Machine Learning Project 2: Unsupervised Analysis of the Human Development Report

1 Goal of the Project

In the "unsupervised learning" part of the course, you learned what unsupervised learning is. In particular, you studied two types of unsupervised problems: clustering and visualization. In this project, you will use the k-means algorithm to cluster countries according to their characteristics in the Human Development Report and t-SNE to visualize the resulting clusters. You are expected to handle out a (concise) report of max.4 pages, including plots. Concision will be considered in the grades. For implementation, you will use the scikit-learn Python framework (http://scikit-learn.org). A Python implementation of t-SNE is also provided. Note that the provided implementations are written in Python2, which means that their behavior in Python3 is not determined. You are free to choose the implementation of your choice (in Python2 or Python3) to complete this assignment. Your code has to be sent with your report.

2 Data Extraction

Each year, the Human Development Report Office of the United Nations Development Program publishes the Human Development Report on http://hdr.undp.org. You will use the data released in 2007 which consists of 45 indicators for 138 countries. Cleaning has already been done, by replacing missing values by mean feature values and removing some outlying/abnormal countries/indicators. The country names and indicators are described in Tables 1 and 2.

The dataset is stored in the file hdr_data.dat as a Python dictionary with fields X, country_names, indicator_names and indicator_descriptions. This dictionary can be loaded with the load_HDR_data function in the utils.py file. In this project, there is no distinction between training and test data. Data should be normalized (indicators are very different) with the tools described here:

- http://scikit-learn.org/stable/modules/preprocessing.html#standardizationor-mean-removal-and-variance-scaling
- http://scikit-learn.org/stable/modules/generated/sklearn.preprocessing. StandardScaler.html

| 001 | Norway | 036 | Bahrain | 071 | Tunisia | 106 | Ghana |
|-----|----------------|-----|----------------------|-----|------------------------|-----|--------------------------|
| 002 | Iceland | 037 | Estonia | 072 | Fiji | 107 | Bangladesh |
| 003 | Australia | 038 | Lithuania | 073 | Paraguay | 108 | Nepal |
| 004 | Ireland | 039 | Slovakia | 074 | Turkey | 109 | Papua New Guinea |
| 005 | Sweden | 040 | Uruguay | 075 | Sri Lanka | 110 | Sudan |
| 006 | Canada | 041 | Croatia | 076 | Dominican Republic | 111 | Uganda |
| 007 | Japan | 042 | Latvia | 077 | Belize | 112 | Togo |
| 800 | United States | 043 | Costa Rica | 078 | Iran, Islamic Rep. of | 113 | Zimbabwe |
| 009 | Switzerland | 044 | United Arab Emirates | 079 | Georgia | 114 | Madagascar |
| 010 | Netherlands | 045 | Mexico | 080 | Azerbaijan | 115 | Cameroon |
| 011 | Finland | 046 | Bulgaria | 081 | El Salvador | 116 | Swaziland |
| 012 | Luxembourg | 047 | Trinidad and Tobago | 082 | Algeria | 117 | Yemen |
| 013 | Belgium | 048 | Panama | 083 | Guyana | 118 | Kenya |
| 014 | Austria | 049 | Oman | 084 | Jamaica | 119 | Gambia |
| 015 | Denmark | 050 | Romania | 085 | Cape Verde | 120 | Senegal |
| 016 | France | 051 | Malaysia | 086 | Syrian Arab Republic | 121 | Rwanda |
| 017 | Italy | 052 | Mauritius | 087 | Indonesia | 122 | Nigeria |
| 018 | United Kingdom | 053 | Russian Federation | 088 | Viet Nam | 123 | Guinea |
| 019 | Spain | 054 | Macedonia, TFYR | 089 | Kyrgyzstan | 124 | Angola |
| 020 | New Zealand | 055 | Belarus | 090 | Egypt | 125 | Tanzania, U. Rep. of |
| 021 | Germany | 056 | Brazil | 091 | Nicaragua | 126 | Benin |
| 022 | Israel | 057 | Colombia | 092 | Moldova, Rep. of | 127 | Côte d'Ivoire |
| 023 | Greece | 058 | Venezuela, RB | 093 | Bolivia | 128 | Zambia |
| 024 | Singapore | 059 | Albania | 094 | Mongolia | 129 | Malawi |
| 025 | Korea, Rep. of | 060 | Thailand | 095 | Honduras | 130 | Mozambique |
| 026 | Slovenia | 061 | Saudi Arabia | 096 | Guatemala | 131 | Burundi |
| 027 | Portugal | 062 | Ukraine | 097 | South Africa | 132 | Ethiopia |
| 028 | Cyprus | 063 | Lebanon | 098 | Morocco | 133 | Chad |
| 029 | Czech Republic | 064 | Kazakhstan | 099 | Gabon | 134 | Central African Republic |
| 030 | Malta | 065 | Armenia | 100 | Namibia | 135 | Burkina Faso |
| 031 | Kuwait | 066 | China | 101 | India | 136 | Mali |
| 032 | Hungary | 067 | Peru | 102 | Cambodia | 137 | Sierra Leone |
| 033 | Argentina | 068 | Ecuador | 103 | Botswana | 138 | Niger |
| 034 | Poland | 069 | Philippines | 104 | Lao People's Dem. Rep. | | - |
| 035 | Chile | 070 | Jordan | 105 | Pakistan | | |

Table 1: Country names in the HDR 2007 dataset.

Your first task is to load the HDR dataset. Quickly look into the dictionary fields to see what kind of data is provided. Then, normalize the data for your unsupervised analysis. This task does not need to be described in the report.

3 Clustering and Visualization

Once the data are normalized, you can cluster the instances into several groups. However, you do not know $how \ many$ clusters can be found in the data. Hence, you need to try several number of clusters and choose the clustering which makes the most sense for you. Use the k-means algorithm which is described here:

- http://scikit-learn.org/stable/modules/clustering.html#k-means
- http://scikit-learn.org/stable/modules/generated/sklearn.cluster. KMeans.html

In order to choose the right number of clusters, you need to visualize the clustering itself. First, you can look at the cluster centers. Since they are obtained with k-means, they do not correspond to a particular country (each cluster center is the mean of the countries in the corresponding cluster). However, you can look at the name/indicators of the countries which are the closest to the cluster centers. These countries can be obtained with the find_closest_instances_to_kmeans

| Name | Interpretation | | | |
|-----------------------|--|--|--|--|
| Pop growth | Annual population growth rate (%) 1975-2004 | | | |
| Pop growth 2004 | Annual population growth rate (%) 2004 | | | |
| Price index | Average annual change in consumer price index (%) 1990-2004 | | | |
| Carbon Dioxide 2003 | CO2 emissions - per capita (mertic ton) 2003 | | | |
| Export 1990 | Export of goods and services (% of GDP) 1990 | | | |
| Export 2004 | Export of goods and services (% of GDP) 2004 | | | |
| Elec 2003 | Electricity comsumption per capita (kW/h) 2003 | | | |
| GDP | GDP (US\$ billions) 2004 | | | |
| GDP PPP | GDP (PPP US\$ billions) 2004 | | | |
| GDP pc | GDP per capita (US\$) 2004 | | | |
| GDP pc growth rate | GDP per capita growth rate (%) 1990-2004 | | | |
| Fem Econo Rate | Female economic activity rate (% age 15 and older) 2004 | | | |
| Fem Econo 1990 | Female economic activity rate (index, 1990=100, % age 15 and older) 1990 | | | |
| Fem Econo 2004 | Female economic activity rate (index, 1990=100, % age 15 and older) 2004 | | | |
| Health Exp | Health expenditure per capita (PPP US\$) 2003 | | | |
| Babies | Infant with low birth weight (%) 1996-2004 | | | |
| Internet 1990 | Internet users (per 1,000 people) 1990 | | | |
| Import 1990 | Import of goods and services (% of GDP) 1990 | | | |
| Import 2004 | Import of goods and services (% of GDP) 2004 | | | |
| Tertiary female ratio | Gross tertiary enrolment - ratio of female to male 2004 | | | |
| Babies immunized | One-years-olds fully immunized against measles (%) 2004 | | | |
| Manufactured Exp 2004 | manufactured exports (% of merchandise exports) 2004 | | | |
| Foreign invest 2004 | Net foreign direct investment inflows (% GDP) 2004 | | | |

| Name | Interpretation |
|-------------------------|--|
| Military 2004 | Military expenditure (% GDP) 2004 |
| Public Health 2003 | Public health expenditure (% of GDP) 2003 |
| Private Health 2003 | Private health expenditure (% of GDP) 2003 |
| Primary export 2004 | Primary exports (% of meschandise exports) 2004 |
| Public Health | Public expenditure on health (% of GDP) 2003-2004 |
| Refugees asylum | Refugees by country of asylum (thousands) 2005 |
| Refugees origin | Refugees by country of origin (thousands) 2005 |
| Armed forces | Total armed forces (thousands) 2006 |
| Parliament Women | Seats in parliament held by women (% total) |
| Female Male income | Ratio estimated female to male earned income |
| House women 2006 | Seats in lower house or single house held by women (% total) |
| Pop 1975 | Total population 1975 (millions) |
| Pop 2004 | Total population 2004 (millions) |
| Pop 2015 | Total population 2015 (millions) |
| Tuberculosis detected | Tubreculosis cass detected under DOTS (%) 2004 |
| Tuberculosis cured 2004 | Tubreculosis cass cured under DOTS (%) 2004 |
| Trad fuel | Traditional fuel consumption (% total energy requirements) 2003 |
| ODA pc donnor 2004 | ODA per capita of donor country (2004 US\$) 2004 |
| ODA to least dev 1990 | ODA to least developed countries (% of total) 1990 |
| ODA to least dev 2004 | ODA to least developed countries (% of total) 2004 |
| ODA received | Official developement assistance (ODA) received (net disbursements) Total (US \$ millions) |
| ODA received pc | Official developement assistance (ODA) received (net disbursements) per capita (US \$) |

Table 2: Indicator names in the HDR 2007 dataset.

function in the utils.py file. Second, you need to reduce the dimensionality of the data in order to visualize them on your computer screen. This can be done with the tsne function in the tsne.py file. Eventually, the data can be visualized (using the 2D coordinates given by t-SNE and the country names) with the show_annotated_clustering function in the utils.py file.

Your second task is to cluster the HDR data with the k-means algorithm for $k=2\ldots 10$ clusters. Choose one clustering which contains not enough clusters, one clustering which contains enough clusters and one clustering which contains too many clusters. Show the t-SNE visualization of these clusterings (and only those) in the report. In each case, give the names of the countries which are the closest to the centers. Explain/discuss why you chose each of these three clusterings (not enough clusters, enough clusters, too many clusters). In each case, can you give an interpretation of the clusters? Notice that your choice (e.g. of the "good number" k of clusters) is subjective and may be different from the one of other students working with the same methods on the same data.

Tip: the quality of the visualizations obtained with t-SNE may be sensitive to its meta-parameter: the perplexity. The right perplexity (interpreted as a soft number of neighbors) must be chosen. Notice that the t-SNE coordinates do not depend on the clustering, i.e. they can be precomputed before each clustering with $k=2\ldots 10$ clusters. This way, you will be able to compare the clusterings on similar visualizations

Tip: if you need to open several figures to display the clusterings, you can use the function matplotlib.pyplot.figure. Also, the find_closest_instances_to_kmeans function returns two sets of values, which are retrieved as: closest_instances, closest_indices = find_closest_instances_to_kmeans(...).