North African, and South Asian countries, which share similar latitudes, spanning great distances from east to west. These countries tend to be Islamic as well, which would suggest political and cultural similarities. Perhaps these forces can explain the apparent cohesion of group opinions, and why they are not wishy-washy.

Some of the categories in which Afghanistan differs more from the views of its cluster could represent priorities with more variation and less correlation than other priorities, possibly representing the categories with less differentiating power. Because of this it would be harder for the algorithm to group countries based on the more variant priorities. Following from the pigeon-hole principle and the fact that we have more priorities considered than categories, it's expected that certain categories would have more selective weight. In this example, perhaps Afghanistan was grouped with countries that agreed more so on the priority of trustworthy government and political freedoms than sanitation and internet access. Given the tragic wars that have been waged, and terrorist related chaos in Afghanistan, as well as some of the other counties in its cluster, it is not surprising that trustworthy government and political freedoms would be important. Though occurring elsewhere in cluster 3, the Arab Spring was a clear demonstration of these priorities. Specifically, the activities of groups like the Taliban and Isis, who are now spreading into Afghanistan, as well as other conflicts that have been going on for many years are possibly reasons for why their people may especially cherish political freedom.

It is somewhat odd that Jamaica is also grouped in cluster 3. It's extremely far away, and is neither Islamic nor Asian. However, the point of using an algorithm to group these countries in clusters is to find similarities that we wouldn't necessarily have looked for or seen ourselves. While learning algorithms certainly have a degree of bias, using an algorithm can eliminate *our own biases* and show that maybe Afghanistan and Jamaica aren't that different after all.