

## HEALTHY BIRTH, GROWTH & DEVELOPMENT

knowledge integration

December 5, 2017

# **Country Segmentation Tool**

#### Dave King

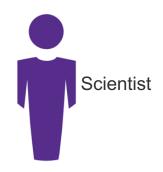




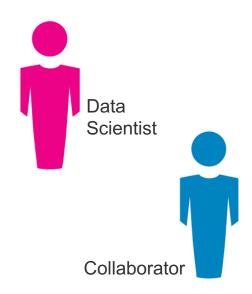


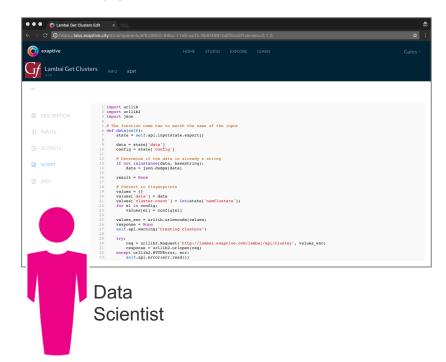










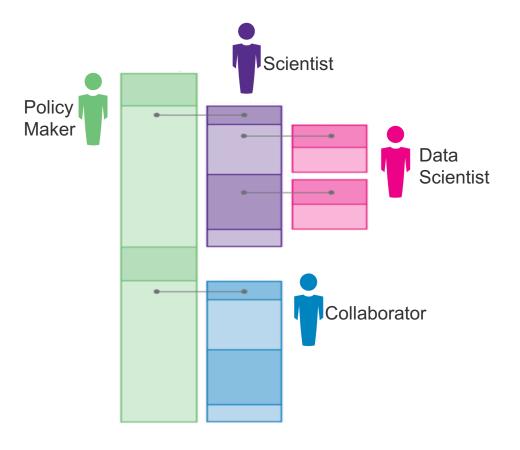


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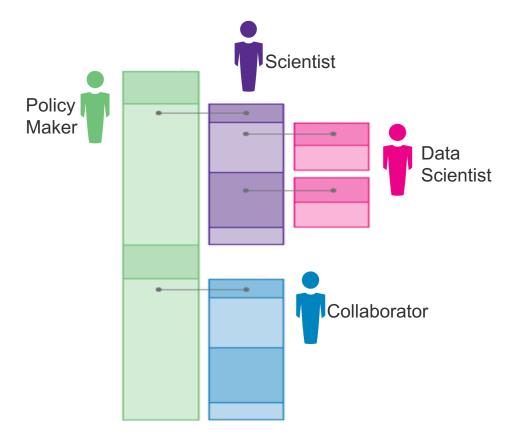
#### HBGDki India O Lambai Get Clusters Edit × O https://labs.exaptive.city/#/components/ef828650-94bc-11e6-aa1b-8b6f4991bd08/edit?version=0.1.0 Scientist Lambai Get Clusters INFO EDIT Chrome File Edit View History Bookmarks People Window Help ♥ 🚳 🕅 5 + 🛜 🖫 [9] Thu 10:54 AM 🔍 🍮 🖃 import urllib import urllib2 import json ■ DESCRIPTION # The function name has to match the name of def data(self): 🗎 City Servers 🗎 Client Cities 🗎 Boards 🗎 Wiki 🗎 Scrum 🗎 Xaps 🗎 Tech 😊 Active Zoom Meetings Cther Bookman state = self.api.inputstate.export() data = state['data'] config = state['config'] # Determine if the data is already a stri if not isinstance(data, basestring): SCRIPT data = json.dumps(data) result = None # Convert to fingerprints values = {} values['data'] = data values['cluster.count'] = int(state['num( for el in config: values[el] = config[el] values\_enc = urllib.urlencode(values) response = None self.api.warning("Creating clusters") req = urllib2.Request('http://lambai. response = urllib2.urlopen(req) except urllib2.HTTPError, err: self.api.error(err.read()) C Mapbox C OpenStreetMap Improve this ma Data Cluster 6 FAO5 - Average supply of protein of animal origin -Scientist DHS48 - Body Mass Index (BMI), women IPUMS141 - Sex ratio, 15-24 years -FAO17 - Value of food imports over total merchandise exports FAO15 - Cereal import dependency ratio FAO13 - Depth of the food deficit 0.2 -FAO1 - Average dietary energy supply adequacy DHS21 - Age at first marriage, women

#### HBGDki India The https://labs.exaptive.city/#/components/ef828650-94bc-11e6-aa1b-8b6f4991bde Scientist Lambai Get Clusters **Policy** € Chrome File Edit View History Bookmarks People Window Help ♥ 🚳 🕅 5 ++ 🛜 🖵 😥 Thu 10:54 AM Q 🧑 🔚 import urllib import urllib2 import json Maker ≜ Secure https://labs.exaptive.city/studios # The function name has to match the name def data(self): ☐ City Servers ☐ Client Cities ☐ Boards ☐ Wiki ☐ Scrum ☐ Xaps ☐ Tech ☐ Active Zoom Meeting Cther Bookm state = self.api.inputstate.export() data = state['data'] config = state['config'] # Determine if the data is already a str if not isinstance(data, basestring): SCRIPT data = json.dumps(data) result = None COMPARING KUWAIT AND YEMEN # Convert to fingerprints values['data'] = data values['cluster.count'] = int(state['nu Kuwait and Yemen look very different today. Kuwait enjoys relative health and stability, for el in config: while Yemen suffers significant malnutrition and stunting. How and when did their paths values[el] = config[el] values\_enc = urllib.urlencode(values) Graph shows difference between two countries (increase/decrease in distance score, larger number means less self.api.warning("Creating clusters") req = urllib2.Request('http://lambai response = urllib2.urlopen(reg) except urllib2.HTTPError, err: **CLUSTERING OF 34 MOST** self.api.error(err.read()) Average Stunting Percentage by Cluster Cluster # of Countries ID Countries **HBGDki** Data Angola, Mozambique, Ma Not in the 39 In the 39 countries that bear the brunt of stunting Afghanistan, Nigeria, DR Combining analysis of 134 countries Scientist Algeria Egypt, Iraq, Yemen, Guate with analysis of 39 countries that bear Brazil Chad, Mali, Niger, Burkina the highest stunting burden: China Cameroon, Sudan, Madas 6 Iran Tanzania, Kenya, Uganda North Korea 8 Myanmar, Vietnam, Pakis 19 countries fall into 3 overlapping groups Morocco Principal Factors by Cluster Peni FAO13 - Depth of the for Top 3 Most Discriminating N Cluster Ten positive exemplars fall into same phenotype South Africa 92 - Colon&Rectum femal FAO1 - Average distany energy supply under broad analysis, and separate into sub-Turkey 374 - Female 0-4 years (9 DHS21 - Age at first man 94 - Colon&Rectum femal phenotypes under more granular analysis. Vietnam 114 - 1-59-Diarrhea Angola 300 - One-year-olds immu Three additional countries represent positive 312 - 1-59-Meningitis Cote d'Ivoire 33 - TB mortality, all forms exemplars that belong to a separate broad phenotype. Ghana 27 - TB mortality, all forms 31 - TB incidence, all form Six countries represent negative exemplars, of which Afghanistan 81 - Children per woman two share a granular phenotype with positive 248 - Youth (15-24) literad Egypt 246 - Adult (15+) literacy i exemplars and four belong to phenotypes that contain Burundi no positive exemplars. Madagasca Pakistan 80

#### HBGDki India The https://labs.exaptive.city/#/components/ef828650-94bc-11e6-aa1b-8b6f4991bde Scientist Lambai Get Clusters **Policy** Chrome File Edit View History Bookmarks People Window Heln ♥ ® 🕅 5 + · · · □ □ Thu 10:54 AM Q 👩 🖃 import urllib import urllib2 import json Maker ≜ Secure https://labs.exaptive.city/studio # The function name has to match the name def data(self): ☐ City Servers ☐ Client Cities ☐ Boards ☐ Wiki ☐ Scrum ☐ Xaps ☐ Tech ☐ Active Zoom Meeting Cther Bookm state = self.api.inputstate.export() data = state['data'] config = state['config'] # Determine if the data is already a str if not isinstance(data, basestring): SCRIPT data = json.dumps(data) result = None COMPARING KUWAIT AND YEMEN # Convert to fingerprints values = {} values['data'] = data values['cluster.count'] = int(state['nu Kuwait and Yemen look very different today. Kuwait enjoys relative health and stability, for el in config: while Yemen suffers significant malnutrition and stunting. How and when did their paths values[el] = config[el] values\_enc = urllib.urlencode(values) Graph shows difference between two countries (increase/decrease in distance score, larger number means less self.api.warning("Creating clusters") req = urllib2.Request('http://lambai response = urllib2.urlopen(reg) except urllib2.HTTPError, err: **CLUSTERING OF 34 MOST** self.api.error(err.read()) Average Stunting Percentage by Cluster Cluster # of Countries ID Countries **HBGDki** Data Angola, Mozambique, Ma Not in the 39 In the 39 countries that bear the brunt of stunting Afghanistan, Nigeria, DR Combining analysis of 134 countries Scientist Algeria Egypt, Iraq, Yemen, Guate with analysis of 39 countries that bear Brazil Chad, Mali, Niger, Burkina the highest stunting burden: China Cameroon, Sudan, Madas 6 Iran Tanzania, Kenya, Uganda North Korea 8 Myanmar, Vietnam, Pakis 19 countries fall into 3 overlapping groups Morocco Principal Factors by Cluster Peni FAO13 - Depth of the for Top 3 Most Discriminating N Cluster Ten positive exemplars fall into same phenotype South Africa 92 - Colon&Rectum femal FAC1 - Average dietary energy supply under broad analysis, and separate into sub-Turkey 374 - Female 0-4 years (9 94 - Colon&Rectum femal phenotypes under more granular analysis. Vietnam 114 - 1-59-Diarrhea Angola 300 - One-year-olds immu Three additional countries represent positive 312 - 1-59-Meningitis Cote d'Ivoire 33 - TB mortality, all forms exemplars that belong to a separate broad phenotype. Ghana 27 - TB mortality, all forms 31 - TB incidence, all form Six countries represent negative exemplars, of which Afghanistan 81 - Children per woman Collaborator two share a granular phenotype with positive 248 - Youth (15-24) literad Egypt 246 - Adult (15+) literacy i exemplars and four belong to phenotypes that contain Burundi no positive exemplars. Madagasca Pakistan 80



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https://labs.exaptive.city/x/gates/gcgdatastory

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#### **HBGDki Country Genotyping**

"Happy families are all alike; every unhappy family is unhappy in its own way" -- Leo Tolstoy, from Anna Karenina

This famous quote has come to be used for more than just describing families, it has come to be referred to as "The Anna Karenina Principle" - the recognition that just because certain communities exhibit similar outward signs of distress doesn't mean that the inner root causes of that dysfunction are the same. In the case of global stunted growth there are many unhappy countries, 90% of the world's stunting burden is shouldered by 38 countries. But just because these countries are similar in one problem area, doesn't mean that they should all be grouped together. We know that stunting interventions have a wide range of effectiveness and that interventions that may have been effective in one pilot study may not be as effective when attempted again in a different place. What we don't know, however, is in what to attribute this variance in efficacy. Is the intervention just not consistently effective, or is that the environments in which it has been introduced are not consistent? The questions that the Country Genotyping project seeks to answer are:

By better understanding the similarities and differences between countries, can we make better decisions about how to spend our limited research resources? Can we better target intervention recommendations to the communities where they will have the maximum impact?

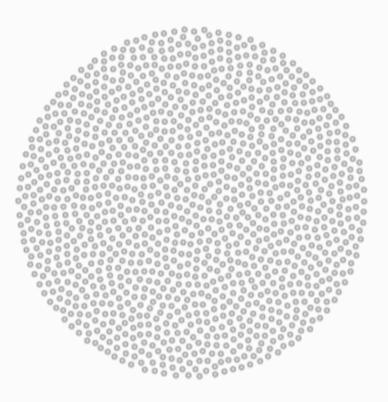
While the Country Genotyping methodology can be applied in a wide variety of situations, we've focused on using it to help researchers decide the best set of "positive exemplar" countries to perform in-depth studies on.

The SckKids Global Center for Child Health, in partnership with the Gates Foundation and bgC3, is in the process of planning a series of fieldwork studies in countries that have improved stunting more than their peers. Unfortunately, there are more countries worthy of study than resources available, so a subset of countries must be selected. How to make this selection? There are logistical criteria that certainly factor in - it is hard to study a country which does not allow researchers access, and it is easier to study a country where researchers may already have connections to local organizations and government. However, we believe that the best criteria for selecting a country for study is to what degree it is believed that anything learned from that study will have applicability for other countries working to improve healthy birth, growth, and development.

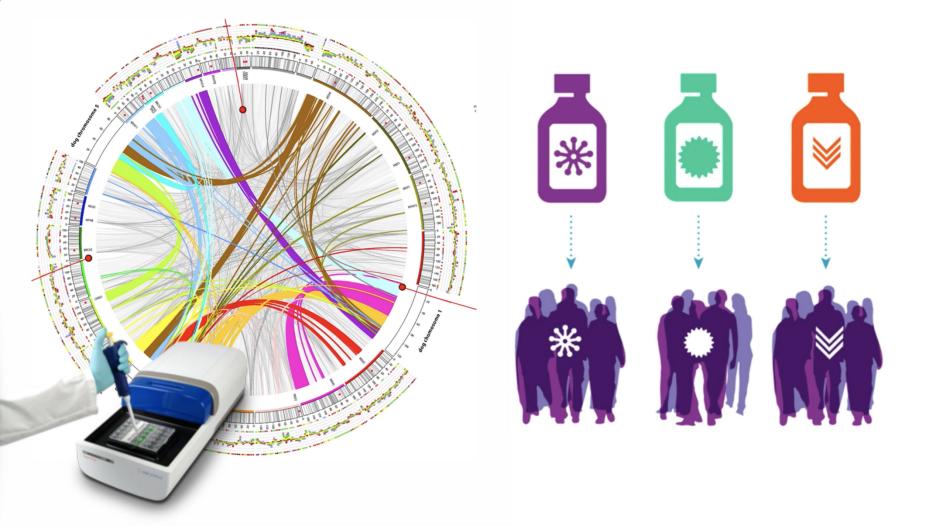
The Country Genotyping Project, applied to the question of which "positive exemplar" countries to study further, aims to identify, through an impartial data-driven method, the best subset of positive exemplars suited to applying their lessons learned to other countries.

#### **General Approach**

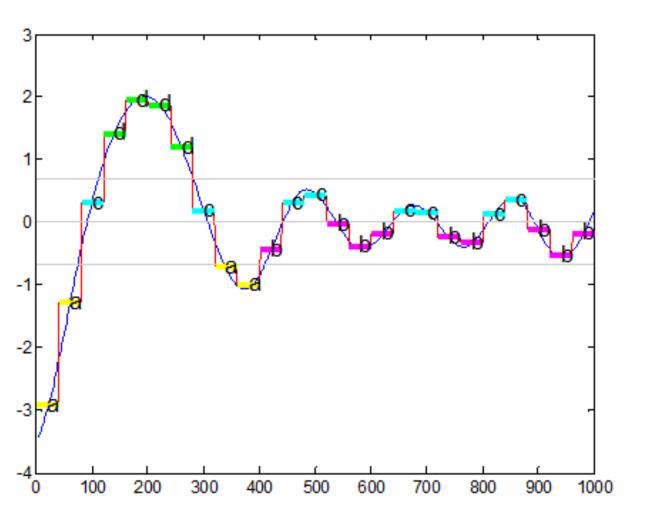
To tackle this problem, we've borrowed an approach from precision medicine that we believe can yield dividends when applied to countries instead of just people. The whole field of precision medicine is based on the Anna Karenina principle - the idea that people exhibit similar symptoms for different reasons, and that the key to improving patient outcomes is to match the right treatment

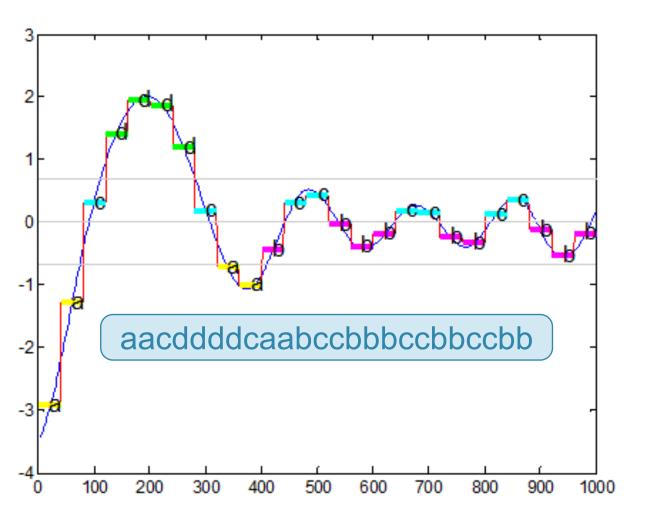










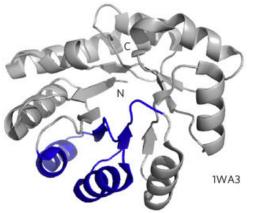


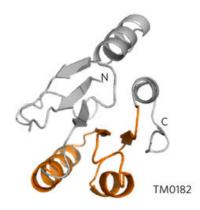


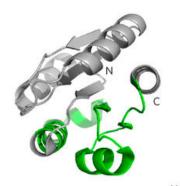
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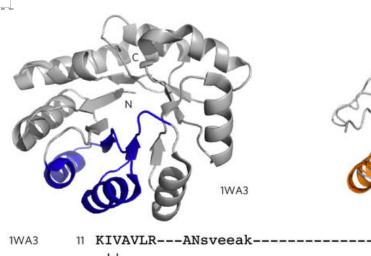


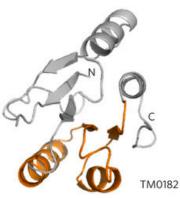




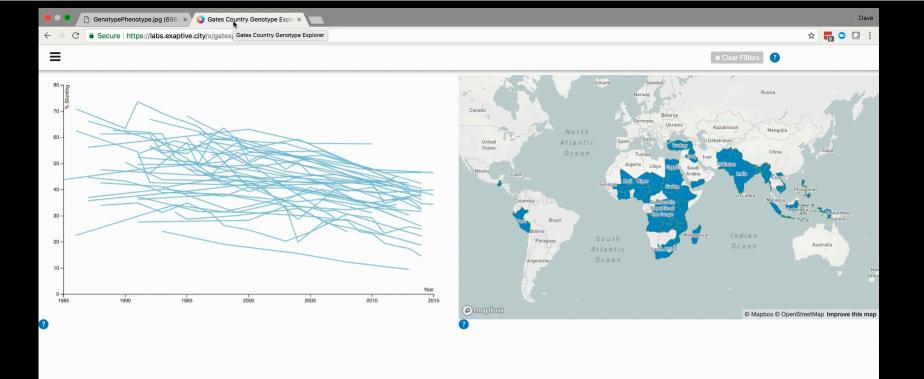
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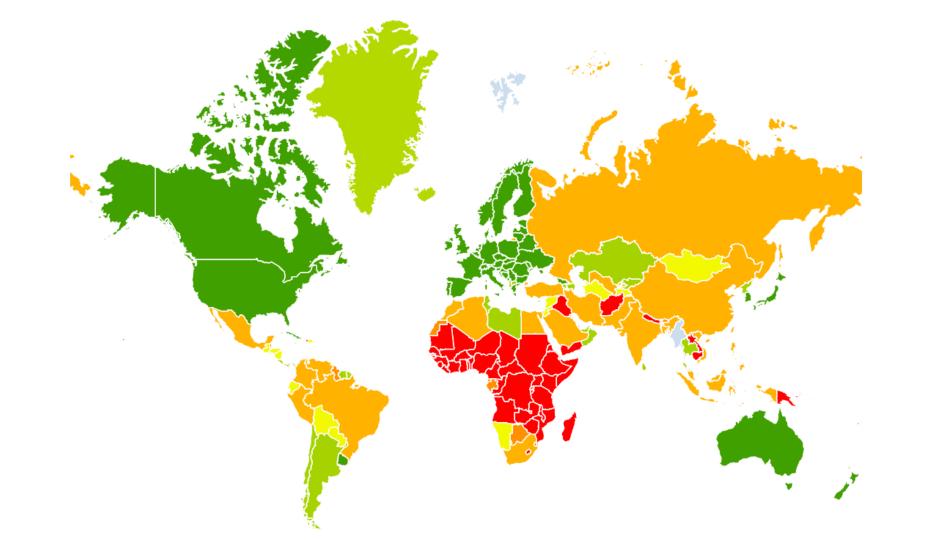
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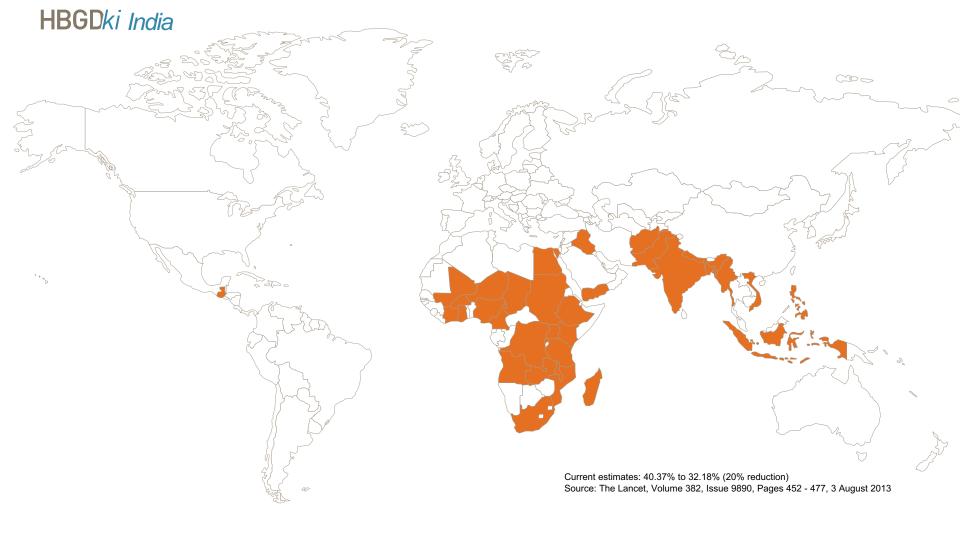


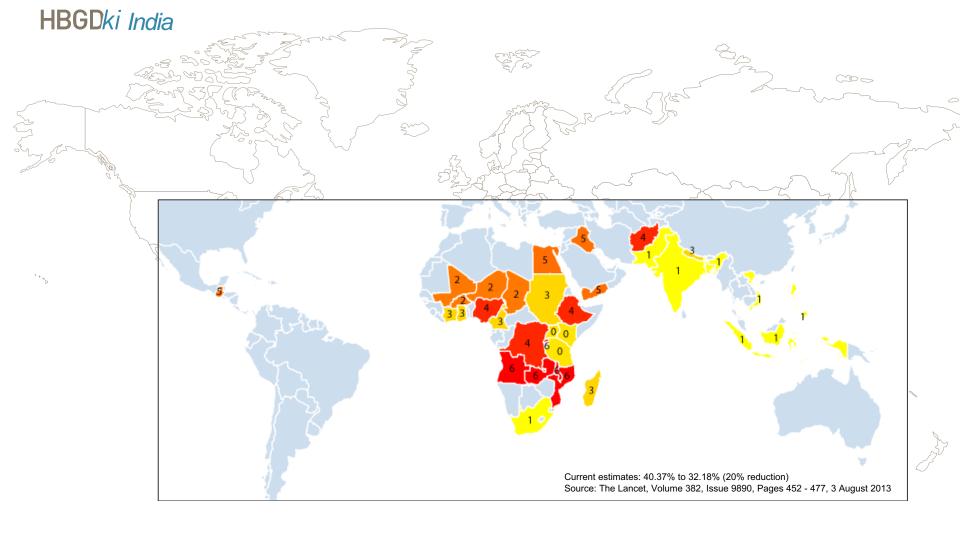




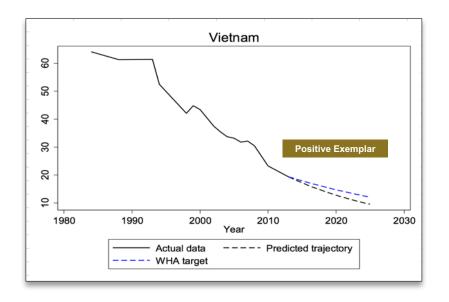


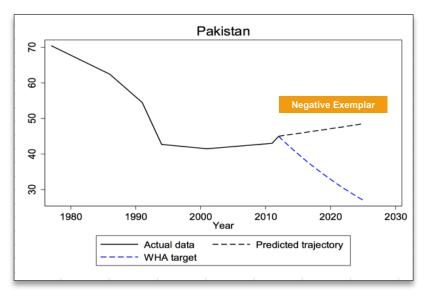






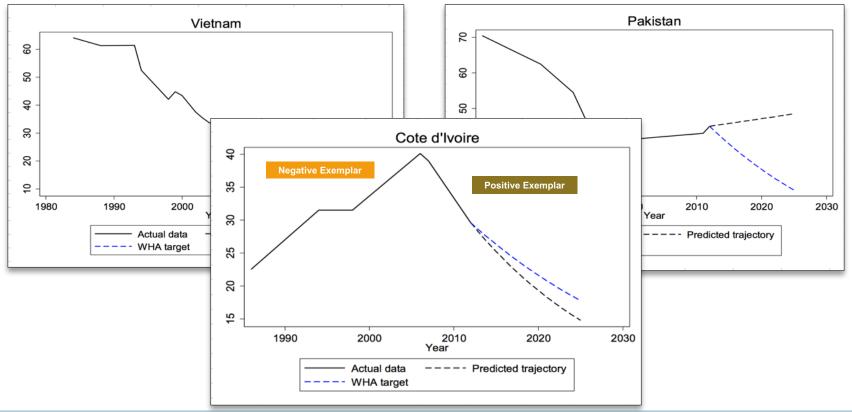
## **Positive/Negative exemplar analysis:**







## **Positive/Negative exemplar analysis:**





**Exemplars among the 39 countries that bear** the greatest burden of stunting:

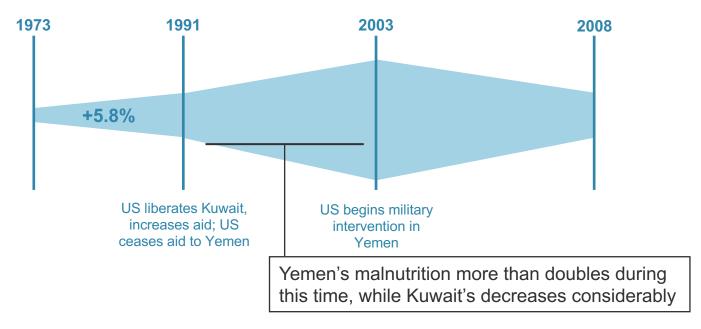


		(2) SAX Fingerprint Segmentation on Time-Series Trajectories of Non-Stunting Metrics										
	Segmentation cluster 1	Segmentation cluster 2	Segmentation cluster 3	Segmentation cluster 4	Segmentation cluster 5	Segmentation cluster 6	Segmentation cluster 7					
	FAO1 - Average dietary energy supply adequacy  FAO12 - Share of food expenditure of the poor  FAO16 - Percent of arable land equipped for irrigation  FAO10 - Domestic food price index	FAO12 - Share of food expenditure of the poor  FAO16 - Percent of arable land equipped for irrigation  FAO19 - Domestic food price volatility	FAO3 - Share of dietary energy supply derived from cereals, roots and tubers  FAO12 - Share of food expenditure of the poor  FAO10 - Domestic food price index	IYCF2 - Ever Breastfed %: Female  IYCF52 - Continued Breastfeeding 1 Year: Female  IYCF53 - Continued Breastfeeding 1 Year: Male	FAO5 - Average supply of protein of animal origin FAO12 - Share of food expenditure of the poor FAO19 - Domestic food price volatility	FAO1 - Average dietary energy supply adequacy  FAO4 - Average protein supply  FAO3 - Share of dietary energy supply derived from cereals, roots and tubers	FAO18 - Political stability and absence of violence/terrorism  FAO16 - Percent of arable land equipped for irrigation  FAO10 - Domestic food price index					
+												
-												
-/-												

(1) Linear Regression on Log(Stunting)

		(2) SAX Fingerprint Segmentation on Time-Series Trajectories of Non-Stunting Metrics									
			Segmentation of Positive Ex		Segmentation Negative I	Mixed					
		Segmentation cluster 7	Segmentation cluster 6	Segmentation cluster 4	Segmentation cluster 2	Segmentation cluster 1	Segmentation cluster 3	Segmentation cluster 5			
		FAO18 - Political stability and absence of violence/terrorism  FAO16 - Percent of arable land equipped for irrigation  FAO10 - Domestic food price index	FAO1 - Average dietary energy supply adequacy FAO4 - Average protein supply FAO3 - Share of dietary energy supply derived from cereals, roots and tubers	IYCF2 - Ever Breastfed %: Female  IYCF52 - Continued Breastfeeding 1 Year: Female  IYCF53 - Continued Breastfeeding 1 Year: Male	FAO12 - Share of food expenditure of the poor  FAO16 - Percent of arable land equipped for irrigation  FAO19 - Domestic food price volatility	FAO1 - Average dietary energy supply adequacy  FAO12 - Share of food expenditure of the poor  FAO16 - Percent of arable land equipped for irrigation  FAO10 - Domestic food price index	FAO3 - Share of dietary energy supply derived from cereals, roots and tubers  FAO12 - Share of food expenditure of the poor  FAO10 - Domestic food price index	FAO5 - Average supply of protein of animal origin  FAO12 - Share of food expenditure of the poor  FAO19 - Domestic food price volatility			
ession ing)	+	Peru South Africa	Turkey	Vietnam	Angola			Ghana			
(1) Linear Regression on Log(Stunting)	-					Burundi Madagascar Pakistan	Mali	Afghanistan Egypt			
(1) Lin	+/-							Ivory Coast			

#### Looking at shifts in segmentation distance over time: Kuwait vs. Yemen



Kuwait in Iraq cluster Yemen in Afghanistan cluster Kuwait joins cluster with India and Egypt

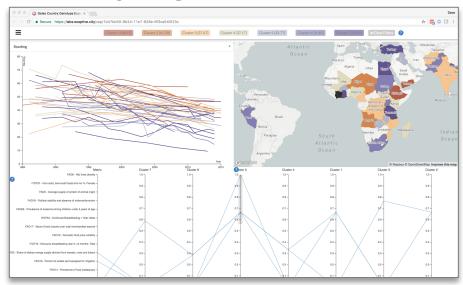
Yemen joins cluster with Ghana and Cote d'Ivoire



Use it Yourself:

Hands-on training to perform India-specific analysis

#### **Country Segmentation Tool**

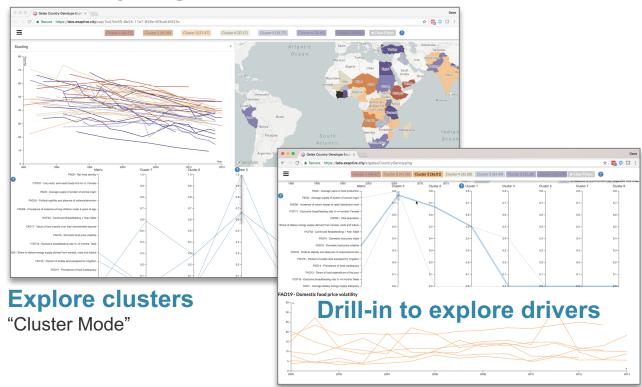


#### **Explore clusters**

"Cluster Mode"

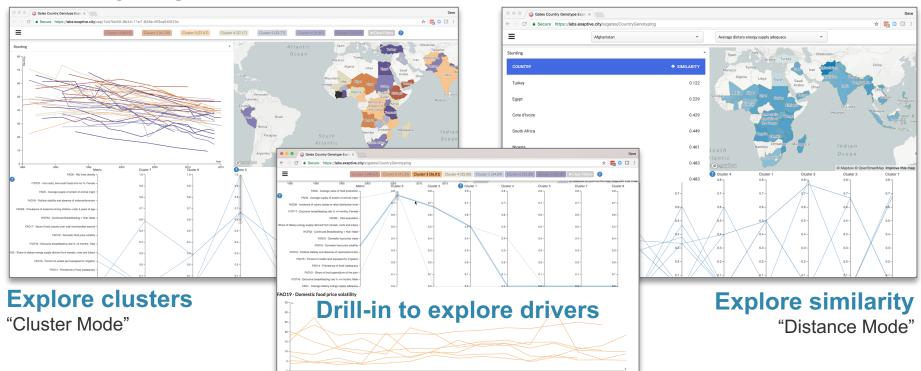


#### **Country Segmentation Tool**



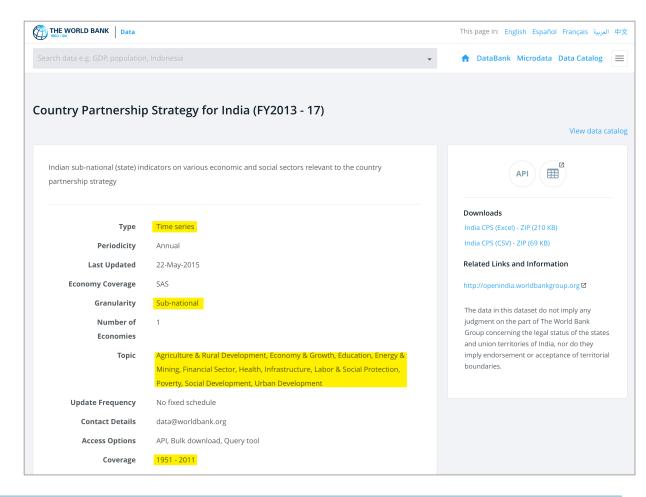


#### **Country Segmentation Tool**



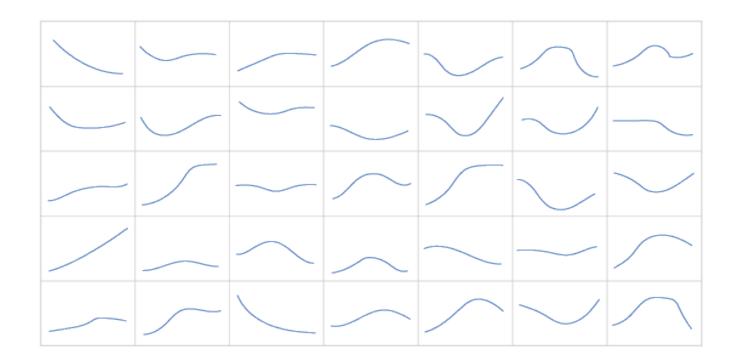


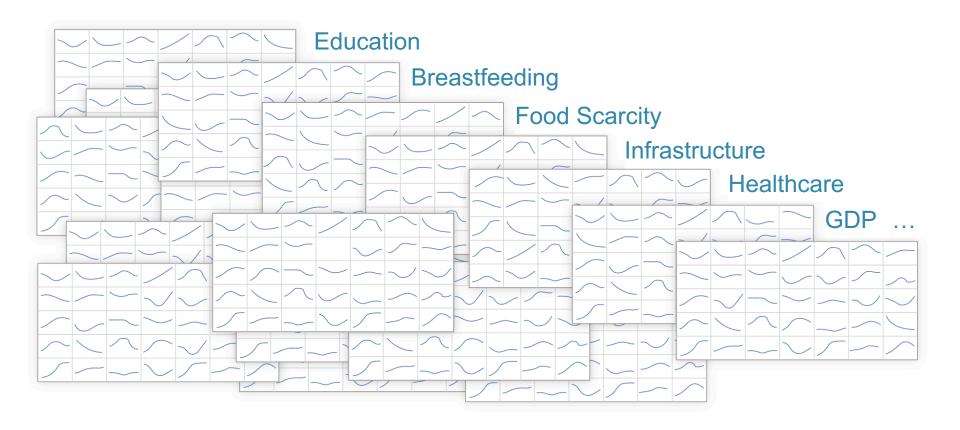
Can "country segmentation" algorithm can also be used for regional segmentation?

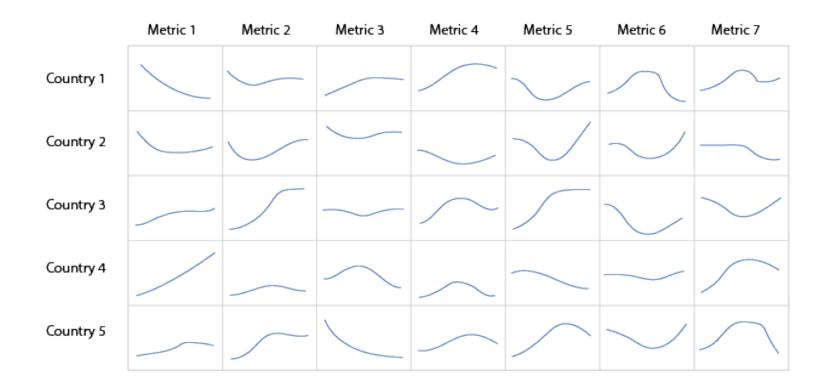


Appendix:

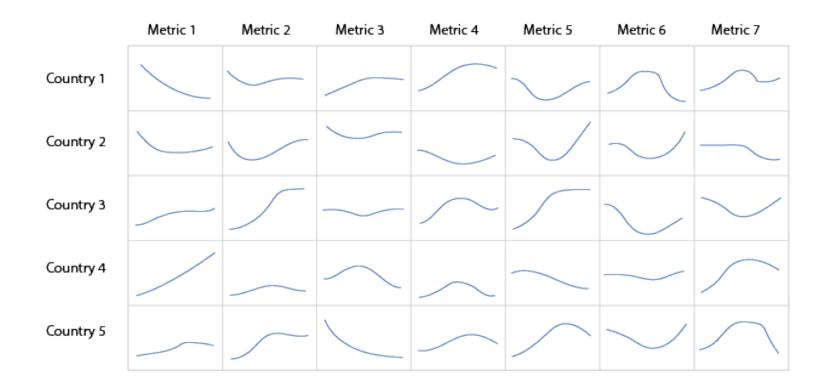
Algorithmic Details

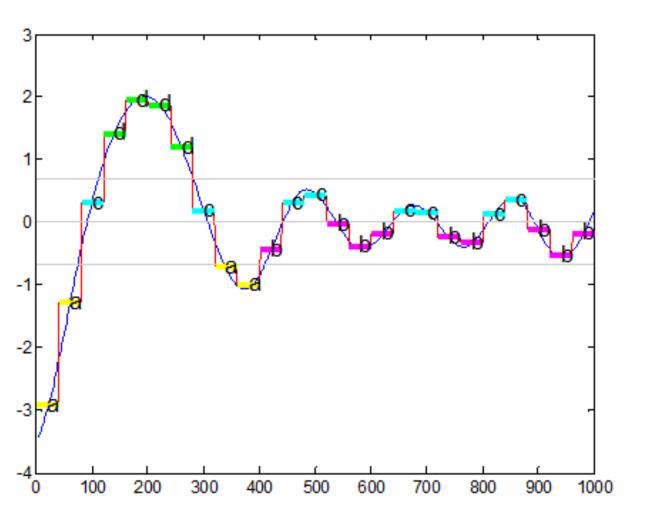


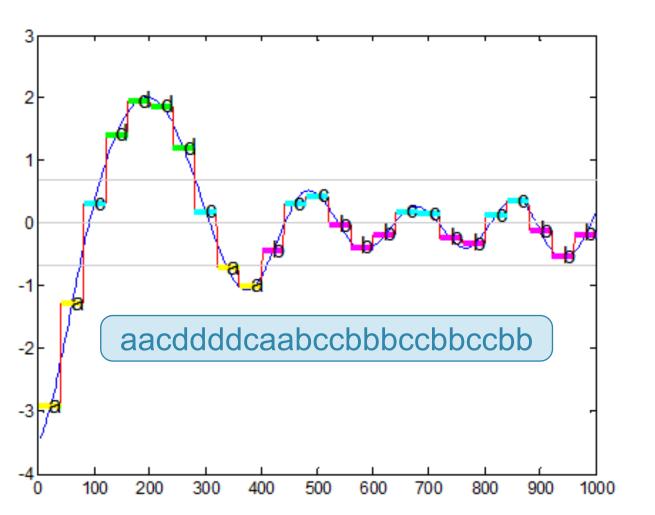




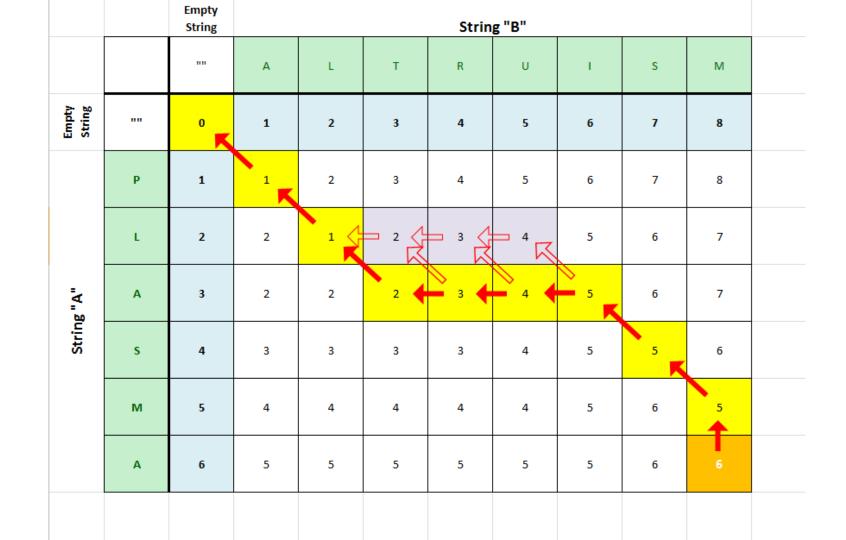
	Metric 1	Metric 2	Metric 3	Metric 4	Metric 5	Metric 6	Metric 7
Country 1	1	3	5	3	4	1	5
Country 2	2	2	3	1	5	1	2
Country 3	2	3	4	2	4	1	2
Country 4	1	2	1	3	3	2	3
Country 5	3	1	4	5	5	4	4

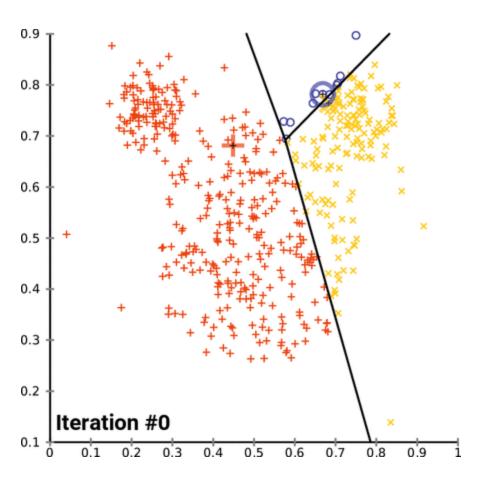






	Metric 1	Metric 2	Metric 3	Metric 4	Metric 5	Metric 6	Metric 7
Country 1	aabcdaffg	ddedghh	jjhhhssd	aabbccdd	aajjkllsss	ccddeefd	dkifdded
Country 2	daffeghg	deghhslif	aaddssd	aaassdg	eeddffss	ccddeeffd	edfkggh
Country 3	aabcdaffg	ddsseefh	eedfjkk	aabcdaffg	aabcdaffg	aabcdaffg	ddeeffgh
Country 4	aabcdaffg	aabbees	bbcccdde	aabcdaffg	aabcdaffg	ggffdkkk	cccddeeh
Country 5	aabcdaffg	jjdffhgl	llefdggs	aabcdaffg	aabcdaffg	aabcdaffg	dddeffg





	Metric 1		1	Metric 2	Metric 3	Metric 4	Metric 5	Metric 6	Metric 7
Country 1		1		ddedghh	jjhhhssd	aabbccdd	aajjkllsss	ccddeefd	dkifdded
Country 2		2		deghhslif	aaddssd	aaassdg	eeddffss	ccddeeffd	edfkggh
Country 3		2		ddsseefh	eedfjkk	aabcdaffg	aabcdaffg	aabcdaffg	ddeeffgh
Country 4		1		aabbees	bbcccdde	aabcdaffg	aabcdaffg	ggffdkkk	cccddeeh
Country 5		3		jjdffhgl	llefdggs	aabcdaffg	aabcdaffg	aabcdaffg	dddeffg

	Metric 1	Metric 2	Metric 3	Metric 4	Metric 5	Metric 6	Metric 7
Country 1	1	3	5	3	4	1	5
Country 2	2	2	3	1	5	1	2
Country 3	2	3	4	2	4	1	2
Country 4	1	2	1	3	3	2	3
Country 5	3	1	4	5	5	4	4

