Visualizing Ethnic Fractionalization, Conflicts and Power Relations

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ABSTRACT
Why do ethnic conflicts arise? This question has been a persistent one in the field of political science, and has generated various theories and approaches attempting to explain conflict proliferation from different angles. Consulting current political science literature and Prof James Fearon, an expert on ethnic conflicts, we identify two main approaches to understanding the problem: one has ethnic fractionalization as the unit of analysis, while the other puts ethnopoliitical configurations of power in focus. In our visualization, we aim to synthesize these two approaches with group-level data by lending ethnic power structures, ethnic fractionalization, linguistic distances and conflict incidence visual meaning. Having merged datasets from multiple sources and generated a new dataset on linguistic distances, we create an integrated visualization system using multiple sources. Methods employed include the use of normalized stacked bars, animated orbital structure and the novel application of MDS on visualizing linguistic distances. At least from preliminary user-testing, our final product has enabled users to relate historical contexts to visualizations, facilitated trend spotting and helped analysts evaluate quality of dataset in new ways.

INTRODUCTION
Recent quantitative scholarship on ethnic politics and conflicts has generated a rich trove of data pertaining to ethnic fractionalization, polarization, power relations and conflicts. Using these data, political scientists have come up with various theories to answer the perennial question of why civil conflicts emerge. Our research reveals two key approaches to understanding ethnic politics and conflicts: one examines ethnic diversity and its relation to armed conflict, as represented by works of Easterly, Alesina, James Fearon & David Laitin (2003) and Alberto Alesina et al (2003); the other approach puts ethnopoliitical configurations of power in focus and employs a more recent global dataset by Cederman, Wimmer, Min (2009).

While there have been visualizations that visualize country-level data and map conflicts, no attempt has been made to visualize group-level data that can be useful for analyzing the structure of ethnic diversity and power relations. The objective of our system design is to synthesize the aforementioned two approaches in understanding ethnic conflicts, spatializing ethnic diversity and ethnic power relations in one data exploration platform.

More specifically, our visualization seeks to examine why civil conflicts arise by:

1. Revealing internal ethnopoliitical configurations of power within countries and how they change over time;
2. Visualizing civil conflict incidences and their relations to internal power structures of countries;
3. Lending “ethnic diversity”, a key variable in the debate on civil conflicts, greater visual meaning by merging and visualizing data pertaining to ethnic fractionalization, polarization and linguistic distances;
4. Facilitating cross-country comparisons helpful for spotting patterns and testing hypotheses, by enabling user-directed custom selection of countries of interest.

We worked with James Fearon from the Political Science Department, a leading scholar in the study of ethnic conflicts and civil wars, who provided us with a replication data from his famous paper “Ethnicity, Insurgency and Civil War”, as well as invaluable feedback on our visualizations. We also consulted Jeremy Weinstein, a scholar known for his work on ethnicity and development, from whom we learnt a great deal more about the subject matter and ongoing studies in the field amenable to visualization.

After multiple need-finding sessions and in-depth research on current conflict literature, our group decided to visualize three variables of interest: ethnic fractionalization, a metric calculated using linguistic distances, conflict onsets and ethnic power relations.

This paper presents relevant research on the problem at hand, related work that led us to making the design decisions that we did, visualization techniques and finally an assessment of results and insights that our visualization platform has generated.

RELATED WORK
Visualization of conflicts is not new. The need to preempt conflicts in order that appropriate measures can be taken before an outbreak has driven defense agencies and intelligence communities across the world to devise tools and visualizations that can help analysts do trend-spotting. The demand for visualizations that can help us better...
understand the nature of ongoing and future conflicts has been growing, especially post Arab-Spring. Ongoing civil and ethnic conflicts in the African continent have also prompted renewed interest – both in the political science discipline and visualization field – in visualizing conflict data. Preliminary research led us to examining several visualizations that share a similar motivation.

**Visualizing Complex Vulnerability in Africa: The CCAPS Climate-Conflict Mapping Tool**

![Figure 1: CCAPAS Climate-Conflict visualization](image)

In a bid to identify regions in Africa that are most vulnerable to climate change, the Climate Change and African Political Stability Program (CCAPS) created a mapping tool that visualizes a combination of datasets on international development projects, national governance indicators, incidences of conflict and climate vulnerability. Interestingly, this tool allows users to interact and customize visualization by assigning different variables different weights (e.g. if a user thought governance should have more weight within the model it could re-weigh baskets of indicators) so that the resulting visualization can disaggregate data into its component parts. With an intuitive interface and compelling visuals, the tool can potentially be a valuable resource for policy analysts and researchers to assess the complex interactions that take place among environmental, political and social factors. Advanced filters allow the user to identify a subset of conflicts and aid projects.

**World Conflict Visualizer**

![Figure 2: Conflict History Visualizer (www.conflicthistory.org)](image)

This interactive web interface allows users to learn about conflicts that have occurred throughout history from the 18th century all through to present data. In terms of visualization technique it is quite straightforward, involving a simple geographical mapping of conflicts around the world across time. The information panel with a comprehensive list of conflict-related information is useful for a user who would like to engage with historical information on demand.

**Zeroing-on group-level dynamics**

Most platforms available today display country level data on conflict-relevant indicators such as the frequency of protests, quality of governance, incidence of conflicts. While these are certainly useful for trend-spotting across countries, they offer little insight into underlying ethnic structures, diversity and power relations that drive most civil conflicts in history. A simple, straightforward mapping of civil wars and ethnic conflicts may reveal certain clustering effects across geographical boundaries but do not reveal group membership of actors that drive interactions in ethnic conflicts. Our interactions with current political science literature and consultations with Professor James Fearon and Jeremy Weinstein have prompted us to visualize group-level data to uncover group dynamics across time, something that has not yet been attempted.

**Conflict networks**

As far as we are aware of, the only study that looked into group-level dynamics is a paper by Brandes and Lerner (2008) in which they proposed a general method for visualizing conflict networks. Using an array of visualization techniques, their method highlights the most involved actors, reveal the opposing groups and provide a graphic overview of the conflict structure.

For instance, given a list of events, their method visualizes the resulting conflict network in which distances are driven by the severity of conflict relationship between parties of conflict. In contrast to pure dyadic analysis, such networks give additional information about indirect ties (e.g. enemies

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of enemies), density complexity and structure of actors’ network environment.

Figure 3: Visualization of conflict network constructed from events related to War in Bosnia. The nodes represent political actors, edges represent conflictive relations)

We find this an interesting visualization technique applicable to our problem at hand, specifically in visualizing linguistic distances.

NEEDFINDING
Consulting James Fearon and Jeremy Weinstein from the Political Science Department and conducting research on the subject matter led us to focusing on two dominant approaches to understanding the rise of civil conflicts: ethnic fractionalization and inter-ethnic group power relations.

Ethnic Fractionalization
The first variable we took interest in for our visualization was ethnic fractionalization. Fractionalization as a variable has been widely used by political analysts in understanding conflicts, economic development and wealth disparities. Easterly and Ross Levine (1997) first argued that ethnolinguistic fragmentation is linked to conflict onset, a thesis that Fearon took up later in his seminal paper “Ethnicity, Insurgency and Civil Conflicts” (2003). Alesina et al. (2007) built on Fearon’s work and studied ethnic polarization and its effects on other development-related variables. The common thread among these studies has been the use of ethnic fractionalization measures, something we thought interesting to visualize.

The best and most widely used data on ethnic fractionalization is the Ethno-Linguistic Fractionalization index generated by a team of Soviet ethnographers in the early 1960s, published as *Atlas Narododox Mira*. Their list of “ethnolinguistic” groups and population figures has been employed by several generations of political scientists, sociologists and, more recently, economists to produce cross-national estimates of “ethnic fractionalization”.

But if one has a theory that says that ethnic diversity matters because ethnic differences make it harder for people to cooperate and coordinate, then one might be interested in some notion of distances between ethnic groups rather than just fractionalization. For instance, even though the fractionalization scores of Belarus and Cyprus are the same, Belarus is much less culturally and linguistically divided than Cyprus.\(^3\) It is this inadequacy of prevailing fractionalization measures that led Fearon to studying distances between groups. To do this he studied group-level data and the structural relationships between languages with the help of tree diagrams, proposing using distance between “tree branches” of two languages as a measure – albeit a noisy one – of cultural distance between groups that speak them as a first language.

The result form his study was a cross-national list of ethnic groups that that had at least 1% of country population in the 1990s, which amounts to 822 ethnic and “ethnoreligious” groups in 160 countries.

Language distances
On closer look at Fearon’s dataset, though, we found these differences to be quite discrete. Right about the same time during our research we discovered an interesting dataset from the Automated Similarity Judgment Program, a project that has attempted a computerized lexicalstatistical analysis of languages worldwide.\(^4\) The ASJP provides a classification of all languages by a single, consistent and objective method and performs various statistical analyses regarding the historical and areal behavior of lexical terms.

Out of interest and curiosity we ran the ASJP software to calculate distance matrices of 5000 language spoken in 223 countries (because there existed countries that were not recognized by the UN in the dataset). This might be well beyond the scope of a visualization project since we are in fact generating datasets by merging them in new ways, but it is helpful in visualizing linguistic distances, the key basis for understanding ethnic fractionalization.

Ethnic Power Relations
The second approach is advanced by Cederman, Wimmer and Min (2009), who based their research on a more recent dataset comprising group-level data across time. Instead of

\(^3\) Byelorussians, Ukrainians, and Russians are quite similar in terms of religion, language and customs; by contrast, Greeks and Turks speak languages that come from completely different families (Indo-European and Altaic).

focusing on ethnic diversity, they see states as being characterized by certain ethnopolitical configurations of power that increase the risk of conflict. For instance, armed rebellions are more likely to challenge states that exclude large portions of the population on the basis of ethnic background. Large number of competing elites sharing power in a segmented state also increases the risk of violent infighting.

The relevant dataset for this variable is the Ethnic Power Relations dataset (EPR), which identifies all politically relevant ethnic groups and their access to state power in every country of the world from 1946 to 2005. It includes annual data on over 733 groups and codes the degree to which their representatives held executive-level state power—from total control of the government to overt political discrimination. The EPR makes temporal analyses possible by capturing changes in ethnic politics over time, unlike static indicators like the ethnic fractionalization index.

Moreover, Cederman, Wimmer and Min has an accompanying “Ethnic Armed Conflict” dataset that includes an important group-level data on conflict onset, a variable that is also central to our problem at hand and would form the basis for visualizing conflicts across time.

METHODS & RESULTS
Informed by our research, we sieved out relevant data and devised several visualization methods that integrate these approaches into one visualization platform.

DATA
Our visualization pulls together data from four datasets:

1. **Ethnic Fractionalization Indices (Fearon):** Fearon’s replication data has country-level data on 1) ethnolinguistic fractionalization value by the Soviets; 2) ethnic fractionalization index by Fearon; 3) religious fractionalization index by Fearon

2. **Ethnic Power Relations (Cederman, Wimmer, Min):** Variables of interest includes 1) Power-

3. **Language distance matrices generated from ASJP software:** This dataset provides matrices of linguistic distances between each language spoken in the country.

Data processing has entailed mergers of various datasets to combine variables of interest into the same data file.

**Visualizing fractionalization with normalized stacked bars**

We considered different visualization techniques to visualizing fractionalization (derived from the number and proportion of groups within each country), and experimented with tree maps, bubble charts and circle packing. Because of the sheer number of countries and ethnic groups we have in the dataset, neither of these methods could deliver the sort of visual clarity we desired.

We decided on what was possibly the simplest but probably most visually elegant solution: normalized stacked bar charts that show percentages of each ethnic group in each country. Stacked bars achieve better visual immediacy insofar as the user is interested in the comparing relative levels of fractionalization.

These bars also double as country selectors. On click, visualizations of power relations, linguistic distances and conflict timeline appear at once. Clicking on rectangles that compose the bars highlights the ethnic group both in the normalized bar chart and in the power-relations visualization.

A search bar facilitates instant searching and filtering of countries.

**Visualizing power relations with orbits**

A central variable of interest in the Ethnic Power Relations dataset is the power ranking of each ethnic group in the country. This is an ordinal variable indicating group’s ranked political status in a given year, in this order: Monopoly – Dominant – Senior Partner – Junior Partner – Separatist and Regional Autonomy – Powerless – Discriminated.
Each orbit represents a power rank provided by the dataset, radiating from the center of power. The further away from the orbital center, the less influence the ethnic group has over political processes. Central to the orbital visualization is the idea of in-group and out-group: the two centermost orbits are shared by senior and junior partners, or groups holding dominant or monopoly power—collectively constituting the in-group. Ethnic groups outside of the center rings are excluded from central power and constitute the out-group.

Ethnic groups engaged in conflicts are indicated by color-encoding, in this case colored red. Controlling with a time slider, users can observe temporal changes across three dimensions:

1. population size, indicated by animated changes in bubble sizes;
2. power status, indicated by animated shifts between orbits;
3. Conflict incidence, indicated by changes in color-encodings.

To add visual contour to the power structure, we added a gradient that radiates from the power center. Animation brings into focus transitions in power status of different ethnic groups across time within the power structure. Detailed information of ethnic group, such as population proportion with respect to country population, languages, peace years and settlement patterns are displayed on hovering over.

Conceptualizing power relations in terms of orbital spheres of influence help provide an intuitive frame of reference to the distribution of power across ethnic groups and relative influence in the political process—a dimension well-served by a positioning encoding. Encoding population size gives the visualization an additional dimension that indicates proportion between power and group size, an important determinant of ethnic tensions and likelihood of conflict onset.

Visualizing language distances with classical MDS

The point of visualizing linguistic distances is to make clear the structures and relationships between languages in a country, as well as the dissimilarity between any two languages. The language dissimilarity values come from the Automated Similarity Judgment Program (ASJP) language dissimilarity dataset, which compares any two languages based on character-level differences between words with similar meaning.    

In the initial view in Figure 5.1, languages are represented as circles on screen, sized by population. When the user clicks a circle, it moves to the center and other circles arrange themselves with respect to it, as shown in Figure 5.2.

Features

- Distances between circles approximate the ASJP dissimilarity between those two languages, using the optimal approximation as computed by the Classical Multidimensional Scaling algorithm
- Detailed information on languages (full name, population) is revealed on mouse hover
- When a circle is clicked, it moves to the center, and the remaining circles arrange themselves around it in a semicircle (Figure 1b) such that their new distances to the central circle are the exact ASJP dissimilarity values. Hovering over an edge reveals the exact dissimilarity value.
- The order of the outer ring of circles in Figure 1b follows the best one-dimensional approximation to the ASJP dissimilarities. For example, notice that the Brahui group is separated from the main cluster in Figure 1a (and Kati to a lesser extent), and these two groups are also aligned to the right

References

away from the main cluster in Figure 1b. The semicircle pattern was chosen (instead of a full circle) as it suggests that the languages placed at either end of the semicircle are those with the highest language dissimilarity.

- Brushing and Linking: selecting a language also highlights the ethnic groups related to that language in the ethnic group related parts of the visualization, and vice versa.

**Choice of algorithm**

Figure 2 compares the results of classical MDS (which we ended up using), weighted MDS, and non-metric MDS. Classical MDS plots points so as to approximate the desired dissimilarity values. Weighted MDS, with population sizes as weights, places greater emphasis on preserving distances between points with higher weight. Non-metric MDS preserves the relative ordering of distances between points, but not necessarily the exact distances.

![Figure 7: output in R of three multidimensional scaling methods: 1) classical; 2) weighted by population; 3) non-metric](image)

There was little difference between the output of classical and weighted MDS; however, weighted MDS has a slight tendency to place the points at vertices of a regular polygons at the expense of hiding other structure in the data, because there are generally a small number of languages with high weight. This phenomenon can be seen to a small degree in Figure 5.

Non-metric MDS has the problem of collapsing multiple nodes at single points, as shown in Figure 2. This is because it only considers the relative order of the distances: if extremely small distances are consistent with the desired relative ordering, the optimization algorithm has no incentive against using such small distances, thus collapsing them into clusters of very small size. For these reasons, we chose to use classical MDS. On the other hand, non-metric MDS is generally faster because it does not rely on eigenvector-based methods, which are usually cubic in the size of the matrix; non-metric MDS has been used successfully on datasets of tens of thousands of genes. Non-metric MDS also has the advantage of making fewer assumptions: it only looks at the relative ordering of the given dissimilarities, so the result is not affected if we multiply or add the same value to the whole dissimilarity matrix, which is an advantage if we do not know if our original dissimilarities are scaled appropriately.

**Implementation**

The algorithm for laying out the circles in Figure 1a is as follows:

1. Based on the dissimilarity matrix involving the languages in a country, use the first two coordinates obtained from Classical Multidimensional Scaling (CMDS) to compute a set of circle centers whose pairwise distances approximates the dissimilarities.
2. Size the circles by the population of each language (taking square roots to map population onto an area encoding).
3. Repel the circles to remove intersections: while there are intersecting circles, move them away from each other enough so they no longer intersect. The amount the circles move is inversely proportional to the circle size: this is done because larger circles have a higher chance of intersecting with another circle again after being moved, so we move them a smaller amount to minimize the chance of this happening.
4. Rescale all the circles to fit into the outer (grey) circle in Figure 1a, based on the small circle with the largest sum of its radius and distance away from the center.

The algorithm for the circles in Figure 5 is:

1. Move the selected circle to the center, and set the radius of every other circle to the corresponding language dissimilarity value.
2. Sort the languages based on their first coordinate obtained from Classical Multidimensional Scaling.
3. Assign the circles with angles such that their angles are evenly spaced and form a semicircle as in Figure 1b, and the order of the circles along the semicircle follows the sorted order in Step 2.
4. Repel the circles to remove intersections.
5. Rescale the diagram to fit into the outer circle.

Mathematically, the Classical Multidimensional Scaling algorithm can be seen as finding the rank-two matrix that minimizes the sum of squares of its differences between its

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entries and the original dissimilarity matrix. Classical MDS involves two steps: first double-centering to transform the dissimilarity matrix into a matrix of dot products, and then computing the first two eigenvectors of the matrix of dot products; the first eigenvector gives the x-coordinates of our result, and the second gives the y-coordinates. A readable guide to MDS from an applied point of view can be found in Jaworska (2009)\textsuperscript{10}, while a more conceptual description is given in Torgerson (1952)\textsuperscript{11}.

**Putting temporal changes in context by linking up variables**

One of the most interesting data we have at hand is a time series that shows how power rankings of countries change over time. Conflict incidence and power rankings are important but not meaningful without putting them in historical context. It will therefore be important to track changes in power relations over time, and see these shifts in relation to conflict incidence. An animated power structure controlled by a time slider on a conflict timeline most effectively meets this design purpose. D3 transitions and interpolations have been helpful to this end.

**Conflict Timeline and Time Slider**

![Conflict Timeline and Time Slider](image)

**Figure 8: Conflict Timeline and Time Slider**

The conflicts timeline provides a visual summary of conflict incidents experienced by each ethnic group across years. Years that saw the ethnic group engaged in conflict is color-coded red, lending visual immediacy to conflict incidence among ethnic groups, across time.

Time-based navigation enables the user to observe conflicts incidence and ethnic power relations at play. Moving the time slider updates multiple variables at once: the bubbles in the power structure, color-encodings of bubbles as well as facilitates user-directed exploration since the user can pause at desired points in time.

We have also integrated the visualizations through linking and brushing, so that selection of an ethnic group on clicking automatically highlights variables related to that group in other parts of the visualization. Clicking on an ethnic group in the power structure highlights the languages spoken by the group in the linguistic distance visualization, as well as the associated rectangle in the normalized stacked bars.

This feature has enabled easy cross-referring between power relations, ethnic fractionalization and linguistic distances, making our visualization an integrated whole.

**DISCUSSION**

With the limited time we had, we conducted user-testing with about a dozen people, including Prof. James Fearon, fellow Stanford students and people who had visited our booth and spent extended time interacting with our visualization platform at the poster session.

**Telling stories with visualizations across time**

Most users who interacted with our systems were most interested in finding out visualizations of their home country. While interacting with two Chinese students, they were intrigued by the shifts in ethnic power relations over time, especially the positioning of Tibetans, Uyghurs on the orbits. Moving the time slider, they paused at particular years that exhibited interesting shifts – such as the inward movement of almost all ethnic groups in 1984 - and hovered over particular groups that experienced more drastic shifts in power rankings. What emerged was a story of ethnic tensions among the Tibetans, Uighurs and the Han Chinese over the years:

![Group highlighted red is the Tibetan group, whose rebellion forces were engaged in an armed conflict with the Communist Chinese army in the Kham and Amdo regions subjected to socialist reforms. This guerilla warfare escalated, eventually resulting in the 1959 Tibetan uprising.](image)

**Figure 9.1: China, 1956**

**Figure 9.2: China, 1984**

This was the year that the PRC promulgated the law of Regional Ethnic Autonomy, which first allowed for the setup of ethnic autonomous areas and regions/provinces. Here we see provinces like Tibet co-opted as a regional autonomy, no longer a separatist group.
The Tibetans and Uighurs are currently the two major discriminated groups in China, as reflected in their peripheral positions in the power structures.

Trend-spotting and hypotheses-testing
Our visualization has been useful in spotting trends and patterns, some of which go to supporting hypotheses proposed by political scientists. Wimmer, Cedarman and Min (2009), for instance, have proposed that rebellion, infighting and secession result from exclusion, segmentation, and incohesion respectively. This same pattern – that ethnic exclusion increase risks of ethnic conflicts – had been reported by some users minutes into their interaction with the platform.

Interaction with visualizations can help generate hypotheses amenable to testing with data. A possible extension – which will be discussed later under “future work” would be to include more variables that can help users generate and test a wider range of hypotheses.

Insights into data collection and coding methods
In testing our system, Prof James Fearon took a closer look at the case of Somalia because he was intrigued that Somalia appeared to be classified categorically under a single ethnic group “Somali”, but exhibited great linguistic diversity (as indicated by the existence of six language groups in our language distance visualization). This was an observation he did not expect and had not made when he was analyzing the Ethnic Power Relations dataset previously:

He conjectured that this was because of clan distinctions that Cederman, Wimmer and Min had not factored into their dataset. While it is true that Somalia was relatively ethnically homogenous at independence (the Isaaqs and Hawiyes insisting that they spoke the same language), this has changed over time as the Isaaqs consciously began to differentiate their speech forms to justify recognition for their secessionist republic. A linguistic survey conducted today would produce quite a different accounting of language divisions (as our language distance visualization supports), and by extension a more fractionalized Somalia (as opposed to the homogeneity observed in the ethnic power relations visualization).

This raises interesting questions about the traditional metrics that political analysts have been relying on in comparing degree of fractionalization. The most frequently used metric today is the ELF Index, which is a static metric that, as our Somalia case illustrates, fails to capture the dynamic nature of ethnic fractionalization. If anything, our visualization has revealed, with visual immediacy, how ethnic group encodings and inferences made on fractionalization by political analysts bear non-trivial differences that merit more fine-grained analyses. This could mean going beyond a static index to factoring multiple dimensions, ranging from linguistic divisions to power relations and dynamic changes in ethnic groupings over time. Most studies so far have chosen to zero-in on one factor out of these myriad dimensions; our visualization has brought two perspectives together on one visualization platform, yielding new comparisons between studies that raise questions on the methodologies themselves.

FUTURE WORK
The scope for extensions and future work is large; below we highlight future work that can improve our visualization.

More fine-grained visual encodings of conflicts
Our current visualization highlights years in which ethnic groups are engaged in conflicts, but provides no information on the conflict itself. It is not always true that ethnic groups with red bars on the conflict timeline during the same time period are in conflict with each other. Establishing linkages between parties involved in conflicts – possibly even ethnic groups across countries – and displaying more information on the conflict (e.g. conflict name and location) will aid understanding by providing a better context.

Sorting and filtering with stacked bars
The only dimension encoded by the normalized stacked bars is the proportion of ethnic groups. A possible extension would be to encode other dimensions (e.g. regions, polity scores) with color, or enable filtering with a drop down selector. This will also allow for rapid-fire cross-country comparisons, which can facilitate the exploration of correlations between variables.

Social data exploration
Like we mentioned in the discussion, users came to formulate hypotheses, questioned the dataset and suggested relationships between variables. Given the range of possible interpretations, it would be useful to make this visualization into a web interface like sense.us on which users can annotate and comment on visualizations, building on each other’s interpretations.

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