American cultural regions mapped through the lexical analysis of social media

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INTRODUCTION

Cultural identity is an elusive notion because it depends on a wide range of different cultural factors—including politics, religion, ethnicity, economics, and art, among countless other examples—which will generally differ across individuals, with the cultural background of every individual ultimately being unique. Nevertheless, individuals from the same region can generally be expected to share some cultural traits, reflecting the shared cultural values and practices associated with the region [1]. Identifying the cultural regions of a nation—regions whose populations are characterized by relative cultural homogeneity compared to the populations of other regions within the nation—is very valuable information across a wide range of domains. For example, it is important for governments to understand geographical variation in the values of their population so as to better meet their educational, social, and welfare needs. Similarly, from an economic standpoint, it is important to identify where certain services and products are most required and how best to engage with populations in different regions of the country. In general, defining the cultural regions of a nation is therefore a crucial part of understanding the complex landscape of human behavior that nation encompasses, providing an accessible and broad classification of the populations of a country [2].

Mapping cultural regions has been a particularly active area of research in the US, where there has long been debate over the cultural geography of the country, with a wide range of theories of American cultural regions having been proposed. Seven of the most prominent theories [3–9] are mapped in Fig. 1, showing considerable disagreement. For example, in [5] the geographer Wilbur Zelinsky identified 5 major cultural regions—New England, the Midland, the South, the Middle West, and the West—based on a synthesis of regional patterns in a wide range of cultural factors, including ethnicity, religion, economics, and settlement history. Alternatively, in [6] drawing on a similar but more extensive range of cultural factors, the social scientist Raymond Gastil identified 13 major cultural regions, offering a more complex theory than Zelinsky, including by dividing Zelinsky’s Midland, Middle West, and West regions. The two studies illustrate two basic limitations with these types of approaches that subjectively synthesize a range of data to infer cultural regions. First, it is unclear exactly how relevant cultural factors should be identified. Zelinsky considers fewer factors than Gastil, which may explain his simpler proposal. Second, it is unclear how these different factors should be synthesized to produce a single overall map of cultural regions. Zelinsky places greater emphasis on the importance of initial settlement, which may also explain his simpler proposal.

Given the subjectivity underlying these studies, the lack of agreement over the number and location of American cultural regions (as illustrated in Fig. 1) is not surprising. Only a distinction between the North and South, reflecting the Union-Confederacy border, and a distinction between the East and West, reflecting the path of the Rocky Mountains, are common to these most influential theories of American cultural regions [3–10]. Other-

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wise, between 4 and 12 primary cultural areas have been mapped, typically including the Northeast [3–8, 10], the South [3–10], the West [3–7, 9], and the Midwest [3–7].

In large part, the debate over the geography of American cultural regions has been about which types of cultural factors should be given precedence, and how these factors should be combined. Crucially, these decisions have generally been left entirely to the judgment of the analyst. Quantitative data from the census and elections have sometimes been taken into consideration (e.g. [5, 6, 8, 9]), but less often subjected to statistical analysis (e.g. [8]), while the selection and weighting of these factors has always been subjective. For example, religion and politics are undoubtedly important cultural
factors, but they can be measured in various ways, and it is unclear how important they are relatively speaking and whether their importance varies across the United States.

A basic question is therefore how can we infer general American cultural regions in an objective way? In particular, how can we both identify a complete or at least representative range of relevant cultural factors and somehow combine these factors in so as to map American cultural regions? Defining such regions does not mean that they do not contain internal variation or that they are separated by hard borders—culture is dynamic and complex and humans are highly mobile—but that we can find areas where the cultural practice and values of the people who live within that region are more similar to each other than to those of people who live outside that region.

The goals of this paper are therefore to address these issues, by (i) proposing a novel method for discovering cultural regions by identifying regional patterns in topics of conversation, and by then (ii) proposing a theory of American cultural regions derived from the application of this method to a large corpus of geolocated social media data.

Our starting premise is that cultural regions will necessarily be reflected by regional variation in the topics that people choose to discuss in their everyday lives. If the cultural geography of the US was broadly homogeneous, we would expect topics of conversation to be largely the same across the country, aside from different uses of place names and other such relatively superficial and necessarily regionalized vocabulary items. However, if people from different regions exhibit distinct and systematic cultural characteristics—for example, in politics, religion, music, sport, fashion—as research on American cultural geography has consistently shown, then these patterns of cultural variation will necessarily manifest themselves as patterns of topical variation in the language used by people from these regions [11]. For example, if hip hop music, baseball, tattoos, or some other cultural practice is especially popular in some part of the country, we would expect more discussion on that topic in large samples of everyday language use originating from that region, including on social media. Furthermore, previous works show that cultural factors often show related regional patterns, owing presumably to interrelationships between these different factors. For example, regional settlement patterns can help explain differences in ethnicity and religion which can have long term effects on voting patterns. Consequently, analyzing these regional topical patterns in the aggregate can be used to infer broader cultural regions. Crucially, there is no need to predefine what these topical patterns are or how much they matter: the topics themselves and their relative importance can be inferred through the analysis of everyday language as well. We therefore introduce an automated method for identifying cultural regions based on the automated identification of patterns of regional variation in topics of discussion in very large corpora of geotagged everyday language use. Our method is especially intended to take advantage of the incredibly large amount of geotagged social media data that online communication now provides us with for the first time, although our method could be used to identify cultural regions within any area based on any substantial source of regionalized everyday language use.

Specifically, to map modern American cultural regions, we identify regional patterns in the topics that Americans tend to discuss on social media through a quantitative analysis of ten thousand lexical items in over 3.3 billion geotagged Tweets from across the US, collected between 2015 and 2021. Large corpora of geotagged Twitter data have been used frequently in computational sociolinguistics to identify [12], including to map patterns of dialect variation [13–21], while others leveraged methods such as Latent Dirichlet Allocation to identify regional topical patterns [22, 23]. Despite this wealth of research that has used large corpora of social media to identify regional patterns in language use, we are aware of no research that has used this type of information to infer the location of general cultural regions.

Of course, social media or any other form of language can only provide a partial picture of regional patterns in overall topics of discussion in a region. In general, big data corpora generated from microblogging platforms certainly present a number of biases: incomplete demographic representativeness [24], particularly for users geotagging their Tweets [25], non-homogeneous spatiotemporal distribution [26], or severe topic differences with the offline world [27]. However, if cultural regions are real and pervasive, then we should expect these regions to manifest themselves in any large sample of everyday language that encompass a large proportion of the population, even if the specific topics of interest vary across these different domains. Furthermore, right now, Twitter is the only variety of geotagged natural language data available in sufficient amounts to allow reliable automatic analyses, and is a very popular social media platform used regularly by millions of people from across the US, mostly in interactive contexts [28], serving as a perfect domain to apply our data-driven approach for automatically mapping cultural regions.

Our main finding is that the modern US can be divided into five primary cultural areas, each defined by its own topical patterns. We emphasize that this result stems from a quantitative analysis in contrast to previous proposals based on more or less informative (qualitative) approaches. Further, beyond the specific number of regions it is most relevant to note that our method yields the list of words and topics that define those regions, which highlights the differences in interests, habits and backgrounds that distinguishes each cultural region from the others. Crucially, by means of a dynamic analysis we show that cultural regions of the US are relatively stable over the past few years, offering further evidence that cultural areas are real phenomena that pervade American society.
The rest of the article is structured as follows. The results of the work are first introduced by a description of the dataset collection and pre-processing methodology. Regional variations of word usage observed from this dataset are then explored, before obtaining the principal dimensions of these variations. The main result of the work, the cultural regions of the US and the main topics of discussion that define them, is then presented in detail. The possibility of a variation with time of the results is then explored. Finally, a discussion of the insights brought by the analysis and also of where future works could build on it comes to conclude the work.

RESULTS

Dataset

We analyze geotagged Tweets collected through the streaming API of Twitter, more specifically, using the filtered stream endpoint: https://developer.twitter.com/en/docs/twitter-api/tweets/filtered-stream. This endpoint provides a sample of Tweets in real time matching suitable filters. This allows us to gather 3.3 billion geotagged Tweets from the contiguous US, posted from January 1st, 2015 to December 31st, 2021. Importantly, we discard users tweeting at an inhuman rate, which we define to be any rate superior to 10 Tweets per hour over one’s whole tweeting span. We also discard users tweeting from any platform that is not a Twitter mobile application or their website. In our dataset, we thus retain 17 million users. We strip Tweets of any link, hashtag or user mention, and only keep those which still have more than 4 words after this filter. Hashtags were discarded out of precaution: some of them may be content words, but they may also be related to short-lived trends for instance. As we found that the content of hashtags accounted for less than 5% of the content of the Tweets we collected, they can anyway be safely discarded. We subsequently use the Chromium Compact Language Detector (CLD) [29] to eliminate Tweets written in a language other than English. To attach a geolocation to Tweets, they are geotagged with either the precise GPS coordinates of the device of the user, or “places”, which can be an administrative region, a city or a place of interest. Then, as these geotags may be places of the size of a state, we also remove Tweets with a geotag that did not allow for reliable assignment to our unit areas, which are the US counties and county equivalents (3,108 in total). Certainly, counties vary in both size and population but most of them form a useful division sufficiently large to show a sizeable amount of Tweets and sufficiently small to allow for a careful delimitation of cultural areas (states would be too big units whereas towns would be too small).

From the remaining Tweets, we extract and count the tokens in their text, and assign them to counties. Counties that accumulate fewer than 50,000 tokens are not taken into account, leaving us with \( N_c = 2,576 \) counties which define our sub-corpora. We thus keep 83% of the total number of counties. After this filtering, the full dataset contains 9.1 billion tokens (see Table S1 for a summary description of the dataset). We subsequently convert the remaining word forms to lowercase and aggregate the token counts on these forms. We then remove all function words (like the, and) and interjections (like um, oh) (see Data availability for access to the full list of exclusions), and consider the 10,000 most common remaining word forms. Note that this list of word forms emerges from the data, and is not imposed by any previous topical or dialect classification.

Measuring regional variation

We then measure and map the relative frequencies \( f_{c,w} \) for every word \( w \) in every county \( c \). We illustrate our raw results by plotting in Fig. 2 the relative frequency in each county of four representative words: a today, c mountain, e traffic and g bruh (cells that appear greyed out do not reach a minimum number of Tweets as explained in the paragraph above). In the first case, today appears at relatively stable rates in most of the counties, as expected. Alternatively, mountain is a regionally-dependent word as clearly seen. The item traffic appears more frequently in urban areas. Finally, bruh is an African-American English variant that appears to be especially common in southern counties, where there are large African-American populations.

A word of caution is now required. A relative frequency map alone is not able to fully reveal regional variations due to the wide range of different factors besides regional variation that affect word use and add noise to the signal. To extract the underlying regional signal from each word map, we conduct a multivariate spatial analysis [13, 17] of the relative frequencies of our 10,000 word forms. In order to identify geographical hotspots in the usage of each word (Fig. 2), we compute Getis-Ord’s z-scores \( G^*_i \) for each county \( c \) and word \( w \), which are defined as:

\[
G^*_i = \frac{\sum_{c'} W_{c,c'} (f_{c',w} - \bar{f}_w)}{\sigma_w \sqrt{\frac{\sum_{c'} W^2_{c,c'} - (\sum_{c'} W_{c,c'})^2}{N_c - 1}}},
\]

with \( \bar{f}_w \) the average frequency of \( w \) over the whole dataset, \( \sigma_w \) the standard deviation in \( w \)'s frequencies, and \( W_{c,c'} \) are the elements of a proximity matrix, which we take as equal to 1 if \( c' = c \) or \( c' \) belonging to \( c \)'s 10 nearest neighbors, and equal to 0 otherwise.

The metric given by Eq. (1) ultimately diminishes spurious data variation and smooths spatial patterns, allowing us to discern a regional pattern in a word’s usage. In Fig. 2b, d, f and h we show, respectively, the \( G^*_i \) z-scores for the previous words today, mountain, traffic and bruh. White, light blue or light red counties do not
Figure 2. Maps showing the relative frequency and Getis-Ord $G^*_i$ z-score for the words today, mountain, traffic and bruh, respectively. One can note how the latter metric enables to reveal word usage hotspots, smoothing out the raw noisy signal from the data.

The usage hotspots of mountain display the main mountain ranges of the country. While the map for traffic is correlated with large urban areas (and can be interpreted as a topical word), the dialect word bruh seems to be significantly more used in counties pertaining to the Deep
South. We see here that different attributes that define a culture (interests, behavior, dialect) are captured within our scheme and, notably, are treated on equal footing.

Obtaining the principal dimensions of regional variation

The $G^2$ distributions for all 10,000 top words by usage thus hold valuable information. However, a considerable part of this information can be analyzed more efficiently, since some words may belong to the same semantic field (mountain and peak) or characterize the same particular dialect (bruh and alright). Furthermore, a few variations may simply be uninformative noise, intrinsic to real individuals' behaviors, but also potentially resulting from an imperfect filtering of Twitter data, as aforementioned.

The most important dimensions of regional lexical variation are then found by subjecting the hotspot maps for the complete set of words to a principal component analysis [8, 31]. Another possible approach would have consisted in performing topic modelling, for instance by ways of a Latent Dirichlet Allocation on the word frequency matrix, to then infer a distribution of topics for every county. It is however more computationally intensive, and poses the questions of the selection of the number of topics, their interpretability and their internal coherence [32, 33]. In a case like ours where documents are so large (aggregating all Tweets in a county), it is far from obvious to select a number of topics such that there is little overlap between them, and to know that these topics are actually representative of the dataset as a whole. This is much more clear when selecting components in PCA, as we show below.

From the $N_w = 10,000$ dimensions of our dataset, we thus project to a principal component (PC) space of $N_{PC} = 326$ dimensions. It turns out that these 326 components explain 92% of the observed variance (see Fig. 3f). We do not set this number of components arbitrarily, by choosing one directly or by setting a percentage of variance we wish to explain using these components. Instead, we use the broken-stick rule to fix the number of components [34, 35]. This heuristic compares the decrease of the variance explained by each successive component to the one expected from a random partition of the whole variance in $N_w$ parts. Components, sorted by decreasing explained variance, are kept until they do not explain more variance than their corresponding random part would. With this method, we do not make any assumption about the amount of variance in our data that is simply due to random fluctuations.

We show the projected data along the first four PCs in Fig. 3a-d, which displays a neat visualization of the spatial patterns. The map for each dimension shows two opposing regions (red and blue) which can be linked to their characteristic words, the ones with the highest (positive, in red) and lowest (negative, in blue) loading. For an illustration, in Fig. 3e we show in a word cloud the most characteristic words for each of the two regions in Fig. 3b, which corresponds to the second component. In Figs. S2 and S3 we plot, respectively, the projected data for the proximity matrix $W_{c,c'}$ of Eq. (1) defined based on 5 and 15 nearest neighbors. The results show that the components are not significantly altered by a slight change of the proximity matrix. Figure S4 shows the results when $W_{c,c'}$ is alternatively defined in terms of a fixed distance. In this case, the modifications are stronger because the size of the counties is not uniform. This demonstrates that one should take proper neighbor couplings when dealing with heterogeneous geographical units.

Inferring cultural regions

We are now in a position to generate a single overall taxonomy of American cultural regions by clustering together counties with similar lexical signature. To do so, we subject the previous PC maps to a hierarchical clustering, using the Euclidean distance and the Ward variance minimization algorithm [36]. This is how we define the cultural regions from our corpus, as depicted in Fig. 4. From the dendrogram and the evolution of the average silhouette score for different levels of clustering, we select a meaningful number of clusters $n_{clusters}$ [37]. The hierarchical nature of the clustering is useful to see how regions are grouped together at different levels of clustering, indicating which regions are closer together. Importantly, applying hierarchical clustering to the principal dimensions of variation of the data obtained through PCA allows us to focus on the main regional patterns of variation. Applying the algorithm directly to the 10,000-word distance matrix would yield highly noisy results.

We plot the main divisions in Fig. 4a. This is the main result of our paper. In the map, we present the division into five clusters since it is one of the two best options as characterized by the Silhouette score analysis in Fig. 4b, and at a clear-cut on the dendrogram in Fig. 4d. The optimal choices correspond to the two significant drops in the score: the first (second) corresponds to a cluster number equal to 2 (5).

Indeed, the dendrogram in Fig. 4d shows that the counties can be initially classified into two large-scale subgroups representing a North vs South divide. The North is then further fragmented into the clusters 2, 3 and 4 shown in Fig. 4a, whereas the South group splits into the clusters 1 and 5. For the most part, our map in Fig. 4a is consistent with standard theories of American cultural regions, with all five of our regions finding analogs in existing systems. Yet, taken as a whole our clusters do not match any previous system and reveal non-contiguous culture regions such as the clusters 3 and 4. Moreover, in contrast to previous proposals our results have the advantage of being data-driven, based on variation in the topics people care to discuss as opposed to factors selected by hand by the researcher (and con-
Figure 3. Result of the principal component analysis carried out on our whole dataset. a-d Four maps show the projection of the data along the first four components, highlighting regional lexical variations. Note that the scale on the divergent color scales are not symmetrical around zero in order to utilize the full range of colors of the color map. e Word cloud showing the words with the strongest positive (red) and negative (blue) loadings for the second component, with each word’s font size depending on its loading’s absolute value. f Explained variance of the principal components compared to the broken-stick model on a logarithmic scale, which shows how the number of components to keep is selected at the first intersection of the two curves. The cumulative proportion of the variance explained by the components is also plotted, showing that our dimension reduction explains around 92% of the observed variance. The first four components shown in panels a-d capture alone 31% of the variance.

Subsequently subjected to many more, uncontrolled biases than our Twitter data).

Further, to be able to better interpret the obtained regions, it is insightful to know which words characterize each cluster the most. To infer them, we start by taking the center of each cluster in words-$G^*$-space. Hence, for each cluster we take the average $G^*_c$ score over its counties for all words. From these $n_{\text{clusters}}$ vectors of $N_w$ elements, we calculate the minimum absolute difference between each cluster center’s word’s score and the ones of all other clusters, i.e., we take the distance to the closest cluster’s center along the word’s dimension. More formally, we define the specificity $S_{C,w}$ of word $w$ for cluster $C$ as:

$$S_{C,w} = \min_{C' \in C \setminus C} \left( \frac{1}{N_C} \sum_{c \in C} G^*_c,w - \frac{1}{N_{C'}} \sum_{c' \in C'} G^*_c,w \right)^2,$$

where $C$ denotes the set of clusters, $N_C$ the number of counties belonging to cluster $C$, and $G^*_c,w$ the $G^*_c$ score
of word $w$ in county $c$. For each cluster $C$, we thus define the most characteristic words as the ones with highest $S_{c,w}$ values. In the case of the division in five clusters, the top 5 most characteristic words per cluster are shown in Fig. 4c, according to the specificity metric defined in Eq. (2). In all cases, the five cultural regions are linked to clear and distinct topical patterns (see the Supplementary Information for a more exhaustive list). We stress that these characteristic words are automatically identified based on the quantitative analysis presented above. Notably, for each cluster we see three basic types of lexical patterns.

First, we see words associated directly with those locations, most commonly the names of cities, states, and sports teams. This is basic evidence that the method works: we would expect these words to be associated with the cultural regions that contain them. However, these results also reflect how often people from different cities and states refer to each other. For example, the fifth cluster which is centered on Texas also includes Oklahoma, which contributes various place names to the list of words most strongly associated with this region. This means not only that people in Texas and Oklahoma talk more about place names in their own states, as would be expected, but that they talk more about place names in each other’s states. This is one type of regional topical patterns that our approach draws to identify cultural regions.

Second, we observe words connected with non-regional topics, which nonetheless show regional differences. In this case, our approach can be seen as discovering topical patterns and by extension cultural patterns that distinguish between different regions of the US. For example, cluster 2 is strongly associated with the discussion of a range of American sports, as well as the names of the states that fall within this region. Although we would expect that a region centered around the Midwest would be associated with the names for Midwestern states, their preoccupation with the discussion of sports on Twitter is not so easy to predict.

Third, we find words that are dialect items, i.e., alternative ways of referring to a given concept. This type pattern is especially apparent for cluster 1, which aligns closely with the region of African American population density and is therefore associated with numerous lexical items from African-American English (e.g. *bruh, lawd, tumt*). Although dialectologists do not usually focus on the frequencies of individual words, this results is to be expected: dialect regions, which can be seen as a type of cultural region, have been found to generally align with broader cultural regions [17].

We can now examine each of the five cultural regions we have identified in turn and consider what the words that are mostly strongly associated with each tell us about the culture of that region, as well as the factors that drive cultural variation in the US more generally.

The first cluster [blue in Fig. 4a], which identifies a southeastern region, largely reflects African American culture, as can be predicted based on the close correlation between our map and the distribution of counties with relatively large African American populations (see Fig. S1). Most notably, Tweets from the South are more likely to contain words related to African American culture, including, for example, cuisine (e.g. *grits, cookout*), fashion (e.g. *braids, dreads*), and music (e.g. *rappers, rapping*). As noted above, this cluster is also strongly characterized by many vocabulary items associated with African American English, especially for referring to people (e.g. *bruh, dawg*), as well as many acronyms (e.g. *fyfr, styg*). Place names associated most strongly with this cluster primarily include southern states (e.g. Georgia, Carolina), despite the fact that, in general, references to place names are relatively rare compared to other clusters.

The second cluster [yellow in Fig. 4a] has its core in the Midwest and is clearly characterized by more frequent references to sports. American team sports especially stand out, with 40 words of the top 50 most strongly associated with this cluster being directly linked to this topic. In particular, these are words associated with basketball (e.g. *basketball, rebound*) and baseball (e.g. *baseball, innings*), although football, wrestling, and cheering are also referenced, as well as various more generic sporting terms (e.g. *teams, tourney*). Similarly, many place names are associated with local sports teams (e.g. *Cubs, Chiefs*), although various state names are also strongly associated with this cluster (e.g. *Ohio, Illinois*), as well as the word *Midwest* itself. A smaller number of lexical items are also associated with school (e.g. *locker, choir*). Overall, this cluster therefore shows that sports is a central part of this region.

The third cluster [green in Fig. 4a] can be identified with a discontinuous region that mostly aligns with rural areas of the US, as well as areas that focus on outdoor activities, especially in mountainous regions (e.g., the Rocky or Appalachian Mountains). This cluster is relatively hard to interpret topically, in part because, unlike the other regions, it is characterized by the relative infrequent use of a number of words. In terms of words that are relatively common in this region, the clearest pattern is a relatively large number of words associated with nature (e.g. *mountains, tree*), weather (e.g. *snow, seasonal*), and outdoor activities (e.g. *adventures, trail*). Clearly, people in this region tend to focus more of their natural surroundings. In addition, there are a number of words related to work (e.g. *hiring, jobs*), as well as a numerous place names (e.g. *Colorado, Montana*) that are strongly associated with this region. In terms of words that are uncommon within the cluster, there exist many verbs, especially verbs associated with human actions like communication (e.g. *said, told*), thought (e.g. *understand, confused*), and physical actions (e.g. *put, hit*), which implies overall less focus on the individual. This region is also associated with relatively infrequent use of a wide range of negative words (e.g. *wrong, bad*), which largely hints at a more positive outlook.
The fourth cluster [red in Fig. 4a] also identifies a discontinuous region that primarily encompasses large urban areas in the coasts (Northeast and West). Unsurprisingly, this region is characterized by a wide range of words associated with more urban life (e.g. homeless, traffic), especially terms related to different nationalities and immigration (e.g. Latino, Asian). We also find a relatively large number of place names (e.g. California, NYC). Strikingly, this cluster is associated with a very large number of words with negative connotations, including relating to violence (e.g. violence, attack), danger (e.g. dangerous, crime), cursing (e.g. asshole, fucking), political unrest (e.g. protests, indicted), racism (e.g. Nazi, supremacist), and general negative adjectives (e.g. disgusting, abusive). Quite generally, people from this cluster are more likely to discuss negative topics than other parts of the US, at least on social media. Taken together, the third and fourth clusters suggest an opposition in the
Finally, the fifth cluster [cyan in Fig. 4a], which is centered around South Central States, especially Texas and Oklahoma, is characterized by frequent reference to place names, relative to the other clusters, especially in these two states, as has already been noted. For example, the first five most strongly associated words are Whataburger (a fast food chain from Texas), followed by Texas, TX, Texan, and Dallas. This not only shows that people in this region tend to discuss place more on Twitter, but implies that this cultural region is characterized by a relatively high amount of local pride. Correspondingly, this region is also associated with a relatively large number of dialect terms, both of Anglo (e.g. yalls, fixing) and Hispanic (e.g. queso, taco) origins, reflecting the diverse makeup of this region.

The analysis yielding Fig. 4 was repeated, adding a stemming step at the very beginning of our pipeline. We obtain a very similar result, shown in Fig. 5a, indicating little sensitivity of our results to stemming.

Given the lack of consensus in previous research, our results can help resolve long-standing debates relating to the distribution of American cultural regions. We find that the division between the Southeast and the rest of the US is the strongest. This result attests to the importance of the cultural divide between White and Black America and between the North and the South. Although all previous major theories of American cultural regions has identified a distinction between the North and the South, our southern region is especially similar to relatively recent theories, which identify a southern region that closely aligns with the part of the south with an especially high proportion of African Americans [8, 9]. Another key finding that emerged from our analysis is a broad opposition between coastal and internal areas, which has not previously been identified as important sources of distinction of American cultural regions [3–10] but reflects a modern political trend of undeniable significance [39] that is currently reconfiguring the nation. The discontinuous nature of these regions, which is not required by our definition of a cultural region, is also notable. It demonstrates how patterns in American culture can be distributed across very wide areas, reflecting complex patterns in physical and human geography, and the underlying complexity and dynamic nature of American society. This result is broadly in line with other recent theories of American cultural regions which have also identified discontinuous cultural regions [8, 9].

Our analysis is further useful for understanding the relationship between these regions. It divides the South into two regions, splitting Texas off from the rest of the Southeast, and splits the Midwest off from the rest of the North, divided into discontinuous countryside/coastal regions, rather than contiguous cultural regions. However, on the question of the number of primary American cultural regions, we can only safely say that with our data and methodology, at least 5 distinct regions can be discerned. We do not see it here, but we still cannot discard recent theories that claim that America is fundamentally far more culturally fragmented [7–9].

**Temporal aspect of the results**

Given the success of our analysis, it would be interesting to see how the cultural regions found in Fig. 4 change with time, as has been done in other research analyzing diachronic corpora [40–44]. Although we would not expect significant changes due to the short timescale imposed by our Twitter dataset, we can still carry out a diachronic study to evaluate the validity of our detected cultural regions. To do so, we split our corpus into three datasets corresponding to different year ranges: 2015-2016, 2017-2018 and 2019-2021. These periods have a similar amount of tokens and can be then subjected to comparison (see Supplementary Table 1). We show their maps in Fig. 5a-c. We obtain similar patterns, despite the variety of topics and forms employed on Twitter along the years and the heuristic nature of the clustering method that introduces a small amount of noise in the results. The North-South division is stable over time with small variations that can be due to either fluctuations or incipient structural changes. The latter cannot be conclusive due to the short time period considered in this work.

Next, we take the hierarchical clustering in Fig. 4d and select the county-to-cluster assignment corresponding to the highest level of the hierarchy. This is represented by the two-way division between North and South. For each year in our dataset, we then measure the pairwise distances between counties belonging to both clusters. The distances are calculated as Euclidean distances between rows of the matrix $G_{c,s}$ (see Eq. (1)). We thus obtain the evolution with time of the inter-cluster distances distribution as shown in Fig. 5d. The box plots demonstrate that (i) the median distance is roughly constant over the years, and (ii) the distance distribution shows little variation. Both findings suggest that the detected cultural regions are no artifact of the method, but a genuine data structure that exists within our corpus.

**DISCUSSION**

Overall, our analysis has therefore identified regional patterns of lexical variation of clear cultural importance. Furthermore, the themes associated with each of these patterns provide a new perspective on American cultural geography. For example, although our analysis has confirmed that factors such as ethnicity and religion are important for defining American cultural regions, we found substantial variation in the relevance of these factors across the US. Our analysis has also identified other subtler cultural patterns—such as a focus on social interac-
Figure 5. Effect of temporal segmentation for the data on the obtained divisions. a–c Maps of the data projected along the first PC obtained for the years 2015-2016, 2017-2018 and 2019-2021, respectively. Apart from slight variations in California and Florida, the first component translates the same division between the Southeast and the rest of the US. Note that the scale on the divergent color scales are not symmetrical around zero in order to utilize the full range of colors of the color map. d Evolution of the distributions of inter-cluster distances along the years spanned by our dataset. The box plots show the median, first and third quartile, and the boundaries of the whiskers are within the 1.5 interquartile range value. We use the cluster assignment obtained with the whole dataset and measure the Euclidean distance in $G_i$ space between counties belonging to different counties. The distribution is thus shown to vary little from year to year, which demonstrates the stability of the two-way division we found.

tion, the outdoors, family, and leisure—which have been overlooked in previous research, in part because they cannot be easily studied through the analysis of traditional sources of secondary data. Our method has therefore not only allowed us to map cultural regions, but it has also allowed us to identify cultural factors that are important for defining these regions, at least in this communicative context, providing a foundation for a more complete picture of the American cultural landscape.

Clearly, our study has only analyzed one genre of American English. The specific topical patterns on Twitter would not be exactly replicated in other genres, especially given the communicative purpose and user base associated with microblogging platforms. Nevertheless, assuming that American cultural regions are important and pervasive forces, similar regional patterns should be reflected across all genres. This issue could be further clarified when more richly annotated natural language data becomes available in a near future. Our methods, however, will remain valid for any such dataset. Crucially, we expect that our main idea of inferring cultural regions and the topics defining them from people’s speech will be applicable to any big data resource with linguistic value.

CODE AVAILABILITY

The data processing and plotting of results were carried out in Python with the help of open-source libraries. All code used for this work is hosted on GitHub [45].

DATA AVAILABILITY

All aggregated data generated by our Twitter data analyses as well as our list of excluded words are available for download from a figshare repository [46]. County and state boundary shapefiles from the US census of 2018 that we used to draw our maps are freely available for download at https:
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AUTHOR CONTRIBUTIONS

All authors designed research and performed the data analyses. T. L. built the corpus and wrote the code that produced the results. J. G and T. L. drafted the initial manuscript, and all authors were involved in subsequent revisions. J. J. R., D. S. and J. G. acquired funding.

COMPETING INTERESTS

The authors declare no competing interests.

ETHICAL APPROVAL

This article does not contain any studies with human participants performed by any of the authors.

INFORMED CONSENT

This article does not contain any studies with human participants performed by any of the authors.

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[39] T. Louf, Word counts per US county in geotagged Tweets posted between 2015 and 2021, 10.6084/m9.figshare.20630919.v1 (2023).
I. Cultural regions’ topical patterns

In Fig. 4 of the main text, we present the cultural regions that follow from our analysis described in the Methods section. We hereafter show the most characteristic words for each region according to the specificity metric introduced in Eq. (2) of the main text (the lists are by no means exhaustive). These words are classified into common lexical fields for the different cultural regions.

Cluster 1

**African-American variant forms and acronyms:** bih, frfr, stg, ian, otp, kno, ik, dnd, mfs, yo, sew, asf, wassup.

**Fashion, music and food:** braids, waffle, grits, weave, lil, cookout, dreads, rappers, gucci.
Family and friends: bruh, niggas, mama, dawg, shawty, auntie, folks, bae.

Location related: atl, lsu, georgia, ga, carolina, saints, sc, falcons.

■ Cluster 2

Sports: win, teams, tourney, bracket, scoring, halftime, basketball, fouls, wrestling, innings, baseball.

Spectatorship: cheering, announcers, congratulations, popcorn, hyped, concert, seats, autograph.

Teenage/school life: girls, locker, choir, bffs, classroom, students, grader, alumni.

Location-related: midwest, ohio, illinois, missouri, chicago, stl, minnesota, indiana, wisconsin, kc.

■ Cluster 3

Natural features: mountains, tree, snow, land, view, trail.

Outdoors activities: adventures, spotter, trained, climb, trip.

Thoughts and emotions: thought, think, cry, feel, crying, laughing, worry.

Personal communication: said, understand, say, told, saying, heard, listen, trust, telling. (Importantly, these are negative features, i.e., it is a relatively low frequency of these words that is specific to the cluster.)

Location-related: co, colorado, montana, utah, idaho, byu, mt, ut, va, wy.

■ Cluster 4

Urban features: freeway, homeless, traffic, ave.

Nationalities and origins: puerto, dutch, latino, dominican, asian, immigrants, europe, rico, foreign, countries.

Violence: violence, dangerous, attack, crime, insult, abusive, racist, threat.
**Politics:** political, ban, nazi, indicted, protests, crisis, policies, presidency, elections, taxes, majority, obstruction.

**Location related:** california, giants, nyc, ca, socal, cali, seattle, oregon, nj, sacramento, seahawks, sf, massachusetts, mets.

- Cluster 5

  **Mexican culture:** queso, mexican, tacos.

  **Variety features:** yalls, restroom, fixing, freaking, badass, highkey, fav, tripping.

  **Acronyms:** loml, sm, tbh, fnl, idk, fm, fwm.

  **Emotions and relationships:** cry, heart, hurts, regret, friends, love, marry, boyfriend, laugh.

  **Location related:** whataburger, texas, tx, texans, dallas, cowboys, dfw, antonio, sa, spurs, mavs, as, ok, ou, okc, astros, rangers, austin.

## II. Sensitivity to stemming

We checked the sensitivity of our results to stemming by stripping plural forms from our lower-cased words (the ones left after excluding function words and interjections), to then aggregate our counts by their stemmed counterpart, keep the top 10,000 forms and rerun our analysis. We reproduce Fig. 4 from the main text and show the outcome in Fig. S5. One can spot little differences in the extent of the cultural regions, but they are shown to be mainly the same. This shows that there is little sensitivity of our results to prior stemming of the corpus.
Table S1. Twitter dataset statistics. This table presents the number of Tweets and users in the US for every year between 2015 and 2021 included. The last column gives the total number of tokens that remain after we filter Tweets and users according to the Methods presented in the main text.

| Year | Number of Tweets | Number of users | Number of tokens after filtering |
|------|------------------|----------------|---------------------------------|
| 2015 | $363 \times 10^6$ | $5.93 \times 10^6$ | $0.78 \times 10^9$ |
| 2016 | $805 \times 10^6$ | $6.80 \times 10^6$ | $1.78 \times 10^9$ |
| 2017 | $554 \times 10^6$ | $6.04 \times 10^6$ | $1.53 \times 10^9$ |
| 2018 | $524 \times 10^6$ | $5.49 \times 10^6$ | $1.71 \times 10^9$ |
| 2019 | $426 \times 10^6$ | $4.67 \times 10^6$ | $1.32 \times 10^9$ |
| 2020 | $446 \times 10^6$ | $3.58 \times 10^6$ | $1.29 \times 10^9$ |
| 2021 | $217 \times 10^6$ | $2.76 \times 10^6$ | $0.72 \times 10^9$ |
Figure S1. Proportion of Black Americans per county, as per the 2018 estimates of the US census.
Figure S2. Result of the principal component analysis carried out on $G^*_i$ vectors calculated with a proximity matrix defined by considering 5 nearest neighbors. (a-d) Four maps show the projection of the data along the first four components, highlighting regional lexical variations. (e) Word cloud showing the words with strongest positive (red) and negative (blue) loadings for the second component, with each word’s font size depending on its loading’s absolute value. (f) Explained variance of the principal components compared to the broken-stick model on a logarithmic scale, which shows how the number of components to keep is selected at the first intersection of the two curves. We also plot the cumulative proportion of the variance explained by the components.
Figure S3. Result of the principal component analysis carried out on $G^*_i$ vectors calculated with a proximity matrix defined by considering 15 nearest neighbors. (a-d) Four maps show the projection of the data along the first four components, highlighting regional lexical variations. (e) Word cloud showing the words with strongest positive (red) and negative (blue) loadings for the second component, with each word’s font size depending on its loading’s absolute value. (f) Explained variance of the principal components compared to the broken-stick model on a logarithmic scale, which shows how the number of components to keep is selected at the first intersection of the two curves. We also plot the cumulative proportion of the variance explained by the components.
Figure S4. Result of the principal component analysis carried out on $G_i^*$ vectors calculated with a proximity matrix defined by a 100 km distance band. (a-d) Four maps show the projection of the data along the first four components, highlighting regional lexical variations. (e) Word cloud showing the words with strongest positive (red) and negative (blue) loadings for the second component, with each word’s font size depending on its loading’s absolute value. (f) Explained variance of the principal components compared to the broken-stick model on a logarithmic scale, which shows how the number of components to keep is selected at the first intersection of the two curves. We also plot the cumulative proportion of the variance explained by the components.
Figure S5. Cultural regions obtained when we keep the top 10,000 lemmas from our dataset. (a) Map of the five clusters obtained through hierarchical clustering, selected from a high value of (b) the mean Silhouette score. (c) Five most specific words for the five clusters shown in (a), along with their specificity values. (d) The dendrogram allows seeing which clusters are first joined if going to a higher level of clustering, and thus which ones are closer together. It clearly shows that the strongest division is the one between the North and the Southeast (excluding Florida) with further splittings as the cluster distance increases.