

# Cultural Cartography with Word Embeddings

Dustin S. Stoltz  
Lehigh University

Marshall A. Taylor  
New Mexico State University

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## Abstract<sup>1</sup>

Using the presence or frequency of keywords is a classic approach in the formal analysis of text, but has the drawback of glossing over the relationality of word meanings. Word embedding models overcome this problem by constructing a standardized meaning space where words are assigned a location based on relations of similarity to, and difference from, other words based on how they are used in natural language samples. We show how word embeddings can be put to the task of interpretation via two kinds of navigation. First, one can hold terms constant and measure how the embedding space moves around them—much like astronomers measured the changing of celestial bodies with the seasons. Second, one can also hold the embedding space constant and see how documents or authors move relative to it—just as ships use the stars on a given night to determine their location. Using the empirical case of immigration discourse in the United States, we demonstrate the merits of these two broad strategies to advance formal approaches to cultural analysis.

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Meaning is often at the center of cultural analysis (Mohr et al. 2020:2; Spillman 2020:1). As texts offer widely-available and unobtrusive sources of “meaning in the wild,” formal text analysis has steadily grown as a suite of tools for studying how meaning is articulated by individuals, groups, and organizations (Mohr 1998). The various procedures associated with the formal analysis of texts (books, articles, or social media comments, for example) often entail the exploration of the texts’ *relations* to other elements (e.g., Mohr and Duquenne 1997; Mohr and Lee 2000)—say, the words or authors of those texts (e.g., Lee and Martin 2018; Mische and Pattison 2000). In particular, the meaning of a text is established by the extent to which it references certain concepts or entities (Weber 1984), often by observing the presence or counting occurrences of certain words or phrases (Namenwirth and Weber 2016; Weber 1990).

Lee and Martin (2014) refer to this process as *cultural cartography* in that, like a topographic map of terrain, it selectively simplifies texts in useful ways. The main problem with counting approaches, we contend, is not that word order or subtlety is lost, or that certain words are selected as representative of certain concepts (cf. Breiger, Wagner-Pacifici, and Mohr 2018; Mohr, Wagner-Pacifici, and Breiger 2015). Indeed, “it is precisely because of their impoverishment that maps are useful” (Lee and Martin 2014:12). *Rather, it is that procedures based on counting tokens are appropriate for discrete measures (i.e., either-or) but not graded measures (i.e., more or less).* For example, the spread of populist ideologies across political campaigns, the prevalence of diversity rhetoric among management consultants, or the relative difference between labor discussions in Germany, Iceland, and the United Kingdom are all cases where graded measures are more appropriate than discrete measures for analyzing meaning. Each case refers to generic ideas that can be more and less present or discourses that can

be more and less alike. Concerns about the *magnitude* of conceptual engagement and similarity are central to cultural analysis; but as we demonstrate here, count-based measures are not suited for measuring magnitudes.

The alternative we propose in this paper remains within the spirit of Lee and Martin’s cultural cartography in that we aim to simplify texts in faithful ways while preserving the graded, relational meanings of words (Kirchner and Mohr 2010; Mohr 1998). Word embedding (or word vector) models offer a means to do just this. These models allow us to substitute the comparison of frequencies with the comparison of distances by providing standardized maps of meaning space. **Importantly, these models do not “learn” or “understand” meaning, nor do these procedures substitute for interpretation (Chakrabarti and Frye 2017; Ignatow 2016; Nelson 2020; Popping 2012).<sup>2</sup> Instead, they “condense information to facilitate an intersubjectively valid interpretation” (Lee and Martin 2014:1).**

In what follows, we first review the use of absence/presence and frequencies to measure meanings in texts and the limitations of these methods. Next, we provide a theoretical and technical introduction to the most basic and common word embedding models. Finally, we organize the various applications of word embeddings in cultural analysis into two broad kinds of “navigation.” **The first we refer to as *variable embedding space* methods, which involves holding terms constant to measure how the meaning space moves around them.** Much like astronomers measured the changing relative locations of celestial bodies with the seasons, these methods measure the changing relative locations of words. More technically, these methods entail splitting a corpus by a

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<sup>2</sup> It is a category error to say that word embedding models “understand” meaning (Bender and Koller 2020; Glenberg and Mehta 2009), and is a contemporary example of the “symbol grounding” problem (Harnad 1990; Lizardo 2016).

covariate—e.g., time periods or authors—and training word embeddings on each subset of the corpus. Second, *fixed embedding space* methods use the same map of meaning space to measure how documents<sup>3</sup> or authors<sup>4</sup> change in relation to it. Here, just as ships determine their location relative to stars in the night sky, these methods measure the relative position of authors or documents *vis-à-vis* a single set of word embeddings. This involves representing documents or authors as nebulae or clouds of locations, and thus measuring similarities to other documents, authors, words, or concepts becomes a transportation problem. We illustrate both approaches using the case of immigration discourse and its evolution in the United States.

[TABLE 1. HERE - DEFINITIONS]

## Cultural Cartography with Word Tokens

Formal text analysis often involves summarizing the meaning of texts with reference to the presence or magnitude of certain concepts or entities within those texts (Carley and Palmquist 1992; Griswold 1987; Weber 1984). For example, an analyst may draw on prior theory, close reading, and their own expertise with the subject matter to “code” documents. Consider Wendy Griswold’s “The Fabrication of Meaning.” The evidence Griswold uses to support the empirical claim that ambiguous cultural objects garner more “cultural power” is whether a book review was “positive” or not and referred to the text as “ambiguous” or not (Griswold 1987:1088–9; 1109).

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<sup>3</sup> We use “document” to refer to any aggregate of text: books, articles, chapters, paragraphs, social media comments, and so on.

<sup>4</sup> We use “author” to refer to individuals, groups, communities, or organizations that are responsible for producing texts.

In a series of critiques of formal text analysis, Biernacki (2012, 2014) argued this kind of “coding” was, among other things, opaque in its application of coding criteria (see also Ryan and Bernard 2003). Lee and Martin (2014), in a response to Biernacki, proposed that counting each “token” instance of a word in a text is “the simplest approach we can take” to overcome this problem (2014:15). We take this as our point of departure.

## “BAG OF WORDS” AND KEYWORD SELECTION

### The Document Term Matrix

Counting tokens allows the analyst to define very explicit rules even a computer could execute—i.e., tally every token use of a word in a document for every type of unique word in a corpus. These methods, generally, begin by identifying each unique term in the corpus and then representing each document’s content as a vector<sup>5</sup> of unique term counts. Terms usually refer to single words (i.e., unigrams) after punctuation and capitalization are removed from the document.<sup>6</sup> The result is a *document-term matrix* (DTM), where each document in the corpus is a row and each unique term in the corpus is a column. DTMs are often called “bag of words” representations (Harris 1954), and form the most fundamental data structure of contemporary natural language processing.<sup>7</sup>

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<sup>5</sup> Simply put, a vector is just a list of numbers. In mathematics more generally, this list of numbers is used to define a direction and magnitude in a space.

<sup>6</sup> Terms need not be single words (as they are commonly understood in English). An *n*-gram denotes how many words in a string are considered a single unit of analysis. The most frequent *n*-gram is the unigram (i.e., a single term, such as “bank”), but one can also use bigrams (two words, such as “commercial\_bank”), trigrams (“local\_commerical\_bank”), and so on.

<sup>7</sup> The unigram DTM is an efficient representation of documents (cf. Herbelot, von Redecker, and Müller 2012; Hopkins and King 2010:232). In information retrieval and text classification research, several experiments find that more sophisticated representations do not yield significant improvements (Apté, Damerau, and Weiss 1994; Lewis 1992; Salton and Buckley 1988).

Consider, for example, three lines from Dr. Seuss’s (1960) *Green Eggs and Ham* as our documents: (1) “Do you like green eggs and ham?” and (2) “I do not like them, Sam-I-am.” (3) “I do not like green eggs and ham!” Simplifying these sentences to term counts will produce the DTM in Table 2.

**[TABLE 2. HERE - DTM]**

This simple data structure allows a massive corpus to be “recombined, transferred to paper and made the subject of joint visual attention of (often physically copresent) groups of experts” (Lee and Martin 2014:21). For example, in less than a minute on most laptops, every U.S. State of the Union Address can be reduced to a matrix with 240 rows and 25,844 columns—small enough for any spreadsheet software to handle. Interpretation, then, proceeds by selecting which keywords (here, columns of the DTM) that denote which concepts or entities of interest, and comparing their presence and prevalence in the documents (Bonikowski and Gidron 2016; Namenwirth and Weber 2016; Weber 1990).<sup>8</sup>

Keyword selection is accomplished in one of two ways. Either the analyst relies on prior theory, close reading, and their own expertise to create a list of keywords, or they use a precompiled dictionary. For an early example of the latter approach, consider the Lasswell Value Dictionary (Lasswell and Namenwirth 1969), which provides a list of terms, each referring to one of eight “value” categories—like Power, Respect, and Wealth (see also Stone, Dunphy, and Smith 1966). Similarly, and more commonly used today, the

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<sup>8</sup> As Carley and Palmquist note (1992:609–610), an analyst may also take an exploratory approach to defining the keywords or phrases that denote their concepts. Such an approach would involve identifying concepts and terms through, e.g., a close reading of a random sample of texts and/or using an unsupervised learning algorithm to assist in inductively identifying latent themes in the texts (Nelson 2020), and then using those to create a coding scheme for the remainder of the document corpus.

LIWC (Linguistic Inquiry and Word Count) dictionary began in the 1980s (Pennebaker and Beall 1986) as a list of terms that referred to emotional and cognitive processes, such as Anxiety and Certainty (Pennebaker, Booth, and Francis 2007). There are numerous other pre-constructed, domain-specific dictionaries (e.g., Lynott et al. 2019). After selecting keywords, there are two general ways to proceed: measuring absence/presence or raw counts/relative frequencies. Each approach is discussed below.

## **Absence and Presence**

To measure whether or not a particular keyword was referenced, the analyst would convert the counts in the DTM to the absence or presence of keywords. This involves setting a threshold, usually any count greater than zero, above which a concept is said to be present. The result is a binary matrix where the cells are either “0” (absence) or “1” (presence).

Consider John Mohr’s “Soldiers, Mothers, Tramps and Others” (1994), which coded the ways relief organizations described their clientele (see also Mohr and Duquenne 1997; Mohr and Lee 2000; Mohr and Neely 2009). Mohr simplified these descriptions by identifying terms denoting “identities” in the documents. For example, the identity “blind/deaf” is denoted by the presence of the follow strings: “Speech is defective,” “Defective sight,” “Defective hearing,” “Speech disorders,” “Blind,” “Blinded,” “Deaf,” “Deafness,” “Deaf-mute,” “Deaf-mutes,” and “Dumb”<sup>9</sup> (Mohr 1994:335–338). Mohr then created a matrix of identities (rows) by the relief activities (columns) associated with those identities where the cells are the absence (0) or the presence (1) of a co-occurrence of these identities and activities (1994:342–3). As a result

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<sup>9</sup> Mohr’s (1994) analysis was based on the New York City Charity Directory, 1907 edition. At the time, “dumb” was used as a clinical term for being mute/speechless..

of its intuitiveness and computational simplicity, using the absence/presence of keywords is a widely used method.

## Raw Counts and Relative Frequencies

The number of keyword occurrences is often used to indicate *magnitude*: where higher counts are interpreted as an *increase in engagement* with an idea or *more attention* toward an entity. For example, Mohr and co-authors (2013) used Named-Entity Recognition<sup>10</sup> to identify “actors” in a set of texts. Then, using a heat map which associates darker shades with higher frequencies, they plotted references to different nations each year. This, they contend:

...shows which nations were given *more attention* across the years. We can see there is a *focus* in the early NSS documents on the Soviet Union and Ukraine. Afghanistan and Pakistan are *more salient* in later years. Bosnia is a *hot spot* between 1995 and 2000. Iraq *takes on importance* with the first Gulf War (which begins with the Iraqi invasion of Kuwait in August of 1990 and ends with the victory of coalition forces in February 1991), and it continues to be *increasingly salient* across time. (Mohr et al. 2013:679, emphasis added)

Here the authors link the number of occurrences of a term and the “attention,” “importance,” or “salience” of what it denotes. We contend that counting concrete named-entities within clearly bounded domains—like nation states in national security reports—is where term frequency measures encounter their limits.

## THE LIMITS OF TOKEN-BASED APPROACHES

In contrast to concrete entities like nation states, researchers are often interested in the extent to which texts engage with more abstract concepts—for example, populism or masculinity. This presumes there is a relation between the *number of occurrences* of

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<sup>10</sup> Named Entity Recognition refers to classification tools that may use predefined dictionaries as well as features of the text (e.g., capitalization) to identify named entities, like “Azerbaijan” or “Max Weber” and also classify these as, for example, “Country” and “Person.”



keywords and the author's (often implicit) intentions, and perhaps the perceptions of the reader (Carley and Palmquist 1992; Popping 2000:39). This is conveyed as a *magnitude*: an analyst moves beyond absence/presence to assert that the frequency of keywords is an adequate measure of the relative prevalence of, or engagement with, more abstract or generic meanings within documents. It is here where tensions emerge (Aslanidis 2018:1245–50; Hanna 2013:376–379).

The first tension relates to the fact that the chance a term will appear—either an additional token of a word already in the vocabulary or a unique word added to the vocabulary—is not only related to the intentions of authors, but something more basic: the length of the document (Baayen 2002:2). If the variance in document lengths in a corpus is high, longer documents will have a higher chance of including the keywords than shorter documents (Salton and Buckley 1988:517; Singhal et al. 1996). This is a problem that has bedeviled the study of lexical richness (Malvern et al. 2004; McCarthy and Jarvis 2010). To account for this, analysts will often “normalize” by dividing counts by the length of each document (Baayen 2002:4; Salton and Buckley 1988:517). While this technique was pioneered in the context of information retrieval, there is very little research guiding what this might mean for the formal analysis of culture.<sup>11</sup>

Second, if the analyst is using a large and somewhat diverse corpus—such as several hundred thousand news articles—even the most frequent keyword will only appear in a small fraction of the documents. This is because the frequency of words

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<sup>11</sup> For instance, should the document lengths be from the original documents, the preprocessed documents, or should the counts be normalized by the number of words in the same class, such as nouns or verbs (Ball 1994)? And would these decisions change the substantive meanings of the relative frequencies? It is very likely that these meanings *would* change, since differences in even very standard preprocessing steps can lead to different outcomes (Camacho-Collados and Pilehvar 2018; Denny and Spirling 2018).

follow Zipf’s Law, in which a few common words (usually short function terms, such as “the” or “of”) show up far more often than any other (Moreno-Sánchez, Font-Clos, and Corral 2016; Zipf 1935)—following a “Large Number of Rare Events” distribution (Baayen 2002:5). To summarize, not all words have equal chances to appear; even as the length of the text increases, most words have low chances, and generally, it is assumed that the very few, high-frequency words in Zipf’s distribution are uninteresting (but see Mosteller and Wallace 1963). Therefore, analysts will often select keywords that fall within an arbitrary middle-frequency threshold.

Consider, as a first step into empirics, a density plot of the relative frequency of “immigration” and “Trump” and “Obama” in the “All the News” corpus—a collection of 204,135 news articles from 18 U.S. news organizations, mostly from 2013 to early 2018 (Thompson 2018).<sup>12</sup> After preprocessing (see Appendix A), the term “trump” is the single most common in our sample of U.S. news articles, but is, nevertheless, still not very common. All three approximate a Poisson distribution with a high number of zero counts (Figure 1). If we were to compare the relative frequency of these terms aggregated by month to the proportions of articles containing one instance of the terms (i.e., absence/presence or binary measure), the Pearson correlation coefficients between the binary and relative frequency measures for “obama,” “trump,” and, “immigration” are all very high (0.843, 0.945, 0.916, respectively). These correlations indicate that relative frequency offers little in terms of a measure of magnitude because it is nearly equivalent to simply measuring the absence or presence of a keyword.

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<sup>12</sup> The 18 news organizations are: *The Atlantic*, Fox News, *New York Post*, *The Verge*, *Breitbart*, *The Guardian*, *New York Times*, Vox, *Business Insider*, *Los Angeles Times*, NPR, *Washington Post*, *BuzzFeed News*, *National Review*, Reuters, CNN, *New Inquiry*, and *Talking Points Memo*.

**[FIGURE 1. HERE - RF DENSITY PLOT]**

Finally, as a result of the unique distribution of words in language, measures of relative frequency are highly volatile. Even in news articles that do contain the term “immigration,” for example, it still occurs relatively few times. Therefore, even a random addition of a single token “immigration” will drastically change the rank order of documents. This also means that relative frequencies will be highly varied over time. This is shown in Figure 2, which averages relative frequencies by month-year and then plots the difference in mean relative frequency for each month-year from the previous month-year.

**[FIGURE 2. HERE - RF VOLATILITY PLOT]**

As counts are agnostic to word semantics (Le and Mikolov 2014), the analyst could select additional terms (e.g., synonyms) to denote the same concept or entity (see Appendix B). This, however, leads to the final drawback: keywords either count or do not count as denoting a concept or entity, which fundamentally creates an either-or measure. All the terms equally do or do not reference the concept. Following the relational theory of meaning, however, we would contend that there is a graded relationship between terms and their meanings.

One way to overcome this either-or issue is to “weight” terms. The most widely used example of this are the dozens of “sentiment” dictionaries (Pang and Lee 2008), where terms are not only hand-categorized by whether they are positive or negative (or neutral), but also hand-weighted by their degree of positivity or negativity (e.g., on a scale from -2 to 2). This, however, is labor intensive and results in domain-specific weightings that do not reflect structures emerging from the relations between term usage.

In what follows, we demonstrate how word embeddings can both complement count approaches and overcome some of the weaknesses outlined above.

## Cultural Cartography with Word Embeddings

Word embedding models are one of the most popular developments to come out of natural language processing research in the last decade. As word embeddings are relatively new and quickly advancing, we provide an elementary introduction to the most basic and common models that assumes the reader has little prior knowledge on the subject.

### LANGUAGE MODELING AND RELATIONAL THEORIES OF MEANING

There are two strategies for representing words as numbers: discrete and distributed. In the simplest discrete approach, each unique word is represented by a binary vector where each unique word in the corpus is assigned to a position in the vector (i.e., one-hot encoding). Take our previous example from *Green Eggs and Ham* (Table 2). The vector for each term would be eleven positions long, and assuming the same order as the columns in the DTM, the vector for “eggs” would be {0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0}. Comparing whether two terms (tokens) are the same entails measuring whether their term (type) vectors have a “1” in the same position. Words are either precisely the same, or they are not.<sup>13</sup> The problem is that the relationship between the numbers standing in for the terms do not correspond to the relationship between the meanings of terms (Smith

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<sup>13</sup> Each unique word (type) could be assigned an integer at random, where word (tokens) are the same if their assigned integers are precisely equal. Again, words are either exactly the same, or not.

2019:2). *Two terms that mean similar things (e.g., hog and pig) will be just as different as two terms that mean dissimilar things (e.g., sun and insurance).*

The second strategy involves creating “distributed” representations of terms’ meanings. These representations can be obtained either by imposing semantic relations—such as coding words as, e.g., synonyms, antonyms, or in hypernym or troponym relationships, as they do in the WordNet database (Fellbaum 1998)—or by inducing relations from patterns in natural language corpora (Lenci 2018). Word embedding models take the latter route.

Noam Chomsky famously asserted that corpus linguistics and the statistical study of text was a dead-end (Chomsky 2002:15–20; Harris 1995:96–98),<sup>14</sup> and yet the kernel of the “distributional hypothesis” (Geeraerts 2010:165–181; Sahlgren 2008) is to be found in the work of Chomsky’s dissertation advisor, Zellig Harris. Drawing on Leonard Bloomfield and Edward Sapir in particular, Harris argued (1954:156) “difference of meaning correlates with difference of distribution” (see also Joos 1950).<sup>15</sup> Similarly, the linguist J. R. Firth—influenced by Bronisław Malinowski (Firth 1935; Rose 1980; Young 2011)<sup>16</sup>—stated that words’ meanings can be inferred from their “habitual collocations”:

...a text in such established usage may contain sentences such as ‘Don’t be such an ass!’, ‘You silly ass!’, ‘What an ass he is!’ In these examples, the word ass is in familiar and habitual company, commonly collocated with you *silly-*, *he is a silly-*, *don’t be such an-*. You shall know a word by the company it keeps! One of the meanings of ass is its habitual collocation with such other words as those above quoted. (Firth 1957:11, emphasis in original)

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<sup>14</sup> Among many examples: “It must be recognized that the notion ‘probability of a sentence’ is an entirely useless one, under any known interpretation of this term” (Chomsky 1969:57).

<sup>15</sup> Saussure is often ritualistically cited to motivate such a “relational” approach to language. While his view was relational, he largely ignored semantics to focus on phonology (Norris 1985:62; Stoltz 2019).

<sup>16</sup> Along with Firth, Wittgenstein ([1953] 2009:80, 109) is often cited as positing a similar theory. He too was likely influenced by Malinowski (Gellner 1998:149).

This basic “distributional” hypothesis was supported by early statistical analyses (Church and Hanks 1990; Henley 1969; Rubenstein and Goodenough 1965), leading Miller and Charles (1991:24) to foreshadow word embeddings: “the general idea is to consolidate various kinds of information about a word’s contexts into a single representation that characterises those contexts.” The goal, then, is to assign each word a single vector such that the “gradedness in distributional representations correlates with gradedness in semantic phenomena” (Boleda 2020:228).<sup>17</sup>

This procedure of inferring a word’s meaning by summarizing its (linguistic) context aligns with relational theories of culture—pioneered by John Mohr (Kirchner and Mohr 2010; Mohr 1998, 2000), along with Pierre Bourdieu, Ron Breiger, Ann Mische, Harrison White, Viviana Zelizer and many others (Fuhse 2009; Mische 2011; Pachucki and Breiger 2010; Tilly 2010; Zelizer 2012)—as well as pragmatic, embodied, connectionist, and practice-theoretic approaches to cultural learning (Arseniev-Koehler and Foster 2020; Ellis 2019; Erk 2016; Foster 2018; Glenberg and Robertson 2000; Hinton 1986; Ignatow 2007, 2016; Landauer and Dumais 1997; Lizardo et al. 2019; Osgood 1952; Strauss and Quinn 1997; Turner 2011; Zaromb et al. 2006).

As a result of this wide-spread theoretical commensurability, social scientists are beginning to use word embeddings (Boutyline, Arseniev-Koehler, and Cornell 2020; e.g., Hofstra et al. 2020; Jones et al. 2020; Kozłowski, Taddy, and Evans 2019; Linzhuo,

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<sup>17</sup> It is important to emphasize that words’ meanings can be *inferred* from their linguistic contexts, and thus “difference of meaning *correlates* with difference of distribution” (Harris 1954:156 emphasis added). This is contrary to problematic neo-Saussurean formulations in sociology (Stoltz 2019), wherein words’ meanings are said to be *entirely constituted* by their linguistic context alone. See Bender and Koller (2020:7) for a similar critique of Wittgensteinian formulations: “the slogan ‘meaning is use’... refers not to ‘use’ as ‘distribution in a text corpus’ but rather that language is used in the real world to convey communicative intents to real people.”

Lingfei, and Evans 2020; van Loon and Freese 2019; Ornaghi, Ash, and Chen 2019). This early work largely builds on the fact that word embeddings mirror the stereotypical racial, ethnic, and gender related biases found in the texts they are trained on (Brunet et al. 2018; Caliskan, Bryson, and Narayanan 2017; Lewis and Lupyran 2020).<sup>18</sup> While this can be a concern for some downstream applications—indeed, leading some researchers to attempt to “debias” word embeddings (Bolukbasi et al. 2016a; Gonen and Goldberg 2019)—this is a strength for those wishing to study these associations as features of the social world. Rather than distortions in the semantic space, these are the contours of cultural formations.

## WORD EMBEDDINGS: SOME TECHNICAL DETAILS

### The Term-Co-occurrence Matrix

The simplest distributional model begins by assigning each unique term<sup>19</sup> in a corpus to its own vector and also its own position or “dimension” in that vector. Then, each entry in a term’s vector indicates the frequency it occurs next to the term corresponding to that dimension within a given window, say five terms on either side.<sup>20</sup> The result is a square target-term by context-term matrix, and the cells indicate the frequency a term (row) co-occurs with another term (column) within that window (see

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<sup>18</sup> A wide range of work demonstrates that these models are accurately reflecting co-occurrence patterns in corpora (Ethayarajh, Duvenaud, and Hirst 2019:9; Schuster et al. 2020; Toney and Caliskan 2020), as opposed to “exaggerating” associations. In particular, researchers have validated these associations against traditional techniques, such as surveys and implicit association tests (Joseph and Morgan 2020; Kozlowski, Taddy, and Evans 2019).

<sup>19</sup> Recall that terms can be larger *n*-grams, and most of the pre-trained embeddings include common *n*-grams greater than one.

<sup>20</sup> Goldberg (2016:367–369) provides a more detailed discussion: “the size of the sliding window has a strong effect on the resulting vector similarities. Larger windows tend to produce more topical similarities (i.e. “dog”, “bark” and “leash” will be grouped together, as well as “walked”, “run” and “walking”), while smaller windows tend to produce more functional and syntactic similarities (i.e. “Poodle”, “Pitbull”, “Rottweiler”, or “walking”, “running”, “approaching”).”

also Lee and Martin 2014:15–16). This matrix is often called a *term-co-occurrence* or *term-context matrix* (TCM), and formalizes Firth’s “habitual collocations” (1957:11). Again, consider the three sentences from *Green Eggs and Ham* used earlier, and assume the context window is one line. The TCM would be an eleven-by-eleven matrix like Table 3.

[TABLE 3. SIMPLE TCM ]

## Dimension Reduction

There are two drawbacks to using the TCM alone to represent term meanings. First, using larger corpora, each term’s resulting vector would be very long (as long as the number of unique terms in the corpus) and very sparse (with many zeros indicating two words never co-occur). Second, and more importantly, two target terms are considered similar to the extent they share a matching set of co-occurring terms. For example, we would likely find that “football” and “quarterback” are similar because terms co-occurring with “football” are often the same terms co-occurring with “quarterback” at similar rates, such as “throw” and “catch.” However, there are subtle semantic similarities that simple co-occurrence frequencies cannot pick up. Take the terms “football” and “ballet.” They are similar in that both are demanding athletic activities requiring physical strength and agility, yet different enough as to have very different sets of co-occurring terms. Football might co-occur with “punt” and “juke” and ballet with “assemble” and “pirouette,” but punt and assemble are both related to legs, and juke and pirouette are both associated with the torso. Using a TCM alone, these terms would appear very dissimilar, yet we know that they share some semantic similarities.



For both these reasons, dimension reduction techniques are applied to the TCM (Lenci 2018:157; Martin and Porter 2012; Switzer 1964; Wong, Ziarko, and Wong 1985). The TCM is reduced not by selecting “columns” (i.e., context terms) that are the most explanatory and discarding others (i.e., feature selection), but rather by finding a few latent features summarizing the information in the matrix (i.e., feature extraction). This is motivated by the idea that “co-occurrences collected from corpora are noisy data that hide more abstract semantic structures” (Lenci 2018:157).

To summarize, at their most basic, word embedding models involve creating a TCM and reducing its dimensions. The resulting embedding matrix consists of row vectors that are dense (as opposed to the sparse TCM) and, typically, real-valued. Recent advances in word embedding models attempt to improve the tuning of this low-dimensional mapping (see Appendix A). The  $n$ -dimensional TCM is “reduced” to at least  $n-1$  latent dimensions and thus those original elements have been *embedded* into a “lower-dimensional” space. This notion forms the basis of “embedding” methods in computer science and is a mathematical feature common to many of the matrix factorization tools familiar to social scientists—e.g., factor analysis, principal components analysis, correspondence analysis, and so on.<sup>21</sup>

Next, “for purposes of intuition” (Deerwester et al. 1990), this matrix can be interpreted geometrically, such that the row vectors designate terms’ locations in a continuous space (usually Euclidean). As geometric relations correspond to semantic

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<sup>21</sup> Many of the methods falling under the labels “topic modeling” and “latent semantic analysis” are the application of dimension reduction on a DTM (as opposed to the TCM). One important difference, however, is that the resulting dimensions of the word embedding matrix are not “interpreted” directly (cf. Bodell, Arvidsson, and Magnusson 2019), as one might interpret “topics” or “principal components,” but rather the relations between elements’ locations as defined by those dimensions.

relations, we can make use of operations from linear algebra to extract meaningful associations (Erk 2012). Mainly, distance measures *semantic similarity* between two words, but also adding, subtracting, and averaging vectors produces intuitive results—sometimes referred to as relation induction, relation extraction, or semantic projection—useful for the cultural analyst. The most well-known example is subtracting “man” from “king” and adding “woman” produces a vector near “queen,” or, adding “dance” to “football” will result in a vector close to “ballet,” and adding “south” to “Africa” will be near the intersection of their co-occurrence contexts and thus surrounded by words related to “South Africa” the country, rather than near the cardinal direction or continent, respectively. While there are other kinds of semantic relations one could extract, we focus on similarity (but see the Discussion).

## Corpus-Trained Versus Pre-Trained Embeddings

[TABLE 4. EXAMPLE PRE-TRAINED EMBEDDINGS]

An important consideration when using word embeddings (hereafter just *embeddings*) is whether the analysis requires training on a specific corpus or whether pre-trained embeddings will do. Pre-trained embeddings are word vectors estimated using large-scale and widely-representative, “naturally occurring” corpora (for example, fastText embeddings are trained on Wikipedia data dumps and the 25 billion web pages of the Common Crawl), and thus are not trained on the researcher’s own corpus. Corpus-trained embeddings, by contrast, are word vectors trained exclusively on the researcher’s unique corpus. In general, a researcher will want pre-trained embeddings if they are interested in analyzing how their documents relate to widely shared semantic associations within a given language community. A researcher may want corpus-trained

embeddings if they instead want to analyze any semantic idiosyncrasies within their corpus (e.g., Bonikowski, Feinstein, and Bock 2019 Appendix A), or if pre-trained embeddings are not available for a specific language community.

We contend (along with Spirling and Rodriguez 2019) that researchers should *default* to using pre-trained sources (see Table 4), and only use corpus-trained if required by the research question.<sup>22</sup> A key strength of using pre-trained embeddings is that the computational resources and time required to accurately train these models can be borne once (Lazer and Radford 2017:33). Furthermore, pre-trained embeddings enhance comparability across studies. For example, all that is needed to apply the various techniques we discuss is a pre-trained embedding matrix and a DTM. Therefore, in the following demonstrations, we rely on pre-trained embeddings.

## **Navigating Meaning Space: Variable and Fixed Embedding Space Methods**

While word embeddings have been used for a variety of tasks in information retrieval research and computational linguistics, these techniques are only recently being used in social science and cultural analysis. We therefore provide an organizational scheme for thinking about how embeddings can be used in the social scientific context (see Table 5). Along with all relational approaches, interpretation proceeds by measuring how units of analysis are related to each other. For example, we can know what it means for “immigration” to be a certain distance from “school” when we compare this to its distance from “family.” That is, a fixed “waypoint” must be defined from which we gain

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<sup>22</sup> Furthermore, pre-trained embeddings can often be “retrofitted” to highlight certain lexical relations (Faruqui et al. 2014; Fu et al. 2014; Kamath et al. 2019; Vulić et al. 2018)

our perspective on the relative distances of other points. Therefore, we divide methods based on what unit of analysis is “fixed.”

In our first group of methods, the terms are fixed while the relations between them are allowed to vary. We refer to this as *variable embedding space methods*. We accomplish this by subsetting our corpus by a covariate, usually time or author, training multiple sets of embeddings and then measuring the differences in the relative location of key terms within each of these spaces—much like early astronomers measured how the positions of celestial bodies changed across the seasons. In our second group—which we call *fixed embedding space methods*—we hold the embedding space constant while measuring how documents or authors differ in relation to each other. We accomplish this by measuring the relative locations of documents or authors defined as aggregates of terms in a single set of embeddings—just as ships use the stars at a given time to determine their location. For reach, we first review prior research and then offer an illustration using immigration discourse in the United States.

#### [TABLE 5. EMBEDDING METHOD DISTINCTIONS]

### VARIABLE EMBEDDING SPACE

Kulkarni et al. (2015) offered one of the first studies to fix terms and compare their changing relative position in embeddings trained on text from different time periods. They empirically demonstrate the well-known discursive shift over the 20<sup>th</sup> century where the word “gay” changed from being located beside “cheerful” and “frolicsome” to being near “lesbian” and “bisexual.” Similarly, Garg et al. (2018) track changes in gender and ethnic biases in English over the same time period by comparing the changing distances between gender- and ethnicity-related terms and a list of adjectives and occupational

terms (see also Jones et al. 2020). Kozlowski et al. (2019) analyze the “cultural dimensions” of social class that structure embedding spaces, and demonstrate how specific markers of class shifted over the past century. While the specifics vary, each study uses a “time-lapse” approach in which embedding models are trained on texts from different time periods and then used to measure changes in the meaning space between periods.

Similarly, although we do not demonstrate it here, we could subset a corpus by variables other than time, and train separate embedding models on each subset in order to measure how the meaning of terms varies across, e.g., individuals, communities, or organizations. For example, Bonikowski et al. (2019 Appendix A) divide presidential candidates’ speeches by individual candidates. They then find the 50 nearest neighbors of two focal terms derived from each embedding model. As each model is trained on separate candidates, the associations are specific to the candidate. Similarly, Zannettou et al. (2018) compare models trained on text from different communities: the 4-chan board /pol/ and Gab (see also An et al. 2019; Rho, Mark, and Mazmanian 2018; Schild et al. 2020). In both cases, just like the time-lapse approach where the embedding space is allowed to vary over time, here the embedding space is allowed to vary by authors—either individuals or collectives.

While we only use pre-trained embeddings here, there is a caveat to comparing embeddings trained on separate corpora that is important to mention: embedding matrices must be “aligned” (Hamilton, Leskovec, and Jurafsky 2016:4). We will spare details, but roughly, this involves rotating and scaling of two or more matrices in a way that preserves the distances between terms within each embedding while approximately

aligning the terms across embeddings (Artetxe, Labaka, and Agirre 2016; Mogadala and Rettinger 2016; Ruder, Vulić, and Søgaard 2019).

### **Measuring The Distance Between Terms Over Time**

To demonstrate variable embedding methods, we first show the simplest use, which is measuring how the distance between two (or more) words differs over time. Specifically, we measure how the meaning of “immigration” has shifted in American English using embeddings trained on the Corpus of Historical American English separately for each decade from 1880 to 2000 (Davies 2012)—the same embeddings used by Hamilton et al. (2016) to derive laws of lexical change.<sup>23</sup>

Here, we take the cosine similarity between the vector of “immigration,” on one hand, and the vectors for “job,” “crime,” “family,” and “school,” on the other, for each decade. From the plot of similarities (see Figure 3), we can see that immigration was strongly associated with “job” at the end of the 19<sup>th</sup> century, and while “school,” “family,” and “job” have slowly increased in the 20<sup>th</sup> century, immigration has grown even more associated with “crime.”

**[FIGURE 3 ABOUT HERE - COSINE LINE PLOT]**

### **Measuring The Distance Between Terms and Cultural Dimensions**

Next, we follow Kozlowski et al. (2019) to extract a semantic direction in the embedding space pointing toward a pole of the cultural dimensions of race, social class, and morality—that is, the extent to which a term is more associated with, say, “good” versus “bad,” in the case of the morality dimension (see also Arseniev-Koehler and

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<sup>23</sup> <https://nlp.stanford.edu/projects/histwords/>

Foster 2020). This procedure involves identifying sets of antonyms<sup>24</sup> for each cultural dimension—understood as generic binary oppositions that “individuals use in everyday life to classify agents and objects in the world” (Kozlowski et al. 2019:911). For example, for social class, this would be affluence vs poverty, rich vs poor, and so on. The vector for “poverty,” for example, is then subtracted from “affluence.” This is repeated through the set of class-related antonyms and the resulting vectors are averaged, giving the vector for one pole of the cultural dimension of affluence.<sup>25</sup>

The affluence, race, and morality dimension was constructed using antonym pairs taken from Kozlowski et al. (2019:935–937).<sup>26</sup> We then measure the changing position of the term “immigrant” as well as “citizen” relative to these cultural dimensions. This is repeated using the embeddings for each decade in the Corpus of Historical American English embeddings.

The y-axis of Figure 4 (both panels) shows that, regardless of decade, “citizens” (blue dots) tend to be closer to the “white” pole of the race dimension, whereas “immigrants” (yellow triangles) tend to be closer to the “black” pole. In the x-axis of the left panel, we see that “citizens” in 2000 is closer to the “high class” pole of the affluence dimension than is “immigrants” in 2000. In the x-axis of the right panel, we see that

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<sup>24</sup> The terms opposite one another in the set need not be antonyms, strictly speaking, so long as the terms collectively “index” a shared concept. For example, one could create a “book - movie” semantic direction using words such as “book,” “novel,” “notebook,” and “volume,” on the one hand, and “movie,” “film,” “picture,” and “motion\_picture,” on the other. Clearly, “book” and “movie” are not antonyms; rather, these are terms that may occur in similar contexts but are typically juxtaposed. A more all-encompassing term may be “juxtaposition pairs.”

<sup>25</sup> There are several different procedures for deriving a “semantic direction” from an embedding space (Arseniev-Koehler and Foster 2020:18–9; Bolukbasi et al. 2016b:42–3; Boutyline, Arseniev-Koehler, and Cornell 2020; Ethayarajh et al. 2019; Kozlowski et al. 2019:943 fn 8; Larsen et al. 2015:5; Taylor and Stoltz 2020).

<sup>26</sup> We were not able to use the exact term pairs because the historical embeddings did not have the following for all time periods: advantaged, propertied, sumptuous, swanky, ritzy, uncorrupt, pureness, necessitous; skint, penurious, unmonied, unprosperous, moneyless, transgressive, knavish, afro.

“citizen” has clustered near the “good” pole of the morality dimension throughout the decades, whereas “immigrants” have generally moved closer to “good” over the decades, with 1980, 1990, and 2000 being the closest to “good.”

These associations could be interpreted in one of two (non-mutually exclusive) ways. First, engagement with the “citizen,” “white,” “high class,” and “good” poles of their respective cultural dimensions could be correlated because—unlike “immigrant,” “black,” “low class,” and “bad”—these concepts themselves have been both largely *absent* in U.S. public discourse over time. This interpretation suggests that these “discursively absent” poles have been remarkably stable *unmarked* (and therefore taken-for-granted and normative) categories for citizenship, race, social class, and morality discourses in the United States (Brekhus 1998).<sup>27</sup> The second interpretation is that the temporal stability in how the immigrant-citizen dimension correlates with these other dimensions reflects durable symbolic boundaries in the U.S. This interpretation, for example, corroborates prior research finding the “immigrant-as-nonwhite”<sup>28</sup> vs. “citizen-as-white” has been an enduring cultural structure in U.S. public discourse and attitudes (Mora and Paschel 2020; Sáenz and Douglas 2015).

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<sup>27</sup> A more in-depth analysis of these data with the “marked-unmarked” framework might benefit more from a keyword absence/presence method, since a category’s “unmarked” status is, by definition, signified by its absence.

<sup>28</sup> A more robust and systematic analysis on this subject would want to either construct a “nonwhite-white” semantic direction (as opposed to a “black-white” one), or construct several semantic directions with “white” as one pole and as series of non-white racial-ethnic categories as the opposite poles. These steps would be necessary to more confidently link this finding to the “immigrant-as-nonwhite” symbolic boundary interpretation.



[FIGURE 4 ABOUT HERE - CULTURAL DIMENSIONS PLOT]

## **FIXED EMBEDDING SPACE**

Like variable embedding space methods, the most basic use of a fixed embedding space is measuring the relationship between key terms or cultural dimensions. Arseniev-Koehler and Foster (2020), for example, train an embedding model on over a hundred thousand *New York Times* articles and measure the distance between terms related to “obesity” and key cultural dimensions: gender, morality, health, and socioeconomic status. In addition to showing how terms relate to other terms or cultural dimensions within a given space, an analyst can also use the embeddings to compare how documents (or authors) are related to other documents (or authors). The simplest example would be determining how semantically similar each document is to each other document, or a subset, in a corpus. In turn, similarities can be used for a variety of ends such as comparing document revisions, text classification, measuring content change, building semantic networks, or studying content diffusion (e.g., Ahlgren and Colliander 2009; Berry and Taylor 2017; Strang and Dokshin 2019; Teplitskiy 2016; Zhang and Pan 2019).

### **Word Mover’s Distance**

Prior social scientific research estimating document similarities often relied on discrete word representations. For example, Bail (2012) used plagiarism detection software (Bloomfield 2008) to compare press releases by civil society organizations to media coverage. Similarly, Grimmer (2010) used the same software to compare press releases from Senate offices to media coverage. This software, after lemmatizing two documents, searches for exact matches in strings of six words. This technique, then, treats

words as either the same or not, therefore not accounting for the graded and relational nature of word meanings.

Farrell’s (2016) method is even closer in spirit to the fixed embeddings approach we will demonstrate. To compare the similarity of writings by climate contrarian organizations with news outlets and political offices, Farrell reduced the dimensionality of the DTM by applying SVD, and then compared the cosine similarity of the resulting document vectors (Deerwester et al. 1990). While this procedure formed the backbone of information retrieval systems for decades, recent research demonstrates that similarity measures using embeddings, specifically Word Mover’s Distance (Kusner et al. 2015),<sup>29</sup> outperform these procedures on various baseline tests, including plagiarism detection (Tashu and Horváth 2018).

With Word Mover’s Distance (WMD), documents are represented not just by vectors of counts of unique terms, but also by their embedding vectors. Therefore, a document becomes a cloud of locations in the embedding space. Determining similarity is treated as a transportation problem where the “cost” of moving one document’s cloud of locations to another is equivalent to the semantic similarity between two documents. The DTM provides the “amounts” to be moved and the word-embedding matrix provides the “distances” that these amounts are moved. The result, which we invert so as to be more intuitive, is a square document-by-document similarity matrix. This matrix can also be conceptualized as author-by-author similarities if similarities are averaged or if each document has a single author: for example, Pomeroy et al. (2019) use this procedure to

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<sup>29</sup> One alternative to WMD, and related algorithms, involves taking the average vector of all the words in a document (sometimes called Word Centroid Distance), and then comparing these resulting vectors using cosine similarity (e.g., Berry and Taylor 2017; Lix et al. 2020), which is likely well suited for smaller documents, such as social media comments.

measure the relationship between nation states based on the similarity of their United Nations speeches.

To demonstrate Word Mover’s Distance (using LC-RWMD<sup>30</sup>), we find the document-by-document similarity matrix between our preprocessed corpus of U.S. news articles and a corpus of press releases published by immigration-focus advocacy organizations.<sup>31</sup> We collected a total of 986 press releases from two far-right organizations, the Center for Immigration Studies ( $N = 160$ ) and the Federation for American Immigration Reform ( $N = 379$ ), as well as two left-wing organizations, National Network for Immigrant and Refugee Rights ( $N = 119$ ) and Women’s Refugee Commission ( $N = 328$ ). The publication date of the press releases ranged from 1998 to 2020 (median of 2015), but they were “pooled” together and compared to news articles across time points ranging from January 2016 to July 2017. We find each news organization’s similarity to each advocacy organization by pooling the average of the similarity between their respective news articles per year and the press releases pooled by advocacy organization.

#### [FIGURE 5 ABOUT HERE - WMD PLOT]

Although contemporary research on bias in news media finds that most outlets are fairly moderate (Groeling 2013; Prior 2013; Puglisi and Snyder 2015), we selected three news organizations that are generally considered more right-leaning (*Breitbart*, Fox News, and *National Review*) and three more left-leaning (*Talking Points Memo*, *New York*

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<sup>30</sup> WMD solves this transportation problem using Earth’s Mover’s Distance (Rubner, Tomasi, and Guibas 1998) to compare multidimensional distributions. Several teams have found computationally efficient solutions to this problem (Atasu et al. 2017; Tithi and Petrini 2020; Werner and Laber 2019; Wu et al. 2018). Our method incorporates one such method: Linear Complexity Relaxed Word Mover’s Distance (LC-RWMD).

<sup>31</sup> We collected the press releases using a custom scraper built using the “rvest” R package (Wickham 2019).

*Times*, and *Buzzfeed News*) for our demonstration. We first subset articles to include only those referring to “immigration” or “immigrants” ( $N = 15,769$ ) and plotted their average similarities to the right-wing (red) and left-wing (blue) press releases over time (see Figure 5).

We find that the similarity between articles about immigration and press releases increases from mid-2016 and peaks in early 2017. Interestingly, and in contrast to prior literature finding limited media bias, when right-leaning news organizations write about “immigration” they are significantly more similar to the press releases from right-wing advocacy organizations than they are to those from left-wing advocacy organizations. However, when left-leaning news outlets write about immigration, they are equally similar to the press releases from both left- and right-wing advocacy organizations.

## Concept Mover’s Distance

### Measuring Engagement with Focal and Compound Concepts

Concept Mover’s Distance (CMD) (Stoltz and Taylor 2019; Taylor and Stoltz 2020) quantifies the extent to which a document “engages with” a theoretically-motivated “focal” concept of interest (see Appendix B for a comparison with relative frequencies). Like WMD, CMD holds the embedding space constant while measuring the position of documents relative to it, however, distance is calculated in relation to a focal concept, rather than other documents. CMD can be used to explore how, for example, the concepts of “thought” and “action” were differentially engaged in the *Iliad* and the *Odyssey*, the emergence of “introspection” in the King James Bible, and the linear association between the concept of “death” and actual body counts in Shakespeare’s *First Folio* (Stoltz and Taylor 2019).

Like WMD, CMD relies on a “transportation problem” logic to find the minimum distance that one document must “move” to transform into another document based on distances in the embeddings space. The key distinction, however, is that CMD finds the minimum distance between each corpus document and at least one “pseudo-document” that consists of a single token of a word or words denoting a concept of interest.

In the simplest case, this is a single word associated with a single vector in the embeddings. For example, the cost of moving all the words in each State of the Union address to the vector associated with “conservative,” is each address's relative similarity to “conservative.” Measuring engagement with more “specific” concepts—e.g., “liberal politics” or “conservative politics” instead of simply “politics”—is accomplished by adding relevant terms to the pseudo-document to create *compound concepts*: for example, by using a pseudo-document that consists of the word “politics” *and* “liberal” to measure “liberal politics.”

Consider again the “All the News” corpus. We use CMD (here with pre-trained embeddings), to measure the extent to which all news articles from January 2012 to March 2018 engaged the concept “immigration.” We also measured engagement with each of the following specified concepts: “immigration + job,” “immigration + school,” “immigration + crime,” and “immigration + family.”

Figure 6 shows the smoothed engagement time trends for each concept, averaged by month. According to the plot, engagement with “immigration” and its related compound concepts have followed a similar time trend from 2012 to mid-2018. The “immigration + school” compound concept peaked in late-2014 to mid-2015, which is

perhaps related to the Obama administration's introduction of planned extensions to the Deferred Action for Childhood Arrivals (DACA) policy (of which school requirements were a key element for program eligibility) in late 2014 that were caught up in court battles throughout 2015 and 2016. One such planned extension was the Deferred Action for Parents of Americans and Lawful Permanent Residents (DAPA), which might also explain the smaller “immigration + family” spike during the same time. Whatever the mechanism, however, this spike in engagement suggests that immigration within the contexts of schooling and family seemed to be some of the more prevalent modes of media immigration discourse in late 2014 to 2015 relative to the other measured concepts. The plot also suggests that media immigration discourse of all stripes seemed to peak in mid-2016 to early-2017—coinciding with Donald Trump winning the Republican primary and later securing the U.S. presidency.

#### **[FIGURE 6 ABOUT HERE - CMD OVER TIME]**

Figure 7 plots just the monthly average engagement with “immigration” (i.e., the black trend line in Figure 6, with a lower smoothing factor). The figure shows that media engagement rises predictably with relevant external sociopolitical events: e.g., introduction of the DACA policy, the DACA expansion, and Trump’s “immigrants-as-rapists” presidential running announcement speech on June 15, 2015.

#### **[FIGURE 7 ABOUT HERE - CMD AND EVENT PLOT]**

### **Measuring Engagement with Binary Concepts**

One potential limitation with the CMD as discussed up to this point revolves around “binary concepts”—i.e. relations of juxtaposition. Words that denote concepts in some sort of opposition are likely to be near one another within the embeddings space not

only because they are used in similar contexts, but also because they often co-occur (Deese 1966; Justeson and Katz 1991; Miller and Charles 1991:25–6). As such, culturally opposed words such as “sacred” and “profane” or “good” and “evil” are likely to occupy similar positions in any adequately-trained corpus because they are, in fact, used in similar ways and mutually oriented toward a shared cultural meaning (Boutyline 2017; Goldberg 2011; Greimas 1983). For example, a researcher may be interested in examining engagement with the concept of “evil,” but a document that engages strictly with “good” would still be highly ranked because the distance of any given word in that document is roughly equidistant to “good” and “evil” within the embeddings space.

One method to address this binary concept problem is by combining CMD with the “semantic directions” approach to variable embedding spaces discussed earlier (Taylor and Stoltz 2020). An analyst can measure engagement with one “pole” of a binary by (1) extracting a direction in the meaning space pointing toward a pole of the binary opposition, (2) adding the estimate as a row vector to the embeddings matrix, and then (3) adding a pseudo-document to the corpus that consists of only a single reference to that estimated vector. From there, CMD is used in the same manner previously described: it quantifies the cost to move all words in an observed document to the estimated vector—in effect, measuring engagement with one pole of a binary concept as opposed to the other pole (e.g., “evil” *as opposed to* “good”).

Consider again the “All the News” corpus. Following the same procedure outline in the previous section, we constructed two cultural dimensions: an “immigrant” dimension and a “race” dimension, with larger positive values indicating more engagement with the “immigrant” pole as opposed to a “citizen” pole and more engagement with the “black” pole as opposed to the “white” pole, respectively. The

immigrant-citizen dimension was constructed using the pairs listed in Table 6, and is understood as measuring a persistent symbolic structure rather than a legal distinction (cf. Beaman 2016; Jaworsky 2013).<sup>32</sup>

**[TABLE 6. IMMIGRANT ANTONYM PAIRS]**

Smoothed media engagement time trends with the respective poles of these cultural dimensions (averaged by month-year) are shown in Figure 8. The top panel shows the time trends for engaging each cultural dimension; the bottom panel shows how much each month-year's average engagement deviates from the previous month-year's engagement. As the bottom panel shows particularly well, engagement with immigration and race cultural dimensions in contemporary U.S. news media appears to follow similar trends: when news media engage "immigrant" more relative to "citizen" in their discourse, so too do they engage "black" more relative "white." This trend is also in line with the above analysis using historical embeddings from 1880 to 2000, again pointing to the remarkable temporal stability of "citizen" and "white" as the unmarked categories of U.S. public discourses on cultural citizenship and race (Brekhus 1998) and/or the historical persistence of the "immigrant-as-nonwhite" vs. "citizen-as-white" symbolic boundary (Mora and Paschel 2020; Sáenz and Douglas 2015).

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<sup>32</sup> See footnote 25. While we use "citizen" as the pole opposite "immigrant" to highlight the symbolic structure through which immigrants have been discursively othered in the U.S., citizen is not an antonym for immigrant in any formal way since, obviously, an immigrant can certainly be a legal citizen.



[FIGURE 8 ABOUT HERE - CMD CULTURAL DIMENSIONS PLOT]

## Discussion

We argued that raw counts or relative frequency of words in a document are often inadequate tools to operationalize the “magnitude” of (e.g. “extent of engagement with” or “amount of attention given to”) meanings in a document. Simultaneously, we put forward word embedding models as an alternative (and often complementary) tool for formal text analysis. These models allow us to substitute comparing frequencies with comparing distances by providing standardized maps of meaning space built from term co-occurrences. More importantly, inferring a word’s meaning from its context aligns with relational theories of meaning pioneered by John Mohr and many others, and is thus commensurate with a wide range of social scientific approaches to the study of culture. To demonstrate how social scientists can use word embeddings, we illustrated a variety of methods which we group under *variable embedding space* and *fixed embedding space* approaches (see Table 5).

First, with *variable embedding space methods*, one can hold terms constant and measure how the embedding space moves around them—much like astronomers measured the changing of celestial bodies with the seasons. More technically, this usually entails splitting a corpus by time periods or by author and obtaining word embeddings for each subset of the corpus. The analyst can then measure how the distance between two (or more) terms change from one estimated embedding space to another, or the changing distances between terms and cultural dimensions from one estimated embedding space to another, just as celestial bodies appear closer to, or more distant from, one another depending on the day.

Second, with *fixed embedding space* methods, one can also hold the embedding space constant and see how documents or authors move relative to it—just as ships use the stars at a given time to determine their location. More technically, this involves thinking of documents as clouds of vectors in the embedding space. The analyst can then measure how documents’ (or authors’) distances to terms, cultural dimensions, and other documents (or authors) change across different document-level covariates (such as date of publication, author’s gender, or organizational affiliation), just as ships can determine their respective location by referencing stars as if fastened to the night sky. We then used the empirical case of immigration discourse in the United States to demonstrate the merits of these two strategies to advance formal approaches to cultural analysis

## **EXTENSIONS**

### **Synthesized Embedding Spaces**

One likely extension of the methods discussed is combining variable and fixed embedding space methods—what one might call *synthesized embedding space* methods for mapping meaning spaces. Synthesized embedding space models would involve simultaneously assessing the changing structure of embedding spaces as a function of some external variable—most likely time—and *also* how documents and authors relate to one another or to a concept vis-à-vis some fixed comparable points across the embedding spaces. For example, if we had a sample of English-language news articles from the past century, we could measure how news organizations spanning several decades engage with a concept or cultural dimension using decade-specific embeddings.

## Multilingual Embedding Spaces

In addition to comparing time or authors, another important external variable would be the “language” of the documents—for example, comparing news coverage of the same events in English and Spanish, or translations of the same documents in German and Turkish. Multilingual embeddings (Artetxe et al. 2016; Mogadala and Rettinger 2016; Ruder et al. 2019) take text data from multiple (two or more) languages and project them into the same  $n$ -dimensional embeddings space (Bengio et al. 2003; Chen and Cardie 2018; Søgaard et al. 2019), usually by finding a mapping that minimizes the distances between known word translations while preserving the within-language distances. Following the distributional hypothesis, if two words in different languages are used in similar semantic contexts, then those two words ought to occupy similar positions in the embedding space. For example, in a bilingual mapping with English and Spanish, “dog” will be located near “perro” and “perra” because each of these terms are used in similar contexts—with context words like “fur”-“pelaje,” “canine”-“canino,” and so on. Recent research has illustrated the usefulness of multilingual embeddings for translation tasks (Zou et al. 2013), ontology alignment tasks (Gromann and Declerck 2018), and even for detecting certain forms of cognitive impairment (Fraser, Fors, and Kokkinakis 2019).

## Relations Other Than “Similarity”

Our demonstration, as well as most current social science work using word embeddings, focuses primarily on semantic *similarity*, which allows us to explore relations of polysemy, synonymy, antonymy, as well as metaphor and metonymy (Erk 2012). However, there are also other important relations to be explored: specifically, scale

(e.g., good, greater, greatest), classification (i.e., entailment and part-whole relations like hypernymy, hyponymy, meronymy, or holonymy) or object qualities (Fulda et al. 2017; Grand et al. 2018). Most off-the-shelf public word embeddings already encode these relations, to some extent, and can be extracted with simple post-processing techniques (cf. Fulda et al. 2017; Kim and de Marneffe 2013; Kotlerman et al. 2010; Levy, Remus, et al. 2015). For example, one can use “Hearst patterns” (Hearst 1992)—“such as,” “like,” “including”—to extract hypernymy/hyponymy (Baroni et al. 2012; Roller and Erk 2016). Similarly, Fu et al. (2014) propose a post-processing method for learning a linear projection for hierarchical relations using known hypernym/hyponym pairs (see also Roller, Erk, and Boleda 2014). Other approaches modify the training phase in order to better incorporate hierarchical information (and therefore cannot be used on pre-trained embeddings). For example, Le et al. (2019) use “hyperbolic” space (Nickel and Kiela 2017) rather than Euclidean space (see also Kruszewski, Paperno, and Baroni 2015; Weeds et al. 2014).

## **CONCLUDING REMARKS**

Formal text analysis in sociology was pioneered by scholars like John Mohr, Wendy Griswold, Karen Cerulo, and Kathleen Carley, and even as it continues to evolve with the unprecedented access to large quantities of texts and computational power, the methods of this early era continue to be productive. Although we noted limitations to some of these methods, this is not to say these methods are no longer useful. Rather, word embedding methods should be used alongside, as a welcome addition to the toolbox of the formal cultural analyst for mapping, navigating, and understanding meaning.

The wide variety of options available to cultural analysts interested in computational text analysis signals an exciting time in the field. From word counts and dictionary methods to embeddings and other unsupervised learning algorithms, computational text analysis is quickly becoming as institutionalized as ethnography, interviews, and historical-comparative methods. Looking back, it is quite fascinating to see that John Mohr saw this advent coming with such clarity as far back as at least 1998:

. . . [I]t is probably worth pointing out that we are just now entering what must surely be the golden age of textual analysis. What sets this moment in history apart is the incredible proliferation of on-line and on-disk textual materials. Previously, scholars who were interested in doing some form of content analysis were compelled to spend huge amounts of time readying their texts for analysis. Now one can easily sit at one's desk and more or less instantaneously summon up a fantastic array of cultural texts in electronic form. (Mohr 1998:366)

We are certainly amid the golden age of text analysis in the social sciences—just as John predicted and helped ensure.

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## Tables and Figures

### Tables

**Table 1. Definitions**

Word Embeddings	Vector representations of words in an $(n < N)$ -dimensional space (see Vector Space Model below), where $N$ is the total number of words in a corpus and vectors are dense (i.e. no zero) and usually consisting of real numbers.
Document-Term Matrix (DTM)	A matrix where documents are rows and terms are columns (or vice versa), and a cell entry is a numerical representation of the $j$ th word in the $i$ th document.
Term Co-Occurrence/Context Matrix (TCM)	A symmetric $N$ -by- $N$ matrix, where $N$ is the number of terms in a corpus, with cells numerically representing the extent to which the $j$ th term tends to appear in the $i$ th term's context window.
Relative Frequency	The raw count of the $j$ th term in the $i$ th document divided by that document's total word count.
Word Representation	A discrete number or vector of numbers that stands in place of a word in a corpus to make it machine-readable.

Vector Space Model	A representation of words or documents as locations in a “meaning space” in which semantic relations are understood as geometric relations.
Concept	A generic idea, referenced in natural language using a set of focal words/phrases.
Generic Concept	A concept at a high level of abstraction—e.g., “politics.”
Specified Concept	A concept that has been articulated in some way to refer to an idea or thought at a lower level of abstraction—e.g., “liberal politics.”
Binary Concept	A concept with marked and opposing poles, involving terms which may occur in similar contexts but are typically juxtaposed such as “good”-”evil” or “liberal”-”conservative” or “movie” - “book.”

**Table 2. Simple Document Term Matrix**

	and	do	eggs	green	ham	i	like	not	sam-i-am	them	you
1.	1	1	1	1	1	0	1	0	0	0	1
2.	0	1	0	0	0	1	1	1	1	1	0
3.	1	1	1	1	1	1	1	1	0	0	0

**Table 3. Simple Term-Co-occurrence-Matrix**

	and	do	eggs	green	ham	i	like	not	sam-i-am	them	you
and	2	2	2	2	2	1	2	1	0	0	1
do	2	3	2	2	2	2	3	2	1	1	1
eggs	2	2	2	2	2	1	2	1	0	0	1
green	2	2	2	2	2	1	2	1	0	0	1
ham	2	2	2	2	2	1	2	1	0	0	1
i	1	2	1	1	1	2	2	2	1	1	0
like	2	3	2	2	2	2	3	2	1	1	1
not	1	2	1	1	1	2	2	2	1	1	0
sam-i-am	0	1	0	0	0	1	1	1	1	1	0
them	0	1	0	0	0	1	1	1	1	1	0
you	1	1	1	1	1	0	1	0	0	0	1

**Table 4. Example of commonly used pre-trained embeddings**

	Corpora	Tokens	Vectors	Dimensions
fastText	Wikipedia 2017, UMBC webbase corpus, statmt.org news	16 billion	1 million	300
	Common Crawl	600 billion	2 million	300
GloVe	Wikipedia 2014, English Gigaword 5th Edition	6 billion	400 thousand	50 to 300
	Common Crawl	840 billion	2.2 million	300
	Twitter	27 billion	1.2 million	25 to 200
word2vec	Google News dataset	100 billion	3 million	300

**Table 5. Uses of Variable and Fixed Embedding Spaces**

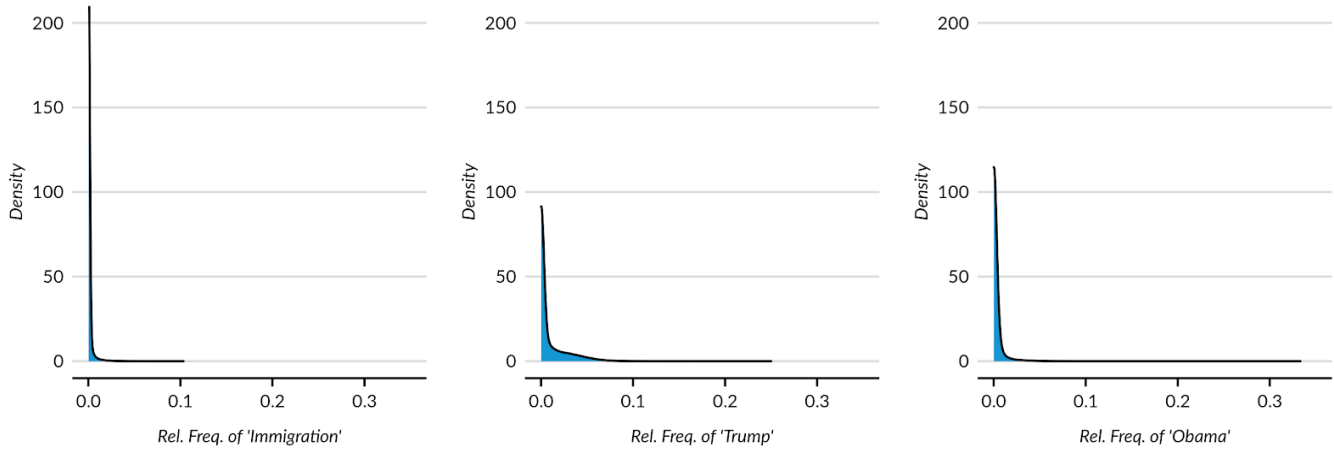
	<u>Points of Reference</u>		
<u>Embedding Space</u>	Terms	Semantic Directions	Documents or Authors
<b>Variable</b>  A corpus is subset by a covariate (typically by time or author), and embeddings are trained on each subset.	How does the distance between two (or more) terms change from one estimated embedding space to another?	How does the distance between terms and semantic directions change from one estimated embedding space to another?	
<b>Fixed</b>  An embedding is trained on a single corpus. Authors or documents are defined as the aggregate of locations of the words associated with them.	How does the distance between documents (or authors) and terms in a single embedding space differ by document covariates?	How does the distance between documents (or authors) and semantic directions in a single embedding space differ by document covariates?	How does the distance between documents (or authors) in a single embedding space differ by document covariates?

**Table 6. Term Pairs for Immigration-Citizenship Cultural Dimension**

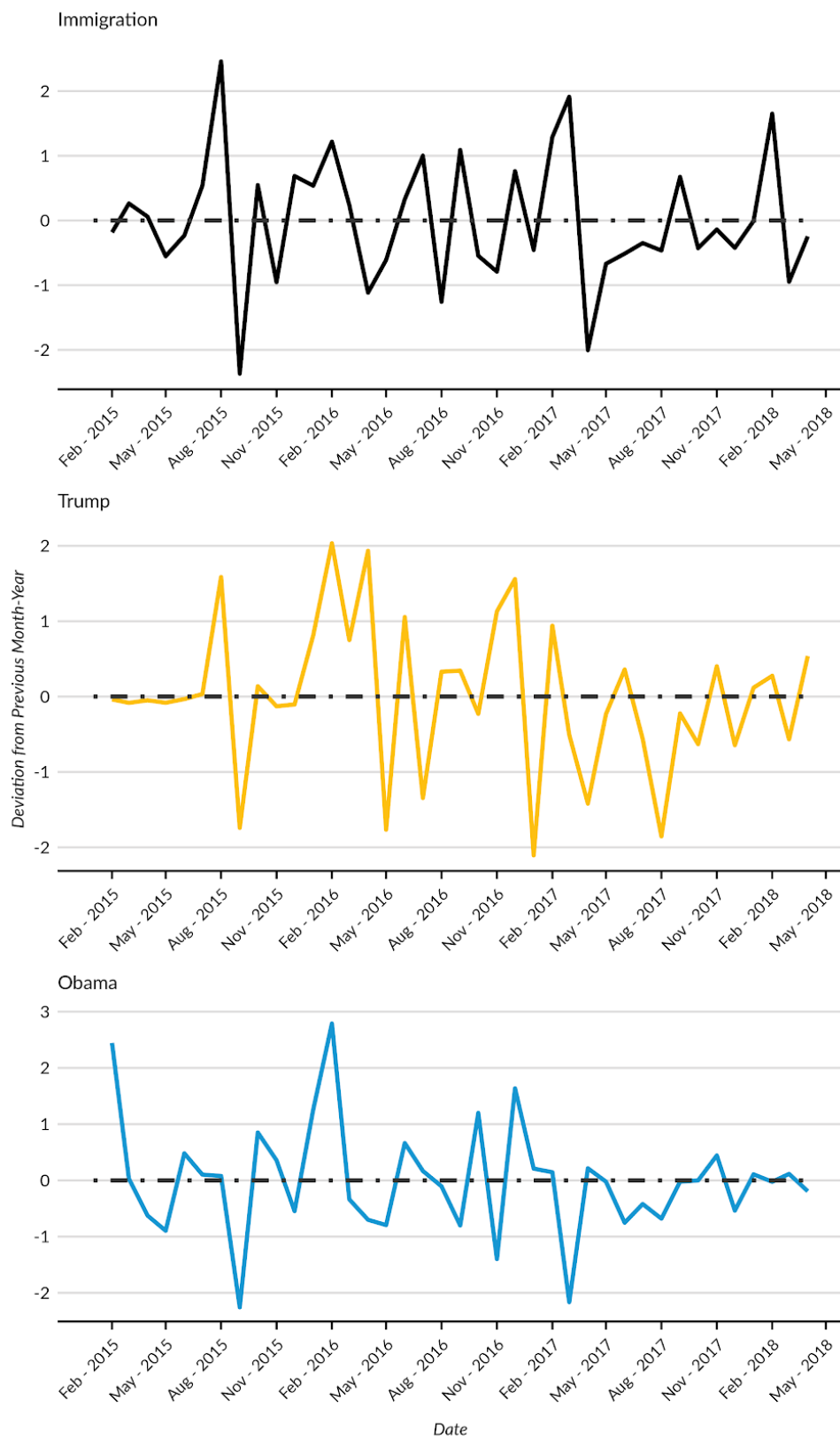
immigrants	citizens
immigration	citizenship
immigrant	citizen
foreign	domestic
foreigner	native
outsider	insider
stranger	local
alien	resident
foreigner	resident
alien	native
immigrant	local
foreign	familiar



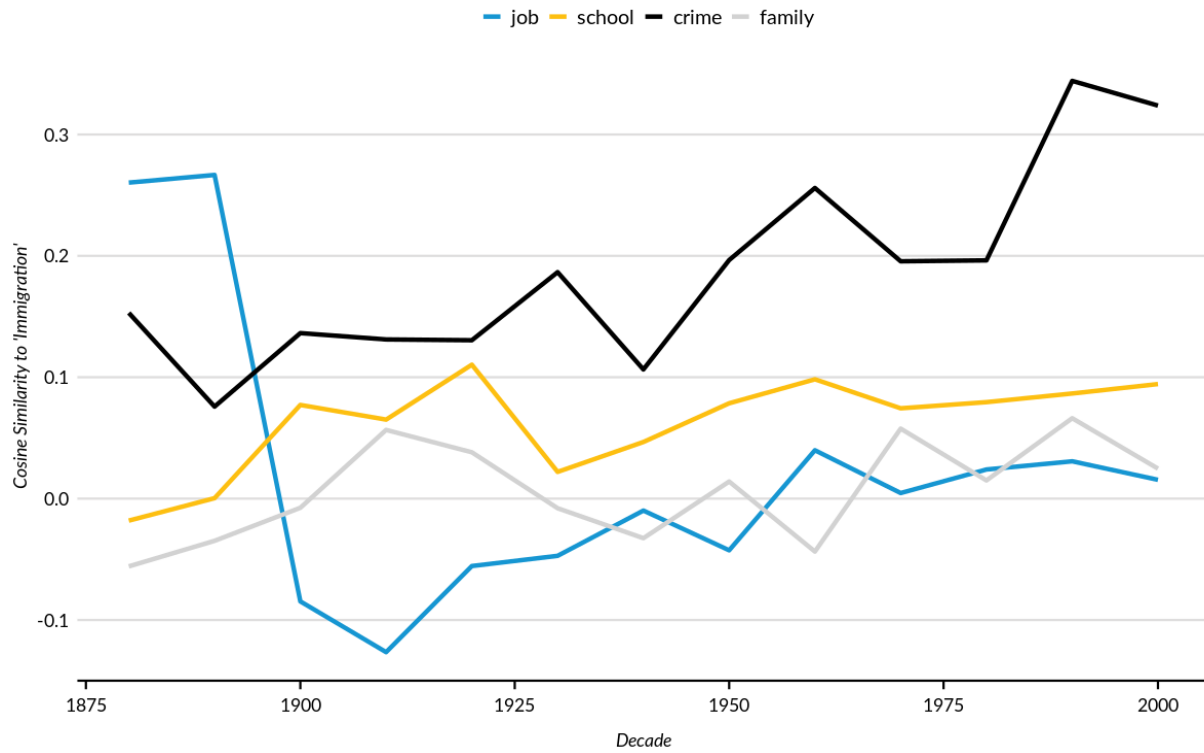
## Figures



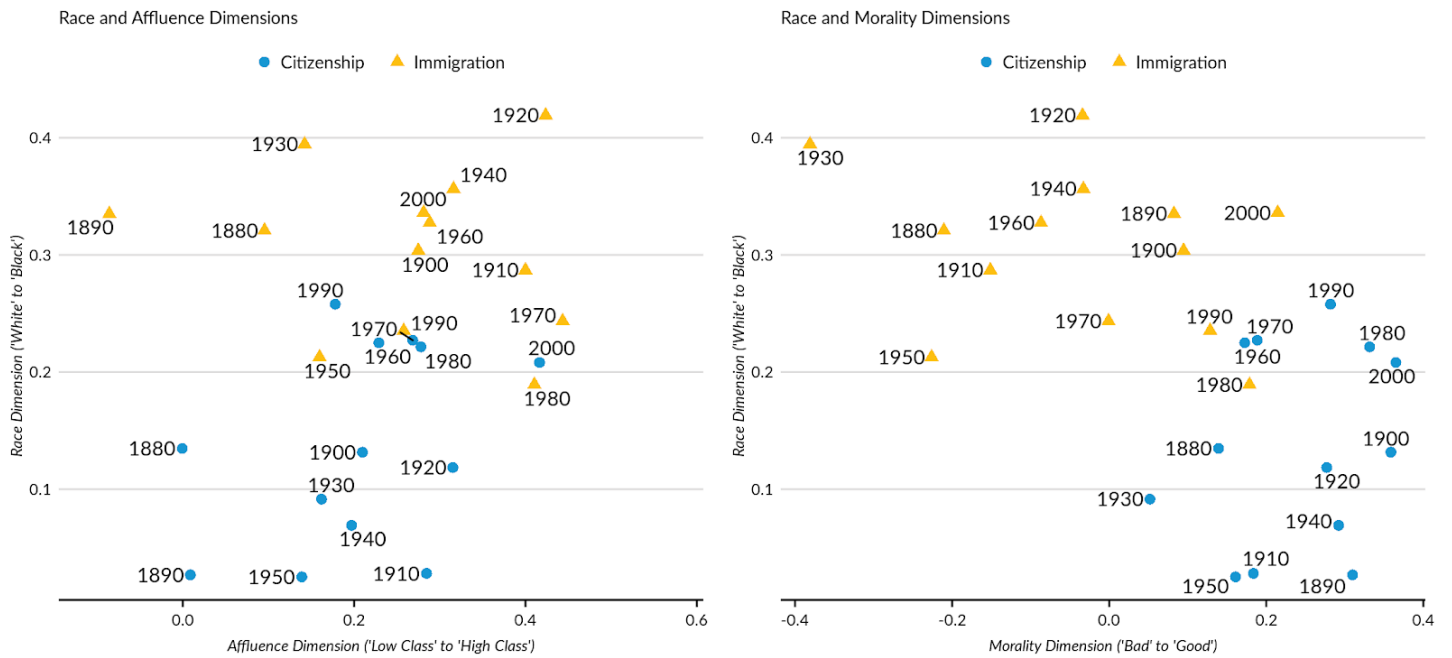
**Figure 1. Density Plots of Relative Frequency**



**Figure 2. Relative Frequency Volatility Plot**



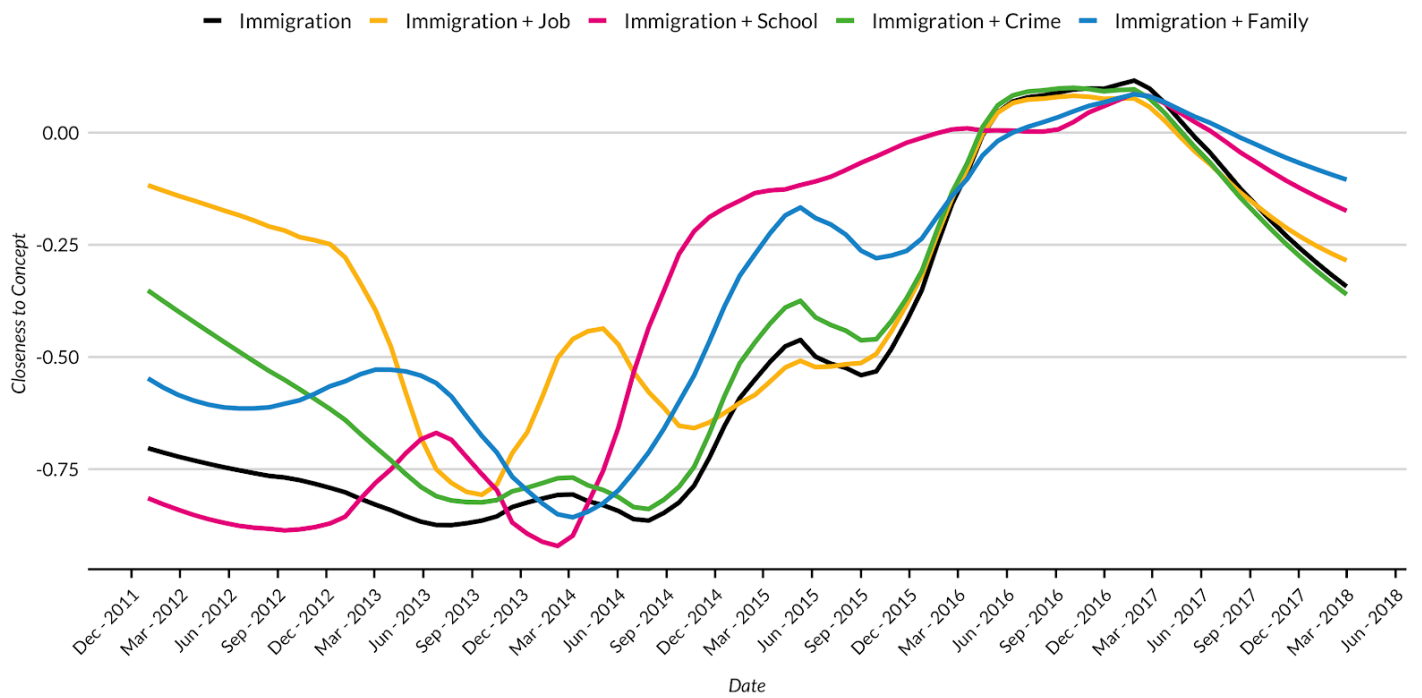
**Figure 3. Cosine Similarity of 'Immigration' and Key Terms by Decade, 1880 to 2000**



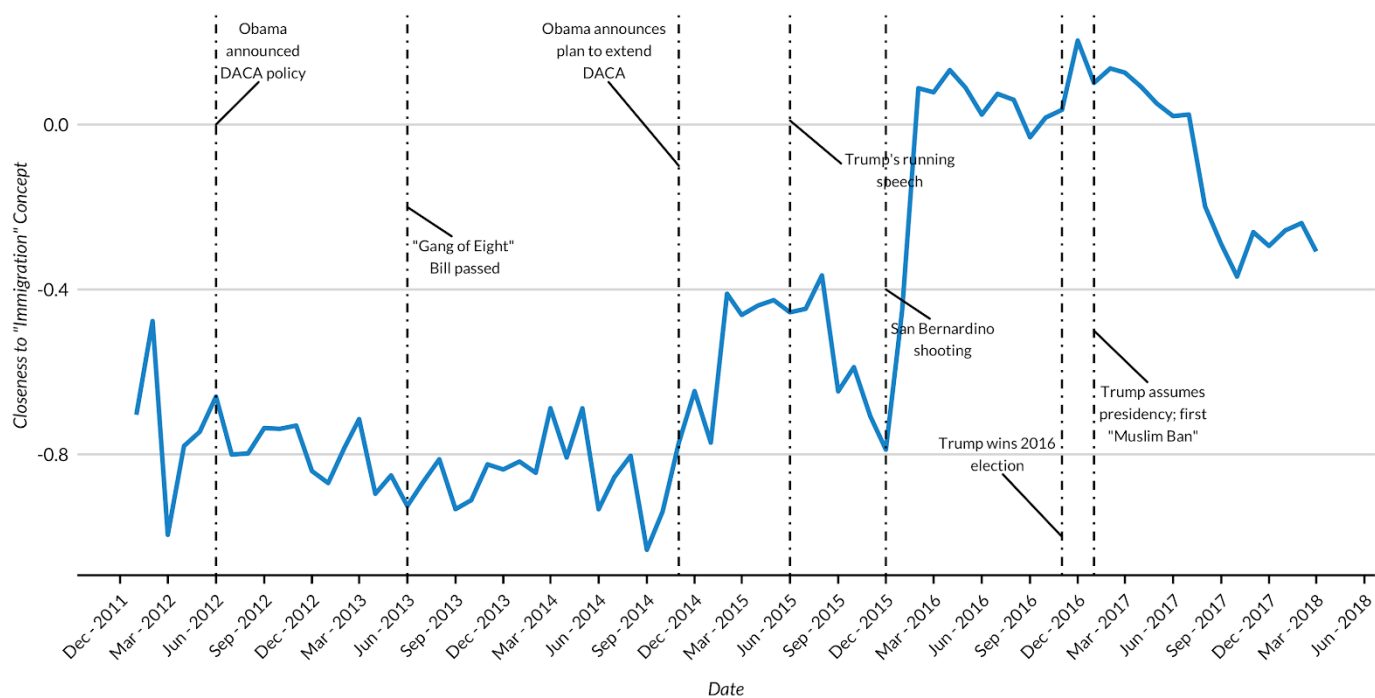
**Figure 4. 'Immigrant' and 'Citizen' on Key Cultural Dimensions, 1880 to 2000**



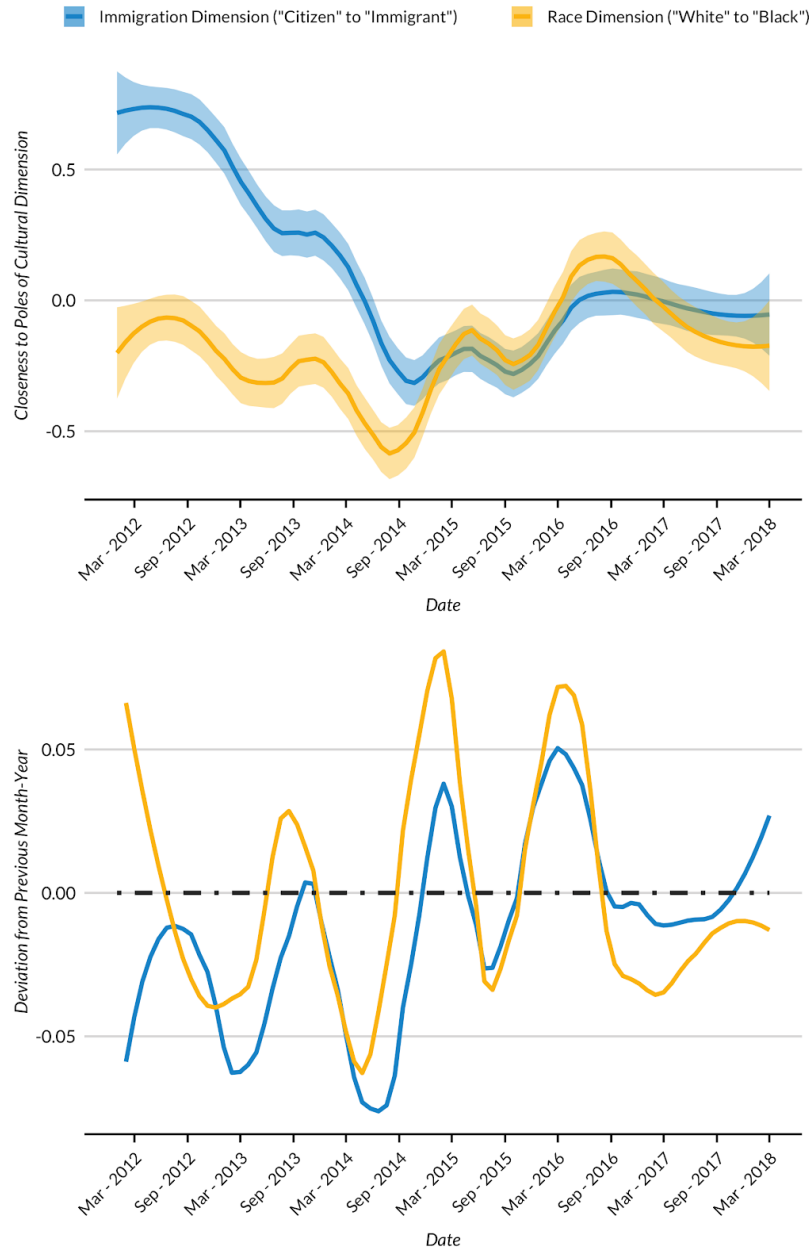
**Figure 5. News Articles' Similarity to Press Releases (with WMD)**



**Figure 6. News Articles' Conceptual Engagement Over Time (with CMD)**



**Figure 7. News Articles' Conceptual Engagement and Key Events (with CMD)**



**Figure 8. News Articles' Engagement with Key Cultural Dimensions (with CMD)**



# Appendix

## A. Word Embedding Models: SVD, Word2vec, GloVe, and fastText

As stated in the main text, at their most basic, word embedding models involve creating a TCM and reducing its dimensions. This can be accomplished with techniques as common as singular value decomposition (SVD) (Deerwester et al. 1990; Levy, Goldberg, and Dagan 2015:213; Turney and Pantel 2010). Recent advances do roughly the same as SVD while improving the tuning of this low-dimensional mapping.<sup>33</sup> Two papers credited with solidifying embedding models as the future of natural language processing were Bengio et al. (2003) and Collobert and Weston (2008); however, it was Mikolov et al. (2013) and the introduction of “word2vec” that popularized these techniques.

Word2vec generally refers to two models, one which predicts a target term from context terms, and the other which predicts context terms from a target term. In the case of the former, Levy and Goldberg (2014) found that the model was implicitly factorizing a TCM: the model does not begin with the TCM, but rather extracts co-occurrence statistics as it iterates through the text. This model was soon followed by GloVe (Pennington, Socher, and Manning 2014) and fastText (Joulin et al. 2016). A primary difference between these models is how they weight very rare or very common words. Furthermore, fastText (Bojanowski et al. 2017) uses “subword” character  $n$ -grams and not full words, the vector of a word is the sum of the vectors of the subwords it comprises

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<sup>33</sup> It is outside the scope of this paper to discuss how various researchers measure “accuracy” or “performance” in producing word embeddings, but this is especially a consideration for the cultural analyst wishing to use corpus-trained embeddings (Spirling and Rodriguez 2019).

(see also Schütze 1993). In particular, this improves embeddings for rare words and agglutinative languages.

The resulting term vectors are “low dimensional” in relation to the term co-occurrences of which they are a reduction; however, they still tend to be between 50 and 500 dimensions, with 300 being the most common for pre-trained embeddings. Figure 2a in Pennington et al. (2014) shows that accuracy on an analogy task improved up to 300 dimensions for the GloVe model (for a detailed discussion see Spirling and Rodriguez 2019; Yin and Shen 2018). This relatively high-dimensionality (in comparison to other kinds of dimensional analysis in the social sciences) is because, in part, relational meanings of words are intransitive (word *A* can be “close” to word *B* in the embedding space, and word *C* can be “close” to word *B*, but this does not necessarily entail word *C* being “close” to *A*), which necessitates high-dimensionality to prevent distortions and allow for greater variation.

While each approach differs somewhat (for a detailed comparison see Goldberg 2016), at core they attempt to find a low-dimensional “embedding” space from otherwise high-dimensional term co-occurrences that accurately predicts the context of target words (or vice versa) or similar tasks, such as solving analogies and translations (Lenci 2018:157; Levy and Goldberg 2014; Levy, Goldberg, et al. 2015). Whereas the models discussed here summarize the contexts of each type of unique word, recent developments output vectors for each token to represent the difference “senses” of each unique word, e.g., *bank* as in river *bank* versus investment *bank*. These “contextualized” word embeddings (Smith 2019:6–7), namely ELMo and BERT, are gaining popularity in computational linguistics and information retrieval, but we are only beginning to see how such models might be applied in the social sciences (e.g., Vicinanza, Goldberg, and

Srivastava 2020). Future work is needed to determine when more elaborate embedding models are preferred over the more straightforward models outlined here (e.g., Dubossarsky, Grossman, and Weinshall 2018).

## **B. Preprocessing**

We “preprocessed” our documents by removing non-ASCII characters, removing URLs, replacing contractions with their full word forms using the contractions dictionary in Rinker’s “qdapDictionaries” R package (Rinker 2018), replacing ordinal numbers with their full text form (e.g., “3rd” to “third”), and removing punctuation, capitalization, remaining numbers, and excess whitespace (i.e., spaces between words that are greater than one). We also removed terms found in the most commonly used pre-compiled “stop list” (Porter 2001). This list includes many of the most frequently occurring words in the English language, e.g., “the,” “of,” and “and” (for a comparison of several lists, see Nothman, Qin, and Yurchak 2018). Finally, we removed sparse terms at a .99 sparsity factor—meaning that terms that were absent in at least 99% of the documents. This resulted in a DTM of 5,301 unique terms, 73,730,192 total terms, and 184,843 news articles, with cell entries indicating the raw frequency of each retained word in each document.

## **C. Comparing CMD to Relative Frequencies**

If a word’s meaning is defined relationally—i.e., by the words that tend to co-occur with it or otherwise be used in similar discursive contexts—then it follows that if we want to measure a concept, we could add together relative frequencies for multiple terms that denote the same concept (i.e., synonyms) or are closely related. For example, if

one wanted to measure engagement with the concept of “politics,” they could find words with a high association with the word “politics” (e.g., a high cosine similarity or Pearson’s correlation) and then add those relative frequencies together for each document. The resulting measure of engagement with “politics,” then, might be the summed term frequencies for, e.g., “politics,” “politic,” “liberal,” “conservative,” “government,” “governance,” “president,” “election,” and so on.

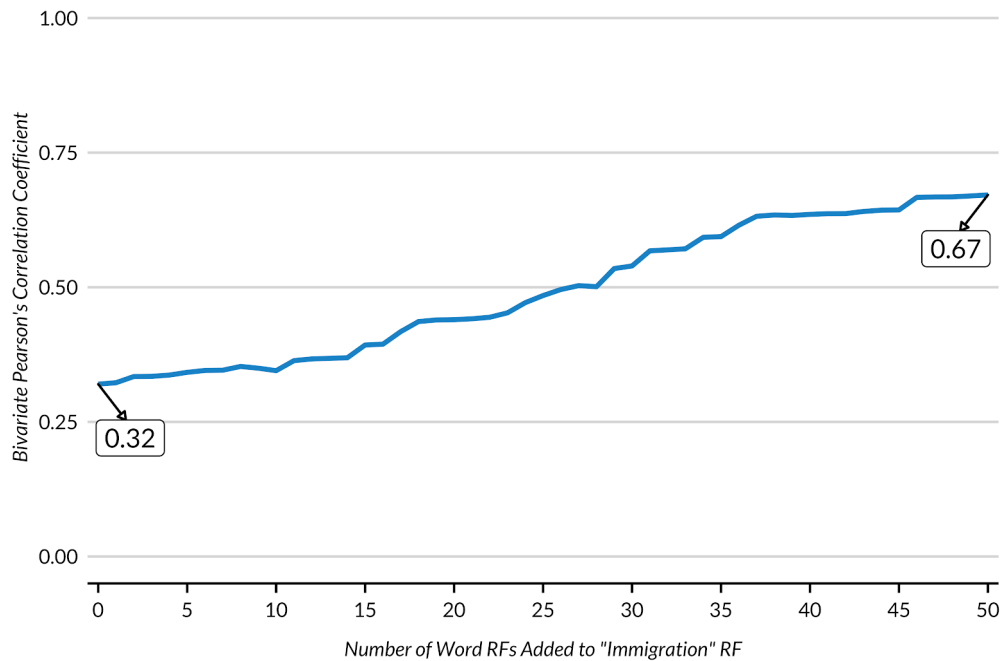
If we treat this sum of a series of relative term frequencies that all have a high association with a core word denoting a concept as a kind of “ground truth” for that concept, then we can test the extent CMD corresponds with summed relative frequencies and does so more efficiently. We estimated the “immigration” CMD for the “All the News” corpus (using the fastText embeddings) and compared it to the relative frequency of “immigration” and its high context words in the “All the News” corpus.

Specifically, we (1) correlated the “immigration” CMD—which was estimated with one pseudo-document containing only one instance of the word “immigration”—with the relative frequency of “immigration” in each document; (2) re-generated that correlation after adding the relative frequency for the word with the highest cosine similarity to “immigration” in the fastText embedding space to the relative frequency for “immigration; and then (3) repeated step #2 a large number of times adding each term with the next highest cosine similarity.

For example, after generating the correlation between the “immigration” CMD and the relative frequency of “immigration” in the “All the News” corpus, we then found the word with the highest context similarity to “immigration” in the fastText embedding space—“deportation”—and added the relative frequency for that word in the “All the

News” corpus to the “immigration” relative frequency and re-calculated the resulting summed vector’s correlation with the original “immigration” CMD. We then repeated that process again, this time adding yet another word—the word with the second highest context similarity to “immigration” in fastText, “immigrants”—to the relative frequency vector.

Figure A1 shows the correlations: i.e., the correlation of the “immigration” CMD with a rolling sum of immigration-related relative frequencies. The correlation between the “immigration” CMD and the relative frequency of just “immigration” is positive but rather weak:  $r = 0.32$ . The next correlation—the linear association between the “immigration” CMD and the “immigration”+“deportation” summed relative frequencies—increases slightly from 0.320 to 0.322. As the plot shows, the association increases (mostly) monotonically: the correlation between CMD with just a single term and the summed relative frequencies steadily increases. After adding 50 terms’ relative frequencies to the “immigration” relative frequency, the correlation with the single-term “immigration” CMD is  $r = 0.67$ . If one were to continue this process to, say, 500 additional relative frequencies, the correlation would reach  $r = 0.92$ .



**Figure C1. Correlation between Concept Mover's Distance and Relative Frequency**

These results show that, at least in the particular case of “immigration” in the “All the News” corpus, the “immigration” CMD becomes more correlated with the summed relative frequencies as the list of term relative frequencies is further specified to be *about* immigration with several hundred synonyms. CMD, then, does a very good job of replicating the ground truth estimate of the “immigration” concept in this news corpus. Importantly, though, the CMD version is much more parsimonious: it only takes one specified term (“immigration”) in the pseudo-document to replicate what may take upwards of 500 or more terms to adequately represent.