

Happy Planet Index clustering script

HarvardX Data Science Capstone Own Project

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This report has been prepared for the [HarvardX Data Science program](#) Capstone course final project submission and consists of three files of original work that can be found [on GitHub](#) (with all commits): this report in PDF, this report in R markdown and an R markdown script file with all the code (also knitted to PDF with results for convenience). Results are read in from data objects stored locally (also saved in the GitHub repository), that were the output of the script file. We were limited in our visualisations by the requirement to publish to PDF.

Summary

Humankind uses diverse progress indicators, most currently Growth Domestic Product (GDP) to gauge economic growth. It is becoming more apparant that this is a limited and myopic view and alternative measures have been emerging over te last years, like the United Nation's Human Development Index. I wanted to have a closer look at two concepts that follow; the Social Progress Index (SPI) and the Happy Planet index (HPI), which take into account the state of our ecosystems. This report describes merging the last avaiable data for both from the year 2016, applying clustering to see how certain countries group, and having a look at their differences. Resulting clusters show that social progress seems to come at the cost of ecological systems that cannot sustain levels of consumption.

Analysis

Raw data

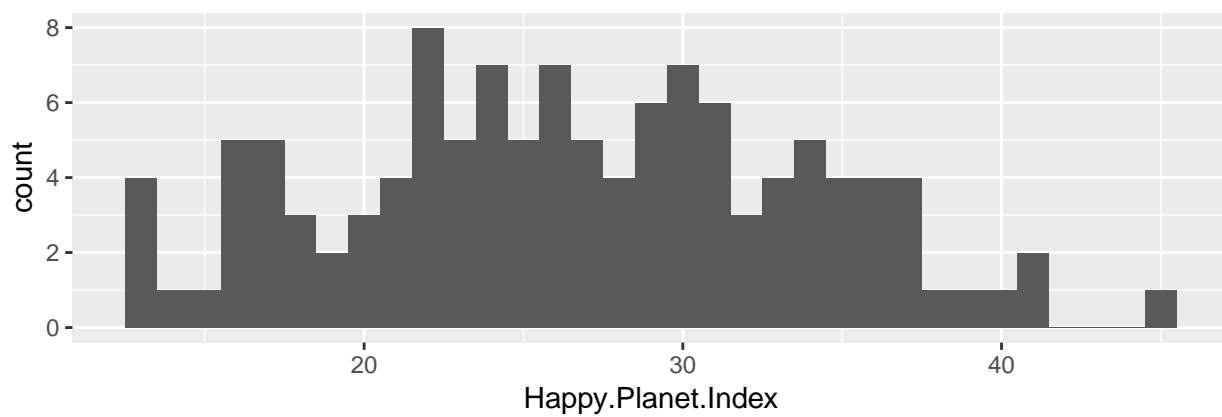
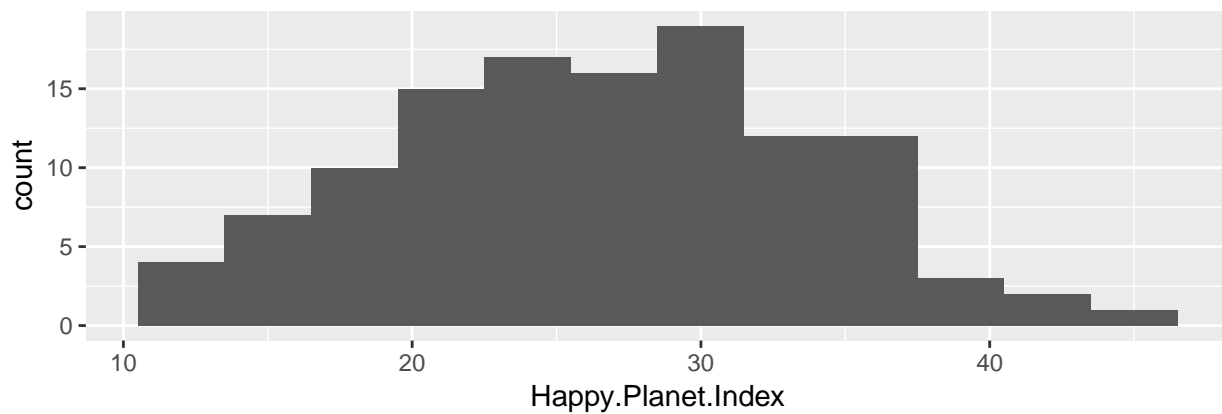
Data was downloaded from the official websites as Excel files and the last common year, 2016 was read in. HPI data in short looks at the amount of happy life years peole in a country achive, divided by the ecological footprint or 'ecosystem costs' to obtain that to balance means and ends. SPI data includes more diverse indicators with the main categories being Basic Human needs, like health and safety, Foundations for Wellbeing, like access to knowledge and quality environment and, last, Opportuniy with freedom, rights and inclusiveness.

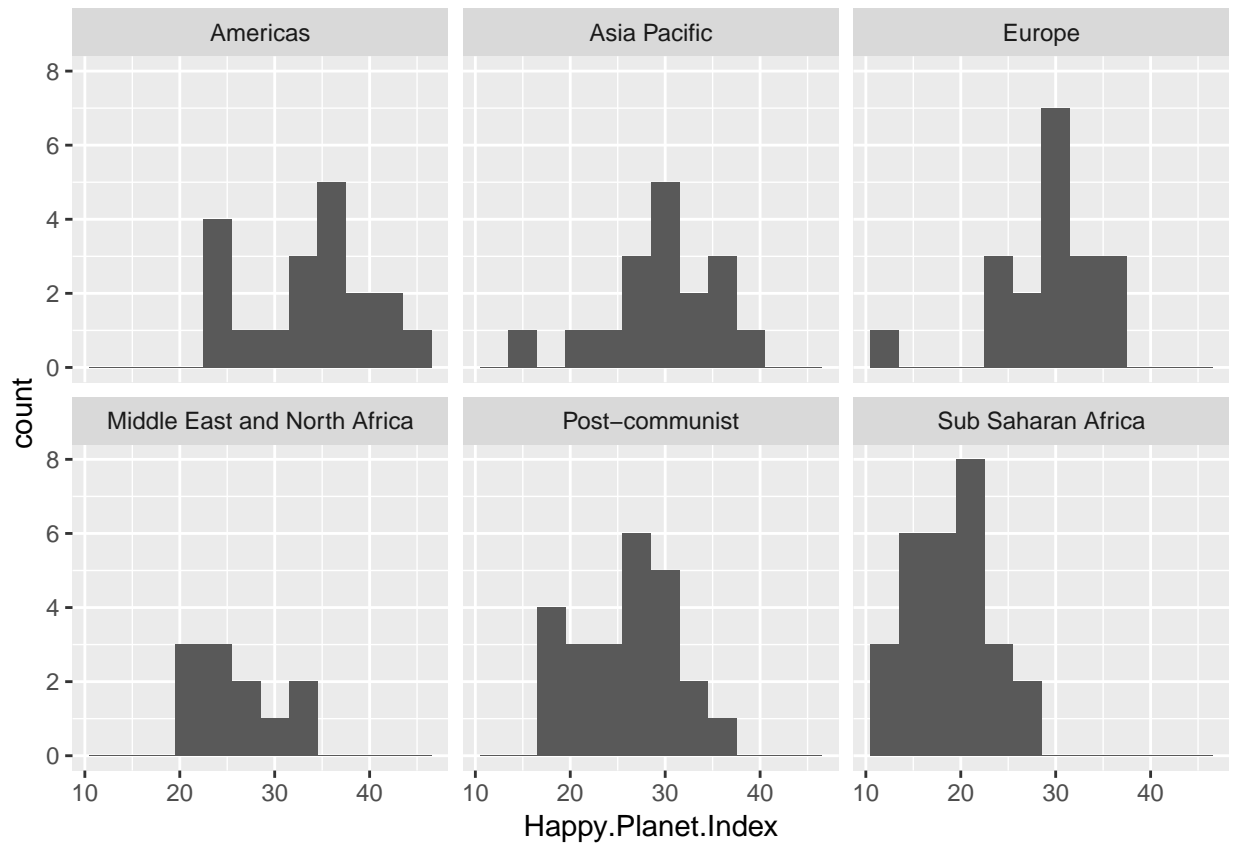
Data preparation

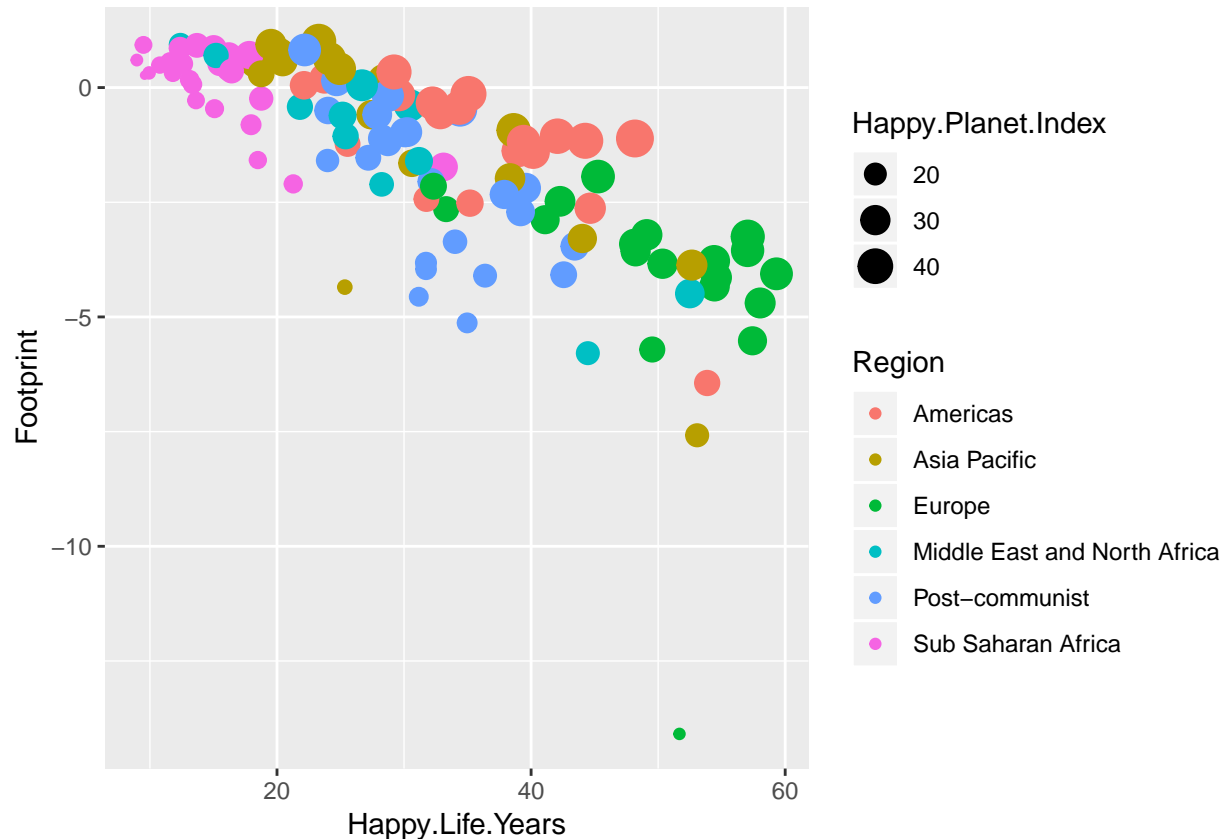
Data from HPI and SPI were joined by Country name. Missing values imputed by mean values. All numeric variables were scaled in preparation for clustering. This leaves us with 118 observations of 86 variables. We explore the data next.

Data exploration

To get an initial view of the data we plot histograms of HPI scores with different bin withs and a scatter plot with major variables.





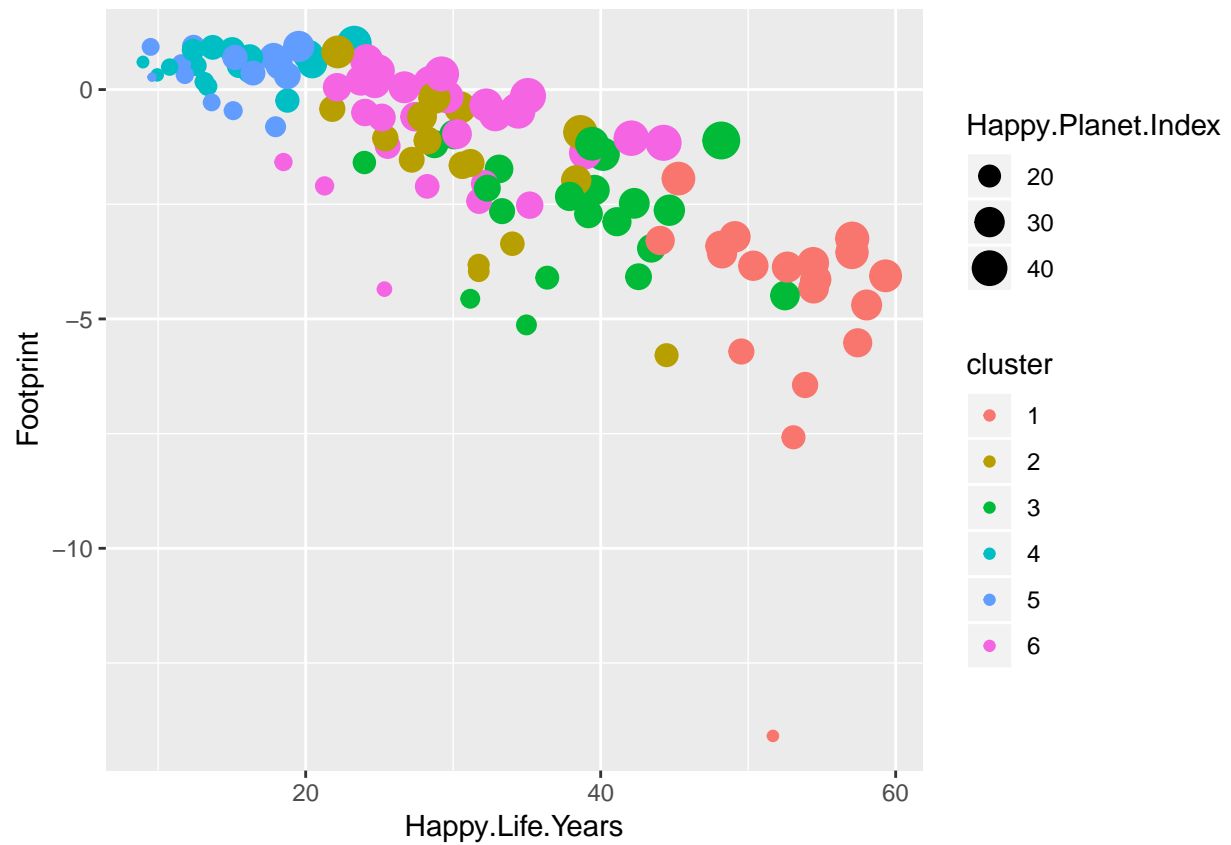


Looking at all HPI scores the histogram seems to show a somewhat normal distribution. The HPI data is already labeled with regions and separating them clearly shows differences, most notably contrasts like the low scores in Sub Saharan Africa and the distributed, yet high scores of the Americas.

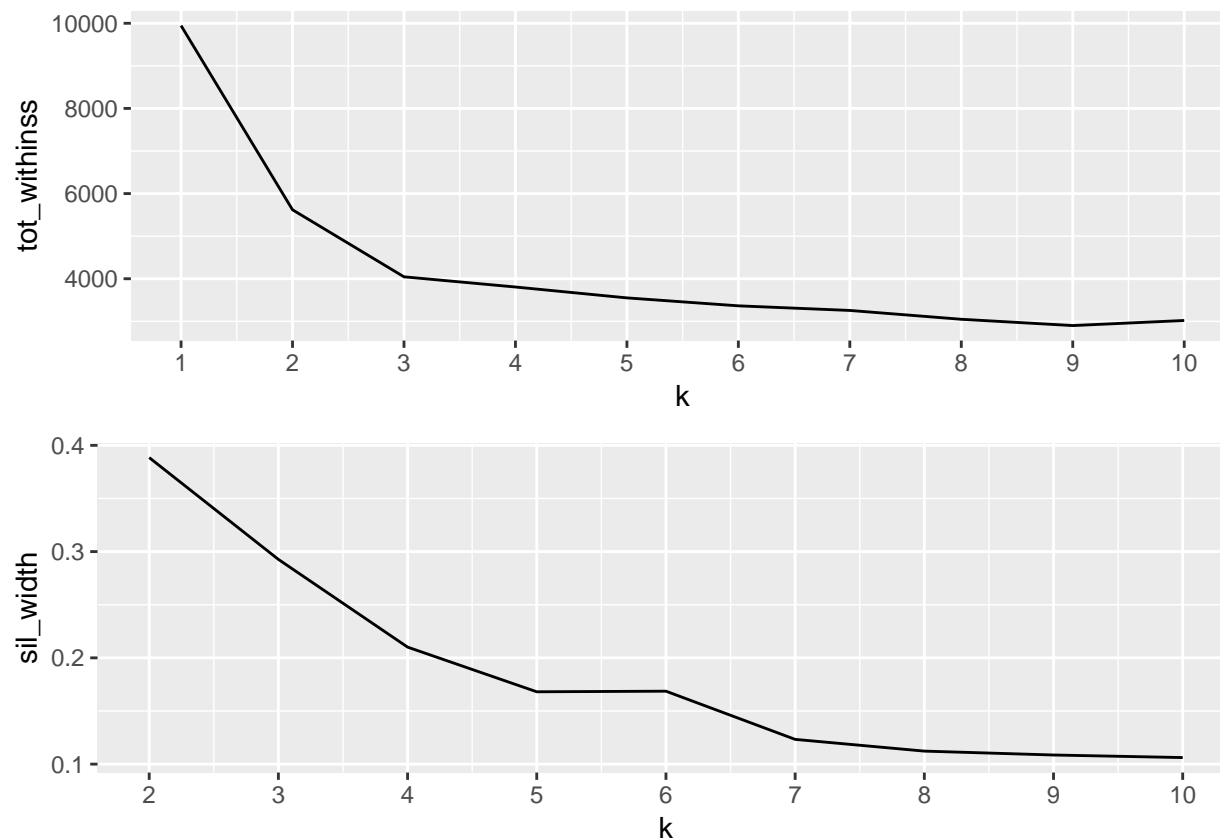
The scatterplot shows HPI on the x-axis and the effective footprint on the y-axis. Footprint data represents how big an area of ecosystems is needed to realise the consumption levels in that country (corrected for many things). 1.73 is the theoretical amount our world would be able to sustain. I chose to show the difference on the y-axis; a positive value means countries consume within planetary boundaries; a negative value shows a consumption rate requires more ecosystem capacity than is available. Here you see differences and the underlying values with notably Sub Saharan Africa and Europe at opposite ends. As we have more data from the SPI I wanted to explore what clustering based on all variables beyond region would yield for insights.

Clustering modeling

As the data provides six regions, we use that for the amount of initial clusters, after which we will calculate the most appropriate amount of clusters. We used K-means clustering.



These clusters differ quite a bit from the geographical regions. Lets calculate the optimal amount of clusters using the Elbow method and Silhouette width.

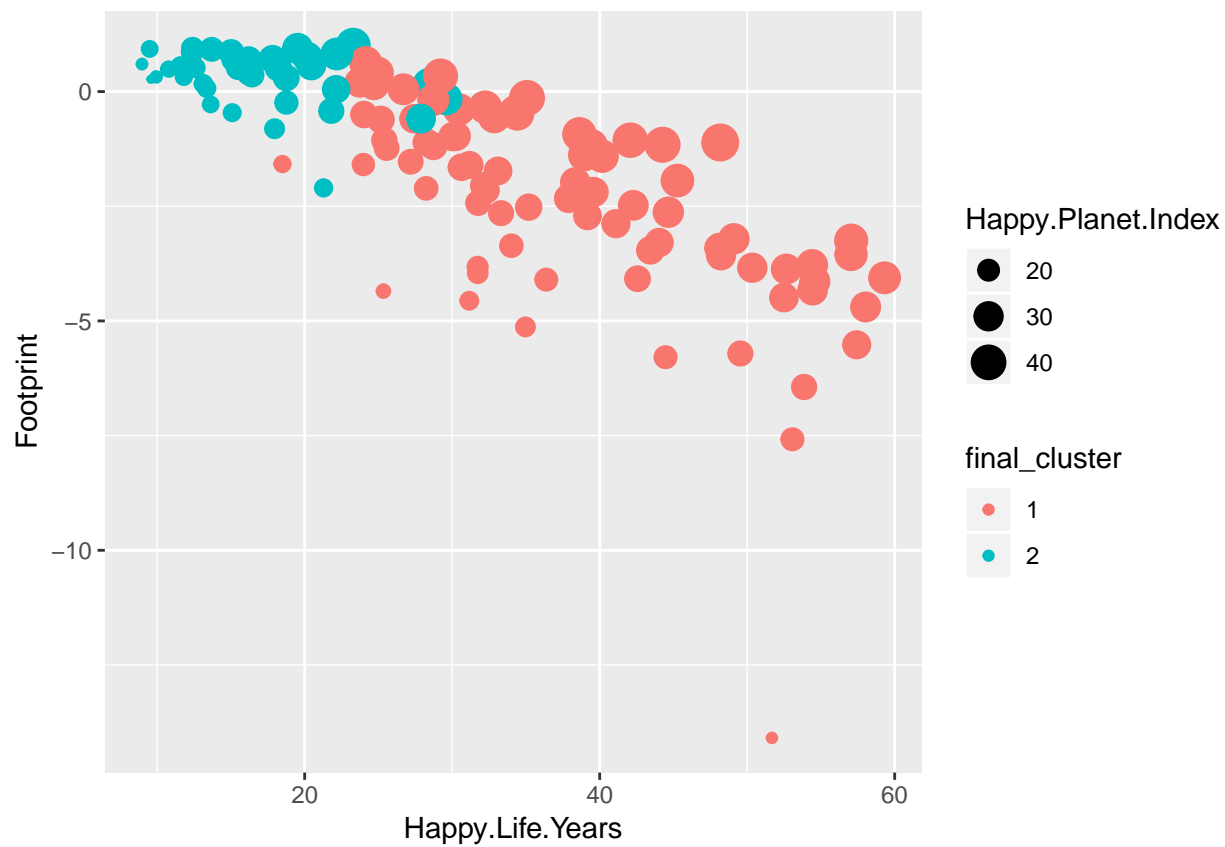


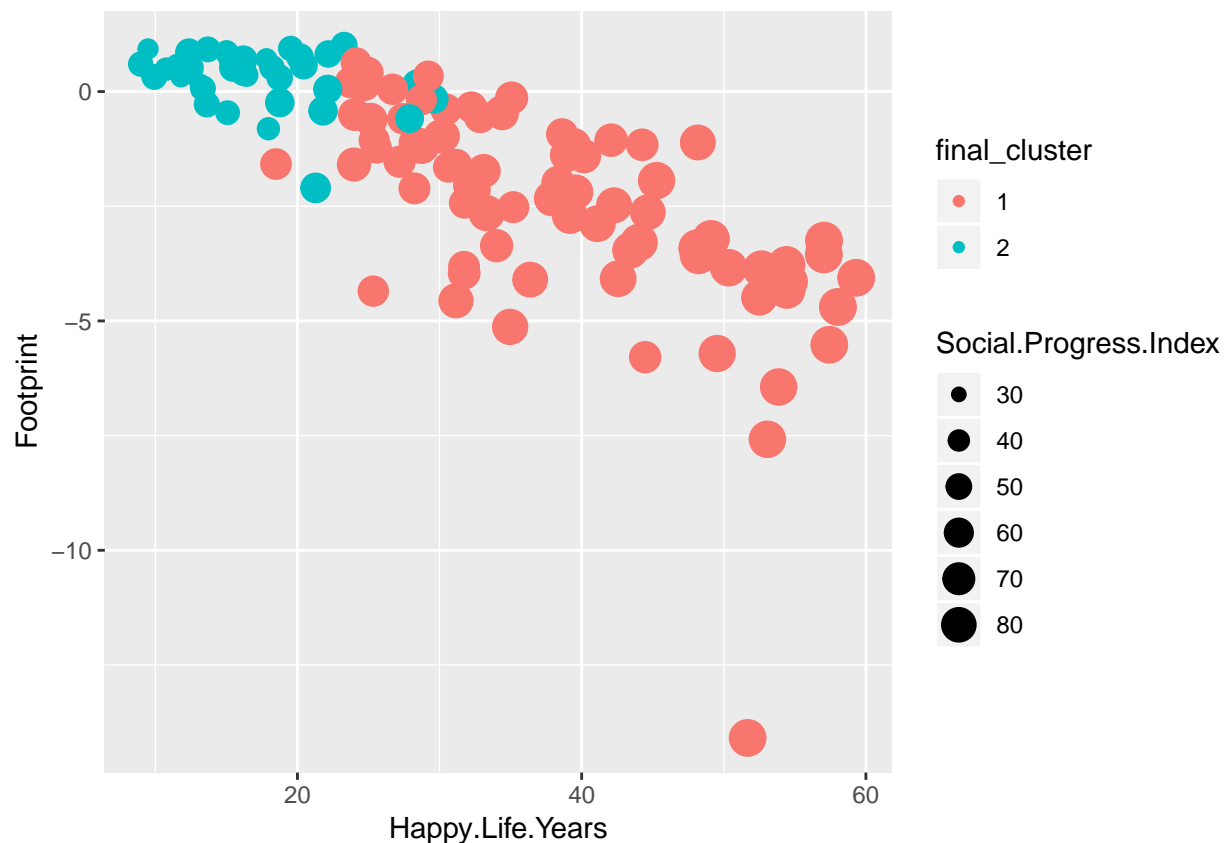
Fitting several cluster models shows two clusters seems to be the best separation. At $k = 2$ we see the elbow bend and the average silhouette width is highest when data is separated in two.

Results

Visualising clustered data

The figures below show the data with clusters identified by color and size representing first HPI and then SPI.

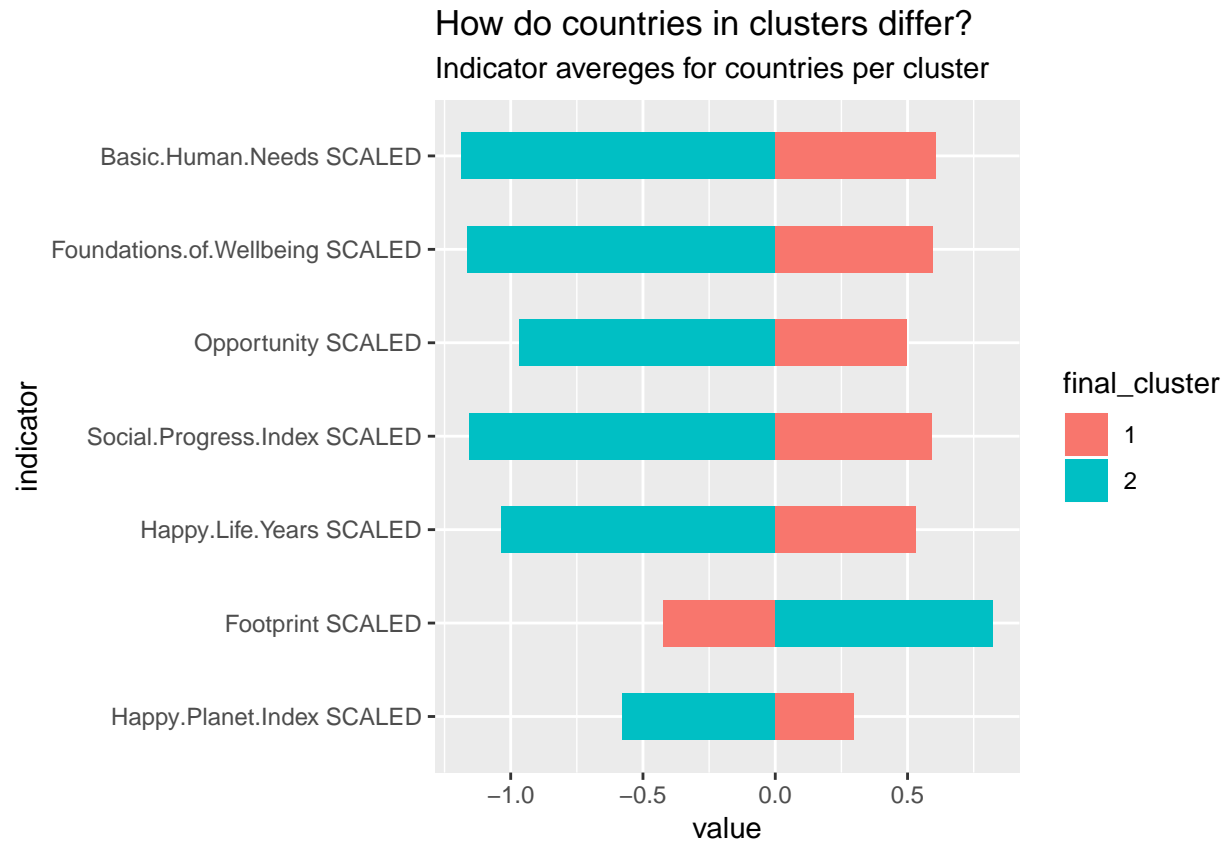




The first cluster seems to have most countries with a positive footprint, meaning their consumption can be sustained, while the second cluster has increasingly Happy Life Years and more negative footprint. Using HPI as size for datapoints accentuates that the lower happy life years and the higher negative footprint, the less is HPI score, whereas SPI score visually seems similar putting an emphasis on social progress.

Cluster analysis

To better understand the differences in countries we plot the average scores per cluster on the major components of both the HPI and SPI indicators.



Conclusions and discussion

We can see a clear distinction between clusters on average scores of a select number of indicators. Countries in cluster 1 score above average except for their environmental footprint; they are doing well socially, but at the cost of our ecological systems. Countries in cluster 2 score well below averages, except for their footprint. Although this graph shows relative performance of clusters, a major concern is the high number of countries with negative net footprint; meaning we are consuming not only the services of our ecosystems, but the production capacity itself, which will lead to increasing footprint pressure. Further analysis into all measures may provide additional insights into differences in these clusters. Particularly interesting would be to explore countries with positive net footprint.

References

1. [How is the Happy Planet Index calculated?](#)
2. [Social Progress Imperative](#)

Appendix

Cluster 1	countries	Cluster 2	countries
Albania	Latvia	Afghanistan	Lesotho
Algeria	Lebanon	Bangladesh	Liberia
Argentina	Lithuania	Benin	Malawi
Armenia	Luxembourg	Botswana	Mauritania
Australia	Macedonia	Burkina Faso	Mozambique
Austria	Malaysia	Burundi	Myanmar
Belarus	Mauritius	Cambodia	Nepal
Belgium	Mexico	Cameroon	Niger
Bhutan	Mongolia	Chad	Nigeria
Bolivia	Montenegro	Comoros	Pakistan
Brazil	Morocco	Djibouti	Rwanda
Bulgaria	Netherlands	Egypt	Senegal
Canada	New Zealand	Ethiopia	Sierra Leone
Chile	Nicaragua	Ghana	Swaziland
China	Norway	Guatemala	Tajikistan
Colombia	Oman	Guinea	Tanzania
Costa Rica	Panama	Honduras	Togo
Croatia	Paraguay	India	Uzbekistan
Cyprus	Peru	Indonesia	Yemen
Czech Republic	Philippines	Kenya	Zimbabwe
Denmark	Poland		
Dominican Republic	Portugal		
Ecuador	Romania		
El Salvador	Russia		
Estonia	Serbia		
Finland	Slovakia		
France	Slovenia		
Georgia	South Africa		
Germany	Spain		
Greece	Sri Lanka		
Hungary	Suriname		
Iceland	Sweden		
Iran	Switzerland		
Ireland	Thailand		
Israel	Tunisia		
Italy	Turkey		
Japan	Ukraine		
Kazakhstan	United Kingdom		
Kyrgyzstan	Uruguay		