Chapter 22

Good maps

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What makes a good map? The question is really quite simple: a good map is what allows you to find what you are looking for. However, since we look for different things—addresses, highways, cities, rivers, mountains, territories, languages, dialects, and many more—there is no such thing as the best map. A single map cannot show all the different things we want to find. Thus good maps are the best we can hope for, maps that let us find particular things. Bad maps, in the same way, are bad because they show us something other than what we want to find. A London Tube map is bad for finding a street address in the city. A street map of London may be bad because it only shows the major roads of the city and not the address we are trying to find. Some maps do a poor job of representing what we need to know, like the neighborhood map of London drawn on a napkin in a pub, not to scale, missing roads or landmarks; they show us what the person drawing the map remembers, which may not be enough for us to find the address we want. Good maps, therefore, have an information model that matches what we are trying to find, one that has the right information in three ways: the right kind of information, information at the right scale, and information that is accurate. Linguistic maps follow the same principles as London maps. They need to show the right kind of information about language; they need to show that information at the right scale; and they need to show their information accurately.

Early linguistic maps did not show the right kind of information about language. Maps with isoglosses assumed that a linguistic feature was used in one place but not in another place, so that it was reasonable to draw a line that separated the area of use from the area of non-use. Language in use, however, never distributed itself so neatly into separate areas. As I have shown in detail elsewhere (Kretzschmar 1992; 2003), drawing lines to represent the use of linguistic features always includes (usually unstated) generalizations about frequency, that some feature is used *more often* on one side of a line from the other side. Isoglosses can also be drawn differently at the option of the mapmaker, to delineate broader or narrower areas of usage because the data is sampled, never a complete record of the linguistic usage of an area.

These problems provoked different interpretations of the isogloss, as a limit of occurrence (the classical definition) or as a transitional area where the use of one feature changed over to the use of another feature. Definition as a transitional area did not solve the problem of the isogloss as a limit, however, because it is never the case that features are used uniformly and uniquely in any area: there is always some mixture of different realizations for the same feature, even in places that ought, we think, to be the center of some area of usage. The basic problem with isoglosses is that, while we may want to represent areas of uniform usage of a linguistic feature, areas of uniform usage simply do not occur, not in any language, not for pronunciations, words, or grammar. For evidence all we need to do is look at maps of features in American English as collected for the Linguistic Atlas Project (`www.lap.uga.edu`). It is possible to make thousands of maps on the web site, and no map shows any area where a feature is uniformly used. We may want language to look that way, features divided into complementary regions, but that is not how it works as people use language, and thus a map based on the assumption of areas of uniform usage will always show the wrong kind of information about language.

When mapmakers bundle isoglosses in order to show dialect areas, areas where several features coexist while they do not coexist on the other side of the bundled lines, the distributional problem just gets worse. Unstated assumptions about frequency multiply, and subjective choices about where to draw the lines similarly amplify. As William Moulton has written (1968: 456):

> "Ideally, an investigator might have plotted all possible isoglosses and let the dialect divisions fall where they may. In practice this was never done, since a plotting of all possible isoglosses seemed to reveal no clear geographical structure at all and even to refute the very notion of 'dialect area'–which was what the investigator set out to demonstrate in the first place. Accordingly, what the investigator typically did was to develop some sort of intuitive idea of the areas he wanted to find; he was then able to pick and choose isoglosses–especially bundles of isoglosses–that could be patched together so as to reveal the desired areas."

Moulton in 1968 was talking about the work of Hans Kurath and other linguists who had pursued the isoglossic model in the first surveys of European languages and American English. This practice continues today in Labov, Boberg & Ash (2006), as shown in Figure 1.

The lines on this map enclose dots (speakers) of different colors (degrees of fronting) so that they are not limits of occurrence or transition areas, and the Northern areas drawn can only be subjective regions. Of course, Labov and his colleagues know a great deal about American English, and we have reason to want to trust their judgment; we just need to realize that that is what the map shows us, judgment, and not objective fact about dialect regions in American English. If we want to find "Northern" speakers of American English the map tells us where to look, but the problem is that the idea of "Northern" speakers is not well supported by the map. If we find the map helpful we agree with Labov and his team, but language does not

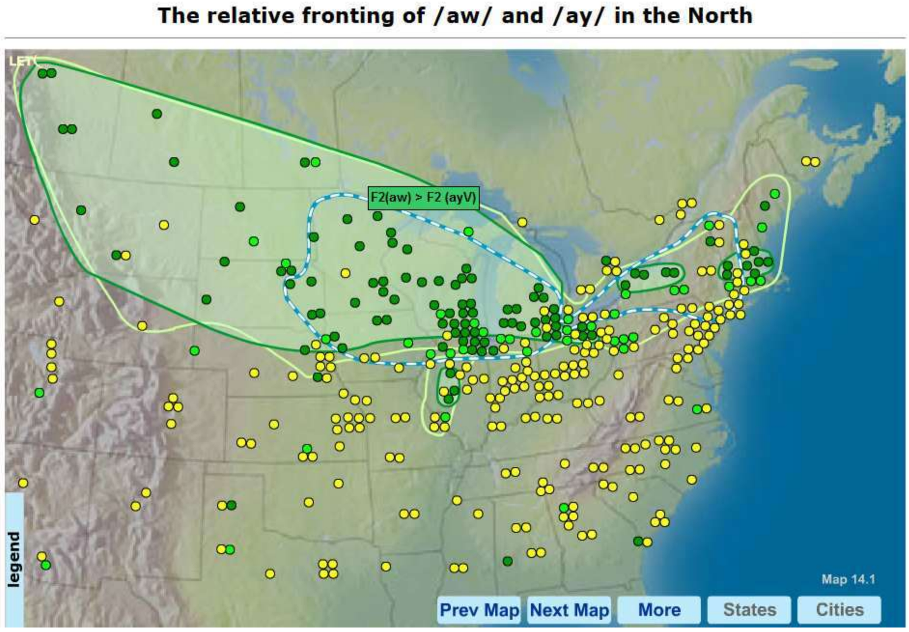

Figure 1: Northern Fronting of /aw/ and /ay/ (Labov, Boberg, and Ash 2006, viewed online at `http://www.atlas.mouton-content.com/secure/generalmodules/anae/unit0031/genunstart.html` on 9/8/2016).

work quite so neatly, and it is a mistake to think that all of the speakers inside of the lines talk the same.

Figure 1 also illustrates the problem of scale. Labov and his colleagues chose two people for their survey from each metropolitan statistical area in North America. They were able to make a national survey that way, but their data does not allow users to make good generalizations about smaller areas. So, for example, Figure 1 shows two yellow dots in Birmingham and two yellow dots in Montgomery, plus a green dot near Tuscaloosa, but on the basis of these five speakers we cannot make a generalization about all of Alabama, or even about urban Alabama. The Linguistic Atlas of the Gulf States interviewed 127 speakers from Alabama, which gives a much better indication of language use at the state scale in Alabama, and it is possible on the Atlas web site to plot responses of those Alabama speakers. In older-style North American sociolinguistics it was thought that sampling did not matter, that choosing just a few speakers from a place was enough to make good generalizations, but the emergence of community-of-practice studies has shown that every place has many different groups of speakers, not homogenous speech.

Modern linguistic maps typically use statistics to make generalizations about how language is used across space. My own work has focused on single features, such as a single variant answer (like *pail* or *bucket*) for the question about the container for water from a well. Figure 2 shows a view of the *pail* response after processing with the statistic known as density estimation (the data is available on the Atlas web site). The map of the Middle and South Atlantic States has been divided in approximately 3000 locations, and the locations have been shaded to represent the likelihood that *pail* might be elicited there, the darker the more likely, based on the nearest neighbors of each location. The sample for the Atlas did not select speakers from all 3000 locations (there were only 1162 informants), so the statistic generalizes from the known locations to make estimates for all of the locations. It is clear from the map that usage of *pail* does not occur in neat areas, and that within any area there may be higher and lower estimates of the probability of eliciting the form. The nearest neighbors method preserves this granularity of responses. It is of course possible to smooth the estimates in order to make neat areas, as shown in Figure 3, the same data processed with smoothing. Figure 3 is less accurate, to my way of thinking, because it creates smooth areas where there really are none; smoothing responds to the idea that language should be used in neat regions.

Recently Ilkka Juuso and I have experimented with a multivariate approach to density estimation, as shown in Figure 4. Different variants for a question, here the question about what to call the event often known as a thunderstorm, are shown in a different color. The least-frequently-occurring variants drop out of the picture, leaving more common variants (*thunderstorm* in blue, *thundershower* in forest green, *thundercloud* in olive green, *thundersquall* in purple), and for those variants the greater the intensity of the color the greater likelihood of elicitation at any location. Figure 4 shows how a multivariate density estimation map compares to a univariate density estimation map, by sketching the outlines of the regions where *thundercloud* appeared in a univariate analysis.

This map retains its accuracy because of the different colors and different intensities. It does not smooth the data into discrete regions. It also operates at its own level of scale, one where only common variants appear on the map; this map will not tell the user where people say any of the dozens of uncommon words for thunderstorm. Still, multivariate density estimation effectively addresses the question of who says what where with regard to thunderstorms.

Grieve, Speelman & Geeraerts (2013) have recently applied modern methods to the data gather by Labov for his North American Atlas. Figure 5 shows raw values for F2 in /ay/ for Labov's data, and just as we would expect, they fail to pattern themselves into neat areas.

Grieve and colleagues then apply spatial autocorrelation statistics to Labov's data (Kretzschmar 1992 had introduced spatial autocorrelation to the field), as in Figure 6 for the same data shown in Figure 5. The prevalence of colors in some regions indicates that the F2 values of /ay/ do have similar neighbors. Grieve and colleagues then conduct a factor analysis on all 38 vowel variables available in the Labov data, and identify four factors that account for a great deal of the variance in the spatial autocorrelation scores (together, 86%). Multiple vowels are implicated in each factor. A hierarchical agglomerative cluster analysis was then conducted on the factor scores, as shown in Figure 7.

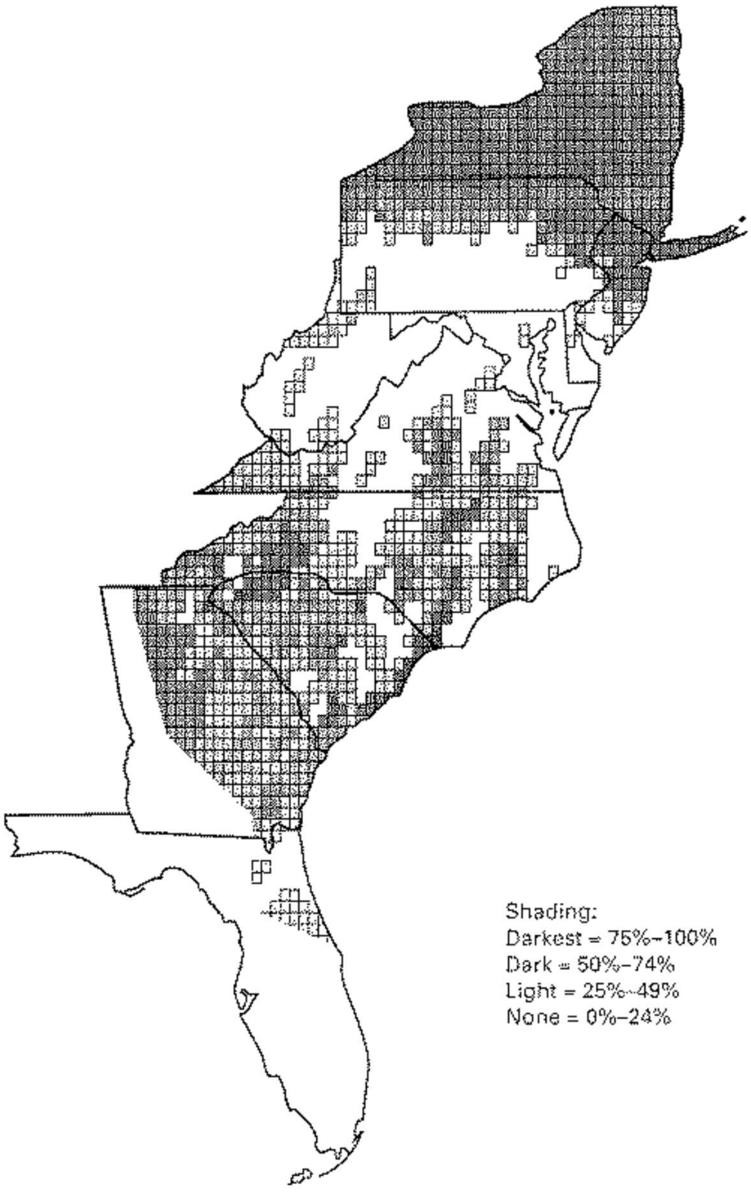

Figure 2: *Pail* responses in the Middle and South Atlantic States, processed with density estimation, nearest neighbors method.

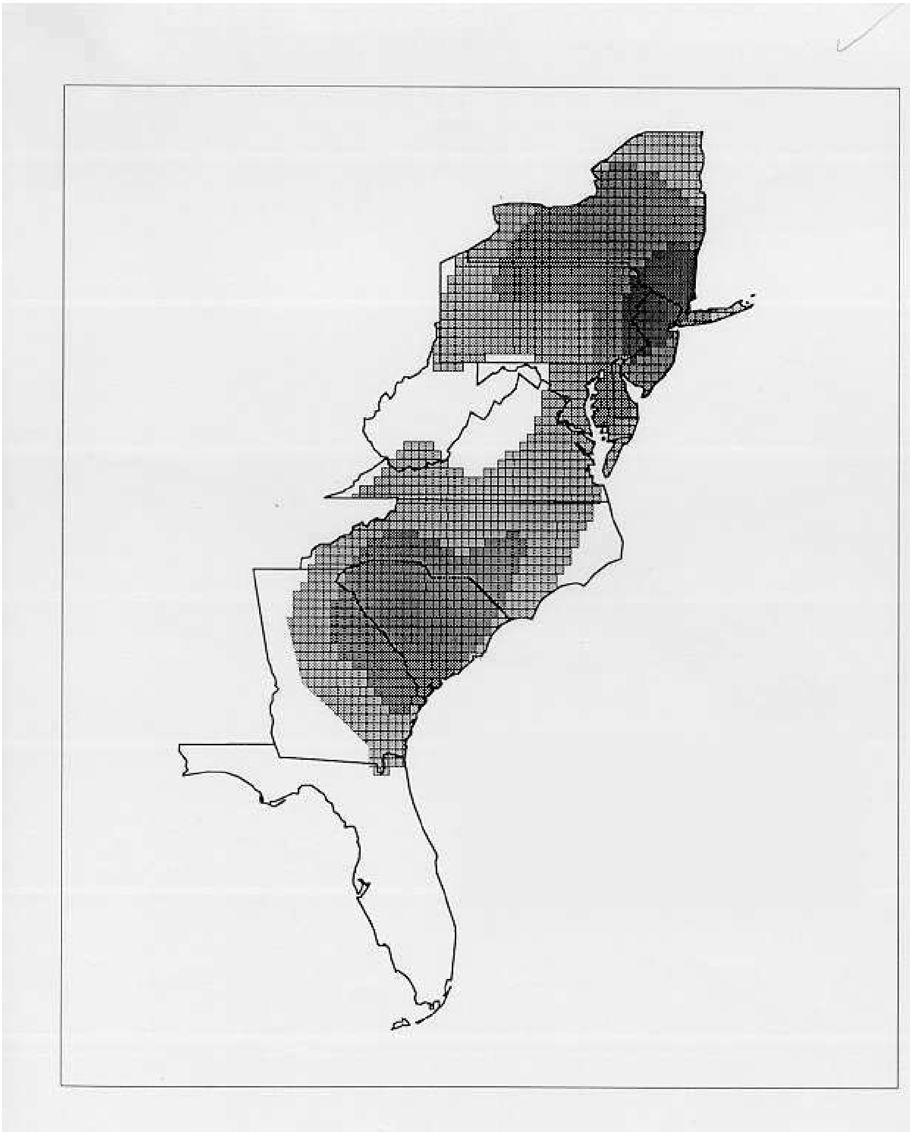

Figure 3: *Pail* responses in the Middle and South Atlantic States, processed with density estimation, kernel method for smoothing.

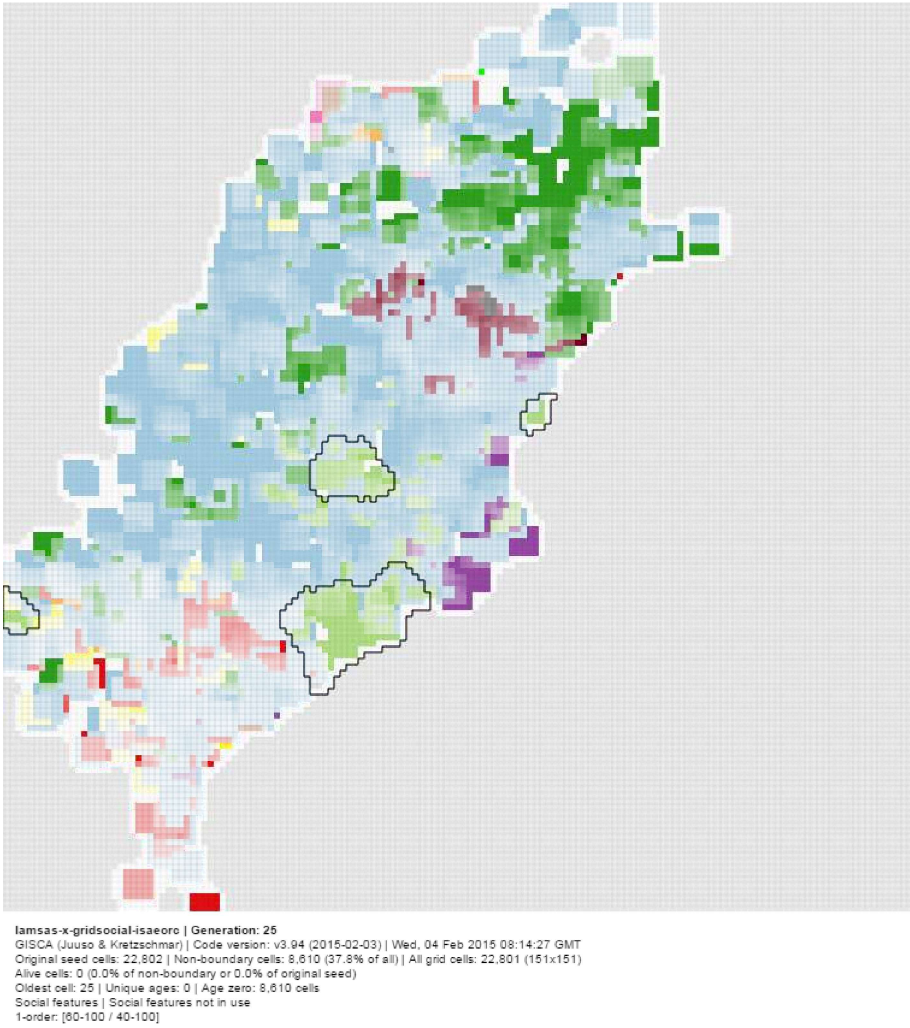

Figure 4: Multivariate density estimation, Middle and South Atlantic words for thunderstorm.

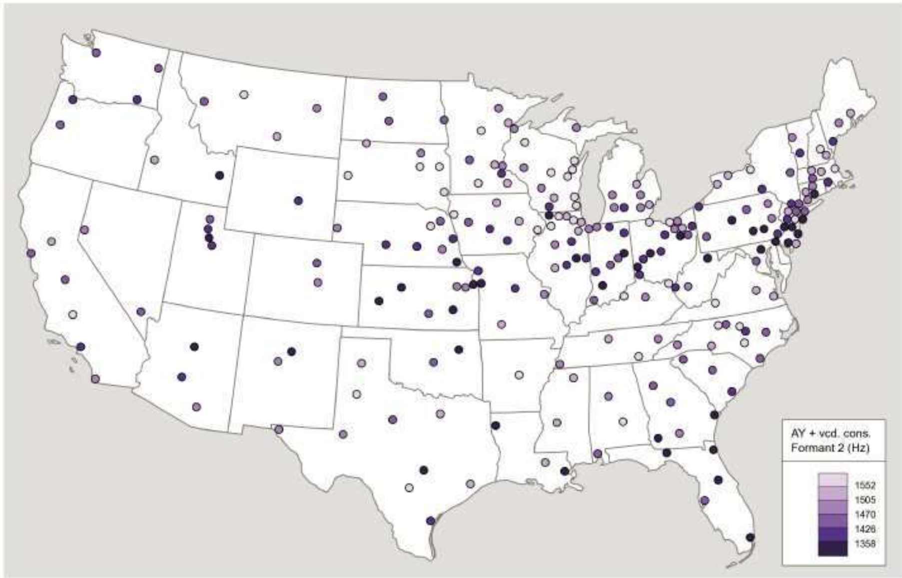

Figure 5: Raw Value Map for /ay/ before voiced consonants (e.g. *bide*) on Formant 2.

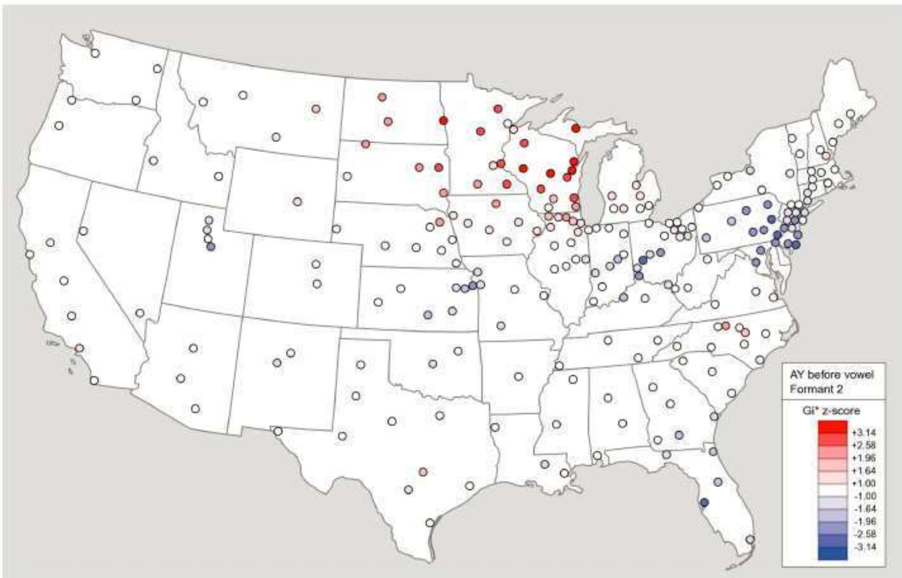

Figure 6: Local Autocorrelation Map for /ay/ before voiced consonants on Formant 2.

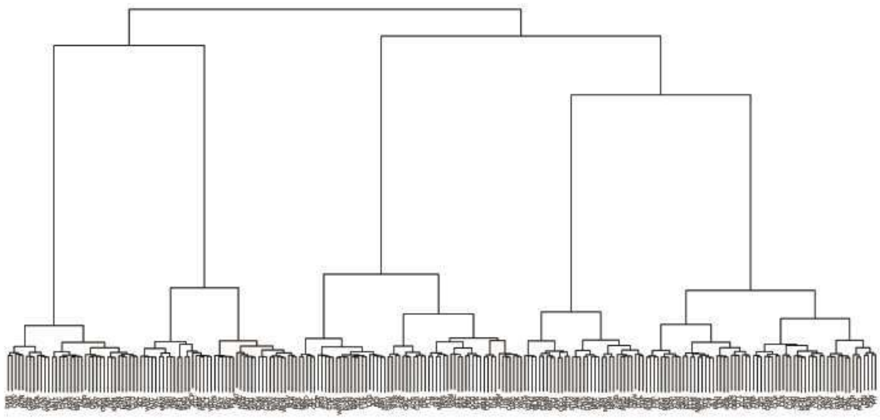

Figure 7: HCA Dendrogram based on Factors 1, 2, 3 and 4.

Grieve and colleagues interpret the HCA dendrogram as yielding five different dialect areas (Northeast, Lower Midwest, Upper Midwest, Southeast, and West), and they make attractive colored maps of the data points in each of the five HCA clusters. These areas are similar to the five areas that Labov and colleagues had named: North, Midland, South, North Central, and West. However, if we look again at the dendrogram, we see that the assignment of five areas represents a low level of agreement, quite far removed from the data point values at the bottom of the chart. It would be equally possible, based on the dendrogram, to name ten areas, since each of the five named categories originates at a bifurcation much closer to the original datapoints. Perhaps we should name twenty or more areas, based on the bifurcations at the next level closer to the data points. What Grieve and colleagues have done, after their modern analysis, is prefer a set of five American dialect areas, probably because that went along with what Labov had said and with what others had said before him (this is the point of Kretzschmar 2003). The last maps produced by Grieve and colleagues lose accuracy, after their careful earlier use of statistics, because they prefer a smoothed version of the data. At some point, naming too many categories from the HCA would violate the scale of the analysis, because Labov's data is not good for lower levels of scale, but the choice of five regions certainly smooths the data more than accuracy should allow.

It is certainly the case the modern linguistic maps are better than earlier linguistic maps because of their effective use of statistics. However, it is still necessary for the analyst to address all three things that make a map good: the right information, the right scale, and accuracy. Statistics alone will not make a map good, and neither is a map good because it looks similar to what previous analysts have offered. We need to maintain appropriate respect for all the aspects of the map as a model in order to make good maps.

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