# World-wide personal freedom: A comparison of 2008 and 2016

#### Introduction

Many events and trends impacting the freedom of individuals have occurred from 2008 to 2016. Starting with the financial crisis in 2008, the fallout of which severely affected the life-trajectories of many of the people not responsible for it (Greenstone & Looney, 2011). Similar outcomes in poverty, redundancies and inequality were the result of years of EU-administered austerity measures in Greece (Matsaganis, 2013; Stylianidis & Souliotis, 2019). The 2010s also brought with them a rise in authoritarianism which has yet to recede (Weill, 2021). This went hand in hand with an erosion of privacy and rise of mass-surveillance under the guise of anti-terrorism in the western world (Bauman et al., 2014), while internet censorship became more widely employed in countries like China or Saudi Arabia, among others (York, 2022). Toward the end of this time frame the Syrian civil war had displaced millions, resulting in immigration law changes across Europe (Hernes, 2018; Hatton, 2020). Although these developments are only some of the most egregious violations of personal freedom across this span of years, they have contributed significantly to gradual decreases in individual liberties.

One conceptualization of personal liberties popularized in Isaiah Berlin's 1958 *Two Concepts of Liberty*, is the differentiation between positive and negative liberty. While the latter refers to a freedom from restraint or being prevented from doing things, the prior assumes the presence of something allowing the achievement of certain ends (Stanford Encyclopedia of Philosophy, 2021). Although admittedly, Berlin's concept is a simple one and has been criticized thusly (e.g., Stanford Encyclopedia of Philosophy, 2021), it can still serve as a starting point in investigating the development of individual liberties from 2008 to 2016. An example of negative liberty could be the removal of border checks, removing a restraint that would potentially disallow freedom of movement. Examples of positive liberties may be the affordable care act established in the US in 2010 or the legalization of same-sex marriages across a number of countries

during the 2010s. Whereas these liberal successes during the time frame exist, there does seem to be a gradual decrease in personal freedoms within the given time frame, especially referring back to the previous paragraph. Thus, in the following, the question of how positive and negative liberties have developed during the years between 2008 and 2016 will be investigated.

To answer this question, the Human Freedom Index data set assembled by the liberal-leaning think tank *Cato Institute*, comprising the abovementioned years, is used. It covers different facets of personal and economic freedoms as measured by other data sources, compiles them, and based on these, calculates freedom scores. Importantly, the Institute's neoliberal ideological sway becomes apparent when looking at the coding of certain measures of economic freedom, as they equate a larger size of government with a lower level of freedom or the fact that the ability to "flexibly determine" firing decisions as an employer is considered a pillar of freedom, among other biased coding decisions. Using assorted measures from the data covering all measures of personal freedom while disregarding most measures of economic freedom and all scores, ranks and percentiles calculated by the Cato Institute<sup>1</sup>, principal component analysis (PCA) and hierarchical clustering (HC) are used to differentiate the freedoms of individuals in different countries.

#### **Methods**

In order to prepare the data for analysis, several steps were taken. First, as mentioned above, "economic freedom" variables were largely removed, with the exception of black market and "visa strength" measures, which may be argued to also belong to personal freedoms. Additionally, tally and final scores and the like which serve only to rank the countries based on other variables were removed in order to reduce redundancy. As the HFI data set is an agglomeration of different data sources, many missing values are present throughout the data set. To deal with this, countries with low response rates across the years of the given time frame were removed entirely. Then, variables with too

<sup>1</sup> Please refer to the appendix for an overview of the variables used and discarded.

many missing values were also removed from the analysis<sup>2</sup>. Due to PCA requiring data without missing values in order to avoid distorted results, the remaining missing values were imputed using the *mice* package in R (van Buuren & Groothuis-Oudshoorn, 2011). Notably, the conditions for this procedure are not given in this scenario, as multiple imputation by chained equations requires the data to be missing at random (van Buuren, 2021). This cannot be expected to be the case in these data, as data sources on personal freedoms, especially in the less free or rich countries may be argued to likely not have been provided due to access to data being prohibited or the respective data not being recorded rather than random failure during measurements. Although this may lead to biased imputation of missing values, this is accepted in order to do PCA and HC.

Principal component analysis is an exploratory data analysis technique used in order to reduce the complexity (i.e., reduce the number of variables) and extract features (i.e., find the important components in the data) of a large data set consisting of continuous and evenly scaled variables. It performs this linear combination of variables by laying out the data points in a n-1 dimensional space with the goal of maximizing their variance, where n is the number of supplied variables. This maximization of variance results in the first principal component and is then repeated, capturing less variance with each further principal component. PCA outputs several interpretable metrics which are interrelated to a great extent. The principal components (PCs) are the new variables, explain a certain amount of variance in the data and serve as axes in the biplots often used to visualize the results of PCA. Scree plots are employed to determine the number of PCs to keep in further analysis and are based on the (cumulative) eigenvalues of the PCs. Furthermore, each of the initial variables and individuals has contribution scores and cos<sup>2</sup> values. The prior is the share of a variable or individual in explaining the variation for a given PC. The latter shows how well the variable or individual represents the given PC. Finally, the coordinates of the individuals (countries) on the axes indicate their values on the PCs which are often used to then conduct further analyses. PCA is used in this paper to reduce the complexity of the

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<sup>&</sup>lt;sup>2</sup> For exclusion criteria for countries and variables, please refer to the appendix.

relatively large data set in use and to extract the main facets of personal freedom of individuals across different countries.

Based on the results of the PCA, namely the coordinates of the countries in the relevant PCs, hierarchical clustering will be performed. Clustering aims to group data based on shared properties, which will be used in the context of this paper to uncover similarities across levels of freedom worldwide comparing the years 2008 and 2016. Similarly to PCA, clustering requires scaled data, which is the case as the PCA output will be used. The decision to use HC is due to it not relying on a predefined number of clusters in the data, unlike algorithms such as K-means or PAM. This is advantageous, as no assumptions can be made about the number of clusters regarding individual freedoms. HC is further divided into agglomerative and divisive approaches, the prior of which will be employed due to its comparatively greater efficiency. It works "bottom-up" by considering each data point its own cluster and step-by-step merging clusters, while divisive HC works "top-down" starting the algorithm with the data as a single cluster. Specifically, the Ward's linkage method HC algorithm will be employed. This agglomerative HC algorithm analyzes the variance of clusters and in the present analysis will use a Euclidean distance matrix as a basis for judging similarity between data points. Following this, partitioning methods such as silhouette, gap statistic and WSS are used to test for a fitting number of clusters. Finally, partitioned dendrograms and world maps will illustrate the clustering results.

#### Results

After running the PCA with the regions of the countries as qualitative supplementary variables, the scree plots of the two years were inspected. Using the elbow criteria, selecting the first two PCs seems reasonable, although there is a difference between the years in regard to the variance explained in PC 3 and 4. As can be seen in Figure 1, whereas for the data from 2008 there is little difference between PC 3 and 4 in explained variance, PC 3 from 2016 does contain around 5 % more explained variance than PC 4. For ease of comparison, however, this is disregarded and only the first two

PCs are included for both years in the further analyses, explaining around 30 and 13 percent of variance respectively.

Figure 1

Scree plots visualizing the explained variance of the principal components

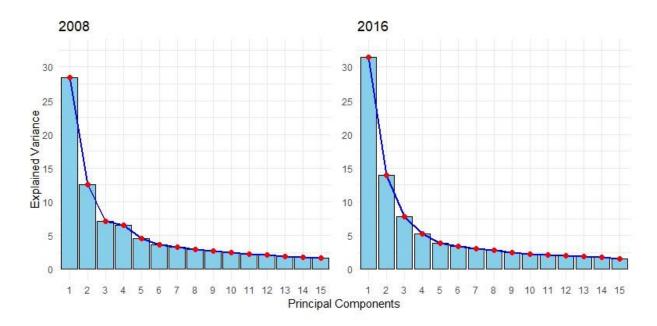


Figure 2 shows a snippet (for better legibility) of the variable biplot of the year 2016<sup>3</sup>. Upon ocular inspection, variables such as procedural justice, political pressure and control of the media, as well as laws and regulations influencing media delineate this component. Indeed, these 3 variables make up both the highest contribution and cos<sup>2</sup> values when looking at the underlying results<sup>4</sup>. Meanwhile, the second component is made up of mostly legal and some security and safety variables such as the business cost of crime, the reliability of police, impartiality of courts and risk of homicide, with these variables scoring the highest contribution and cos<sup>2</sup> values, indicating that these variables both had a greater impact on the component and represent it better

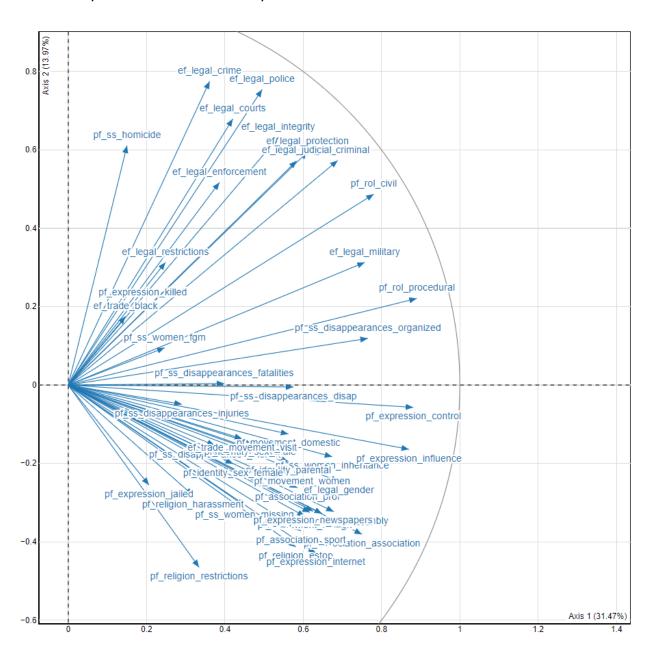
<sup>&</sup>lt;sup>3</sup> For brevity's sake and due to similar results, the plots for 2008 can be found in the appendix.

<sup>&</sup>lt;sup>4</sup> For excerpts of the variable tables, please refer to the appendix.

qualitatively speaking. Interestingly, low negative correlations with the second component can be found with the variables measuring the restrictions against religions and their founding, as well as state control over internet access.

Figure 2

Variable biplot for the first two components of the data for 2016

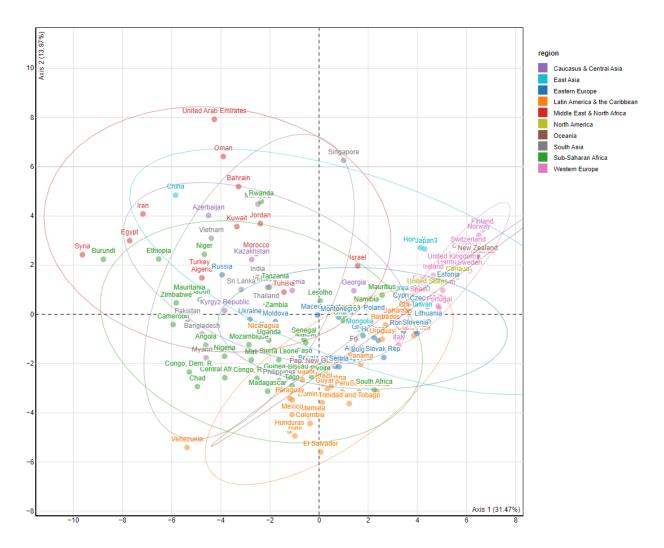


Furthermore, there seem to be two distinct groupings of variables that are roughly orthogonal to one another, indicating uncorrelatedness between the groups and strong correlations within them. These are a cluster mostly consisting of variables on freedom as defined by a functional legal system, while the other one is broader and contains variables on freedom of identity, gender, associations, expressions and movement. In interpreting the two components one may assign the first component the rather broad title "Civil liberties", as the variables with large contributions to it refer to civil justice and primarily negative freedoms. The second component more distinctly seems to cover "Criminal justice and individual safety", with negative correlations in religious freedoms and access to the internet. The components are composed of similar variables for 2008, especially the second component is nearly identical, indicating that the factors extracted from the HFI data set have stayed relatively stable across the 8-year period.

Investigating how the countries map onto these two variables is done by observing their positions in the new two-dimensional coordinate space as shown in Figure 3 for the example of the 2016 data. Additionally, shared colors and ellipses comprising countries of the same regions are used for generalizability. The results generally reaffirm the interpretations of the components above. Component 1, "civil liberties" is highly correlated with the democracies of Western Europe, North America and East Asia. Conversely, de facto dictatorships and authoritarian regimes such as Burundi and Ethiopia map far in the negative along this axis. The second axis, interpreted as "Criminal justice and individual safety", portrays the two extremes: countries in which numerous offences lead to capital punishment and the crime rate is very low, such as Singapore and Oman in the positive coordinates and a grouping of especially South American countries infamous for their lack of personal safety and broken (criminal) justice systems such as El Salvador and Honduras in the negative. The regional clusters suggested by the PCA procedure are then potentially also observed by means of HC.

Figure 3

Country plot for the first two components of the data for 2016 with region ellipses



As outlined in the Methods section, the coordinates of the countries on the two respective principal components are used to cluster them on a world map based on the agglomerative Ward's linking algorithm which minimizes the intra-cluster variance when continuously merging clusters. One of the challenges with hierarchical clustering is that although the number of clusters is not predefined, it needs to be decided upon after running the algorithm regardless. Here, this is solved by a function in R called *NbClust* which applies 30 different indices for determining the number of clusters and proposes the best clustering scheme based on which number of clusters was suggested most

often. For both timepoints, this resulted in 3 clusters, though more clearly so in the data from 2008. Figures 4 and 5 show the countries colored by their clusters on a world map. In both years, the second cluster fairly clearly depicts the primarily democratic nations that are positioned right of the center in Figure 3. The third cluster is composed of the countries in the top left quadrant of Figure 3, indicating their relatively high personal safety and strict criminal justice systems. Assuming the stability of interpretability principal components of the 2008 and 2016 PCAs, the greater spread of the third cluster in 2016 may indicate a rise in internally safe, though unfree regimes. Interestingly, the countries that became part of the third cluster in 2016 were almost entirely comprised of countries that were part of the first cluster in 2008, implying that countries with low personal safety and damaged criminal justice systems resulting in a general instability may serve as steppingstones for authoritarian regimes to form. In general, it seems that the instability engendered by the countries of the second cluster may lead not only to changes into more authoritarian regimes, but also serve as opportunities for development toward democratic systems, as some countries, such as Bulgaria and Ghana, become part of the second cluster in 2016.

#### **Discussion**

The initially posed question aimed to inspect the development of positive and negative liberties between the years of 2008 and 2016. This was unsuccessful mostly due to the fact that the components extracted did not differentiate issues traditionally related to positive or negative liberty clearly, which may be due to the fact that the concept is too vague to be used with data that is not specifically designed to measure it: for example, the decriminalization of drug possession may be considered a positive liberty as it allows individuals to better access public health resources in cases of addiction or just safe consumption, while at the same time being considered a negative liberty because it would mean not to be bothered about personal consumption anymore. More likely, however, this is a case of garbage in garbage out.

Figure 4

Clusters of freedom on world map 2008

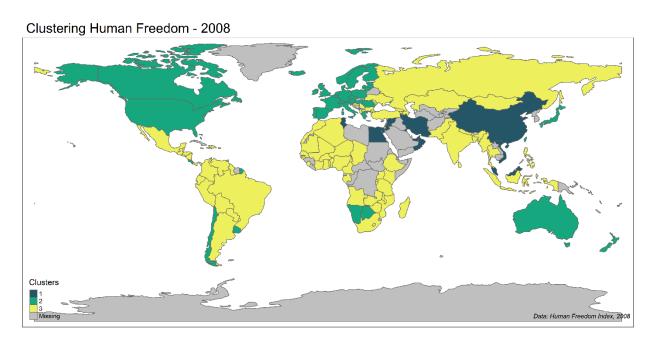
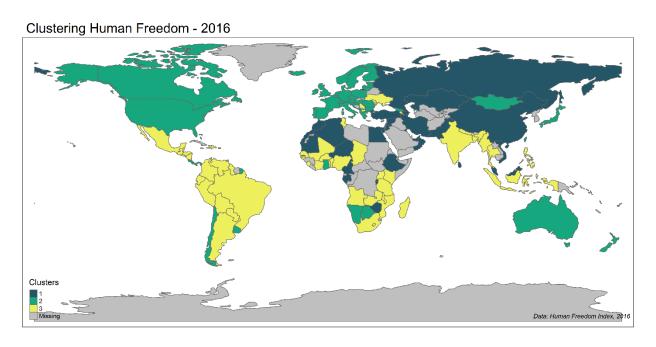


Figure 5

Clusters of freedom on world map 2016



The HFI data set is not only skewed toward negative liberties in the selection of its variables but also penalizes measures that may be considered positive liberties, such as worker's rights. Instead of recoding these, which may have been possible, these variables were entirely removed by the author, being left with a data set that makes it impossible to observe changes in positive liberties, as it does not contain them. Despite this, due to the exploratory nature of PCA and HC, interesting (though highly preliminary as they are only correlative) results were found regardless. Democracies are freer than other forms of state and especially the democracies of western Europe are very close to one another in how free they are. This is likely encouraged by supra-national organizations such as the European Union. In the years of 2008 to 2016 cluster with the fewest losses to other clusters was the one containing democratic countries. This may suggest that compared to the other two clusters, high levels of individual freedom foster stability of type of government, whereas countries in which personal security and defunct criminal justice systems are a common concern, this instability may more easily give rise to authoritarian regimes. Caution is necessary when evaluating these interpretations and further research to back them up is of the essence. All in all, it can be said that this exploratory data analysis with PCA and HC has, despite shortcomings on the side of the data, delivered hints about the difference of personal freedom worldwide and potential patterns of countries becoming more or less free over time.

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# **Appendix**

Countries removed (and based on which criteria):

Belarus, Bhutan, Brunei, Darussalam, Cambodia, Cape Verde, The Gambia, Guinea, Iraq, Laos, Lebanon, Liberia, Libya, Qatar, Saudi Arabia, Seychelles, Sudan, Suriname, Swaziland, Tajikistan, Timor-Leste, Yemen

These countries were removed based on having missing values in more than 42% of variables in the years 2008 and 2016.

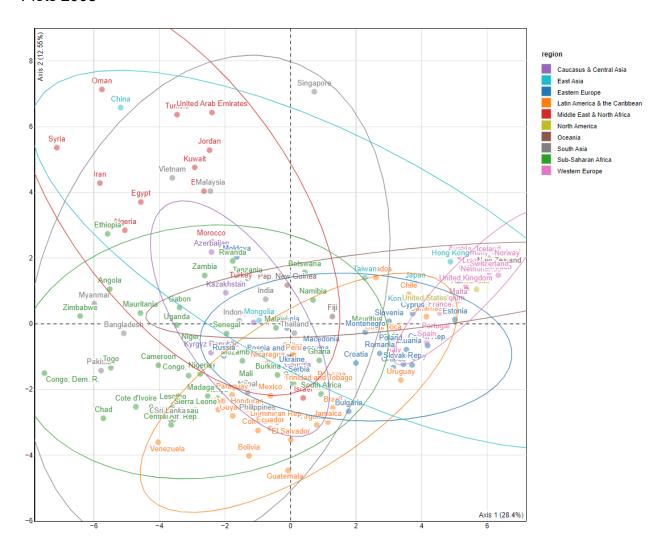
Variables discarded (and based on which criteria):

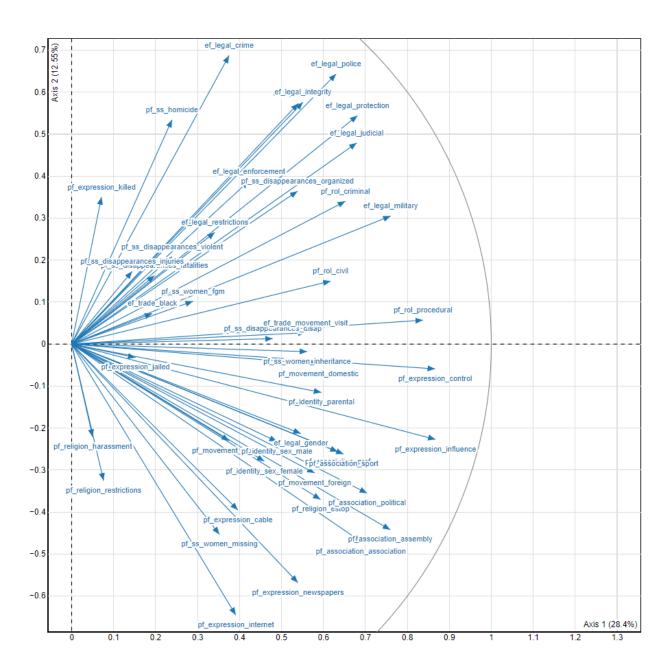
In the data set with the above-mentioned countries removed, variables where in 2008 and 2016 more than 42% of values were missing were removed from the analysis. These are:

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year, ISO_code, countries, pf_rol, pf_ss_disappearances, pf_ss_women_inheritance_widows, pf_ss_women_inheritance_daughters, pf_ss_women, pf_ss, pf_movement, pf_religion_estop_establish, pf_religion_estop_operate, pf_religion, pf_association_political_establish, pf_association_political_operate, pf_association_prof_establish, pf_association_prof_operate, pf_association_sport_establish, pf_association_sport_operate, pf_association, pf_expression, pf_identity_legal, pf_identity_parental_marriage, pf_identity_parental_divorce, pf_identity_sex, pf_identity_divorce, pf_identity, ef_government_consumption, ef_government_transfers, ef_government_enterprises, ef_government_tax_income, ef_government_tax_payroll, ef_government_tax, ef_government, ef_legal, ef_money_growth, ef_money_sd, ef_money_inflation, ef_money_currency, ef_money, ef_trade_tariffs_revenue, ef_trade_tariffs_mean, ef_trade_tariffs_sd, ef_trade_tariffs, ef_trade_regulatory_compliance, ef_trade_regulatory, ef_trade_movement, ef_trade_movement, ef_trade_movement,
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ef\_trade, ef\_regulation\_credit\_ownership, ef\_regulation\_credit\_private,
ef\_regulation\_credit\_interest, ef\_regulation\_credit, ef\_regulation\_labor\_minwage,
ef\_regulation\_labor\_firing, ef\_regulation\_labor\_bargain, ef\_regulation\_labor\_hours,
ef\_regulation\_labor\_dismissal, ef\_regulation\_labor\_conscription, ef\_regulation\_labor,
ef\_regulation\_business\_adm, ef\_regulation\_business\_bureaucracy,
ef\_regulation\_business\_start, ef\_regulation\_business\_bribes,
ef\_regulation\_business\_licensing, ef\_regulation\_business\_compliance,
ef\_regulation\_business, ef\_regulation

## **Plots 2008**





# Variable tables 2008 (PC1 and PC2):

## Active variables

Show 20 v entries				Search:	
Variable	<b>A</b>	Coord⊕	Contrib⊕	Cos2	Cor
pf_expression_influence		0.867	5.89	0.752	0.867
pf_expression_control		0.866	5.87	0.750	0.866
pf_rol_procedural		0.837	5.49	0.701	0.837
ef_legal_military		0.760	4.52	0.577	0.76
pf_association_assembly		0.759	4.51	0.576	0.759
pf_association_political		0.704	3.88	0.495	0.704
pf_association_association		0.689	3.71	0.474	0.689
ef_legal_protection		0.681	3.63	0.464	0.681
ef_legal_judicial		0.679	3.61	0.461	0.679
pf_rol_criminal		0.652	3.32	0.425	0.652
pf_association_sport		0.648	3.29	0.420	0.648
pf_association_prof		0.634	3.14	0.402	0.634
ef_legal_police		0.630	3.11	0.397	0.63
pf_rol_civil		0.617	2.98	0.381	0.617
pf_identity_parental		0.595	2.77	0.354	0.595
pf_religion_estop		0.593	2.75	0.352	0.593
pf_movement_domestic		0.588	2.70	0.345	0.588
pf_movement_foreign		0.579	2.62	0.335	0.579
pf_ss_women_inheritance		0.561	2.46	0.315	0.561
ef_trade_movement_visit		0.557	2.42	0.310	0.557
Showing 1 to 20 of 45 entries				Previous 1 2 3	Next

#### Active variables

Show 20 v entries			Search:		
Variable	A.	Coord	Contrib	Cos2	Cor
ef_legal_crime		0.687	8.37	0.472	0.68
pf_expression_internet		-0.645	7.38	0.416	-0.64
ef_legal_police		0.643	7.32	0.413	0.643
ef_legal_integrity		0.576	5.87	0.331	0.57
ef_legal_courts		0.573	5.81	0.328	0.573
pf_expression_newspapers		-0.568	5.72	0.323	-0.568
ef_legal_protection		0.544	5.24	0.296	0.54
pf_ss_homicide		0.534	5.05	0.285	0.53
ef_legal_judicial		0.479	4.06	0.229	0.47
pf_association_association		-0.470	3.92	0.221	-0.4
pf_ss_women_missing		-0.453	3.63	0.205	-0.45
pf_association_assembly		-0.442	3.46	0.195	-0.44
pf_expression_cable		-0.395	2.77	0.156	-0.39
ef_legal_enforcement		0.388	2.67	0.151	0.38
pf_religion_estop		-0.370	2.43	0.137	-0.3
pf_ss_disappearances_organized		0.364	2.35	0.133	0.36
pf_association_political		-0.355	2.23	0.126	-0.35
pf_expression_killed		0.350	2.17	0.123	0.3
pf_rol_criminal		0.340	2.05	0.116	0.3
pf_religion_restrictions		-0.325	1.87	0.105	-0.32

# Variable tables 2016 (PC1 and PC2):

## Active variables

Show 20 v entries			Sea	rcn:	
Variable	A V	Coord	Contrib⊕	Cos2	Cor
pf_rol_procedural		0.890	5.59	0.792	0.89
pf_expression_control		0.881	5.48	0.776	0.881
pf_expression_influence		0.870	5.34	0.757	0.87
pf_rol_civil		0.780	4.30	0.609	0.78
pf_ss_disappearances_organized		0.765	4.14	0.586	0.765
ef_legal_military		0.757	4.04	0.573	0.757
pf_association_association		0.750	3.98	0.563	0.75
ef_legal_gender		0.691	3.37	0.477	0.691
pf_rol_criminal		0.688	3.34	0.473	0.688
pf_association_assembly		0.678	3.24	0.459	0.678
pf_ss_women_inheritance		0.674	3.21	0.455	0.674
pf_association_political		0.648	2.96	0.419	0.648
pf_expression_internet		0.632	2.82	0.400	0.632
pf_expression_newspapers		0.625	2.76	0.390	0.625
pf_expression_cable		0.617	2.69	0.381	0.617
ef_legal_protection		0.611	2.64	0.374	0.611
pf_movement_foreign		0.604	2.58	0.365	0.604
pf_movement_women		0.597	2.51	0.356	0.597
pf_association_sport		0.594	2.50	0.353	0.594
pf_association_prof		0.585	2.42	0.342	0.585

## Active variables

Show 20 v entries			Sea	rch:	
Variable	<b>*</b>	Coord	Contrib <sup>⊕</sup>	Cos2	Cor
ef_legal_crime		0.775	9.54	0.600	0.775
ef_legal_police		0.754	9.04	0.568	0.754
ef_legal_courts		0.679	7.33	0.461	0.679
ef_legal_integrity		0.632	6.35	0.399	0.632
pf_ss_homicide		0.611	5.93	0.373	0.611
ef_legal_protection		0.595	5.64	0.354	0.595
pf_rol_criminal		0.573	5.21	0.328	0.573
ef_legal_judicial		0.572	5.20	0.327	0.572
ef_legal_enforcement		0.517	4.25	0.267	0.517
pf_rol_civil		0.487	3.78	0.238	0.487
pf_religion_restrictions		-0.465	3.43	0.216	-0.465
pf_expression_internet		-0.429	2.93	0.184	-0.429
pf_religion_estop		-0.413	2.72	0.171	-0.413
pf_association_association		-0.381	2.31	0.145	-0.381
pf_association_sport		-0.372	2.20	0.138	-0.372
pf_movement_foreign		-0.335	1.78	0.112	-0.335
pf_association_political		-0.328	1.72	0.108	-0.328
pf_expression_cable		-0.325	1.68	0.106	-0.325
pf_association_assembly		-0.323	1.66	0.104	-0.323
pf_expression_newspapers		-0.322	1.65	0.104	-0.322
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