Efficient communication and the organization of the lexicon

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1 Efficient communication and the organization of the lexicon

If you were constructing a language, how would you design a lexicon that could most effectively be used by speakers in order to efficiently communicate messages? Should all words be about equally frequent, or should some words be re-used many orders of magnitude more often than others? How long would you make the words in your lexicon: should they all be as short as possible? How would you carve up the semantic space? Would you want the meaning of a word to constrain its form, or should the relationship between form and meaning be completely arbitrary? How would you make sure that babies are able to learn the words in your lexicon?[1]

With natural language, of course, no one has to make these design decisions. Instead, they are sorted out through the organic process of language use and evolution, as people do the messy work of communicating with one another. There is now copious evidence that this process results in languages that are relatively efficient for the purposes of communication. Therefore, some of the observed features of language can be explained by understanding the cognitive and communicative constraints on the language system. This evidence comes from work in the functional linguistic tradition (Bybee & Hopper, 2001; Haspelmath, 2004), in linguistic evolution (Christiansen & Kirby, 2003; Cornish, 2010; Kirby, 1999; Kirby, Cornish, & Smith, 2008), and from a line of work that uses ideas from computer science to model natural language as an efficient communication system (**ferrer2001**; Fenk-Oczlon, 2001; Ferrer-i-Cancho & Solé, 2003; Gibson, Bergen, & Piantadosi, 2013; Gibson et al., 2019; Levy, 2008).

There is reason to believe in pressure towards efficient linguistic structure across domains, including phonology (Boersma & Hamann, 2009; Flemming, 2004; Priva, 2008), syntax (Fedzechkina, Jaeger, & Newport, 2012; Ferrer-i-Cancho et al., 2013; Ferrer-i-Cancho & Solé, 2003; Futrell, Mahowald, & Gibson, 2015; Gibson, 1998; Gibson

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et al., 2013; Hawkins, 1994; Jurafsky, 1996; Kirby & Hurford, 2002; Kravtchenko, 2014; Levy, 2008; Liu, 2008), and pragmatics (Frank & Goodman, 2012; N. D. Goodman, Tenenbaum, Feldman, & Griffiths, 2008; Zaslavsky, Hu, & Levy, 2020), across spoken and signed modalities (Slonimska, Özyürek, & Capirci, 2020). Since this book is about the lexicon, we will limit our scope to lexical topics and questions of lexical design. While the lexicon is of course inextricably linked to a language's phonemic system and its morphological system, we will leave those topics to other work and instead focus mostly on large-scale lexical structure and its relationship to communication.

Specifically, in this chapter, we will use the structure of the lexicon in order to reverse-engineer the *de facto* design decisions that emerge through language use. Understanding these design decisions can help us understand human language processing more generally. We will review work that investigates how the lexicon is informed by—and can therefore illuminate—both cognitive and communicative constraints on natural language.

Central to this project are ideas from computer science, especially information theory, about what makes for efficient communication systems. Information theory (Shannon, 1948) gives us a framework for thinking about how to design a code that most effectively conveys information from a source to a receiver over a noisy channel. Applying these ideas to natural language has been fruitful in explaining features of the lexicon. To that end, rather than attempting a comprehensive review of all work on the organization of the lexicon, we will focus in particular on work in the information-theoretic/communicative tradition.

That is, while the information-theoretic framework gives a set of formal principles for defining efficient communication, it is less straightforward to define a mathematical framework for what makes a code maximally efficient for cognitive processing. This cognitive constraint marks an important distinction between the theoretical systems dealt with in information theory and natural language. Natural languages have to be learnable by babies, and therefore the lexicons must be designed in such a way that they are learnable. There has been extensive work in psycholinguistics and cognitive science on what makes lexical items hard or easy to process (Baayen, Burani, & Schreuder, 1997; Baayen, Milin, & Ramscar, 2016; Frauenfelder, Baayen, & Hellwig, 1993; Vitevitch & Luce, 1998)–and in developmental psychology on what makes words easier or harder to learn (Braginsky, Yurovsky, Marchman, & Frank, 2019; Dautriche, Swingley, & Christophe, 2015; Gentner, 1982; L. R. Gleitman, Cassidy, Nappa, Papafragou, & Trueswell, 2005; J. C. Goodman, Dale, & Li, 2008; Hills, Maouene, Maouene, Sheya, & Smith, 2009; Perry, Perlman, & Lupyan, 2015; Roy, Frank, DeCamp, Miller, & Roy, 2015; Stokes, 2010; Storkel, 2004; Swingley & Humphrey, 2018). We can use this body of knowledge to further understand features of the lexicon and how they emerge.

In the rest of this chapter, we will treat the messy process of human language use as a master designer and explore four major lexical design decisions that human languages must make: the structure of word frequency distributions, the relationship between word form and word length, the degree of lexical arbitrariness, and how to structure lexicons for child language learning. We will see how natural languages navigate these design questions and, in so doing, help us better understand aspects of communication and language processing.

2 How frequent should words in the lexicon be?

In considering the large-scale structure of the lexicon from an efficient design perspective, one of the most important considerations is how many words there should be, how frequency should be distributed across words, and how words should be used to carve up the semantic space. Here, we will explore this question from two perspectives: first by considering the large-scale organization of the lexicon at a macro level and then by examining how this plays out in the efficient structure of more specific semantic spaces, such as color words, kinship systems, and human names. We argue that the latter can be illustrative of the large-scale patterns observed in the former.

2.1 Large-scale structure of frequency in the lexicon[2]

If a lexicon were being designed for efficient communication, would it be better to structure it such that all words are roughly used equally often? Or should the most frequent words be used more often? Natural languages all seem to answer this question in the same way: the most frequent words are used much more often than the less frequent words. Specifically, they all follow roughly the same Zipfian rank-frequency distribution (see Figure 1 for the English version). Zipf (1935, 1949) famously observed that the distribution of words in a language obeys a power law distribution, such that the most frequent word appears in a corpus about twice as often as the second most frequent word, about three times as often as the third most frequent word, and so on.

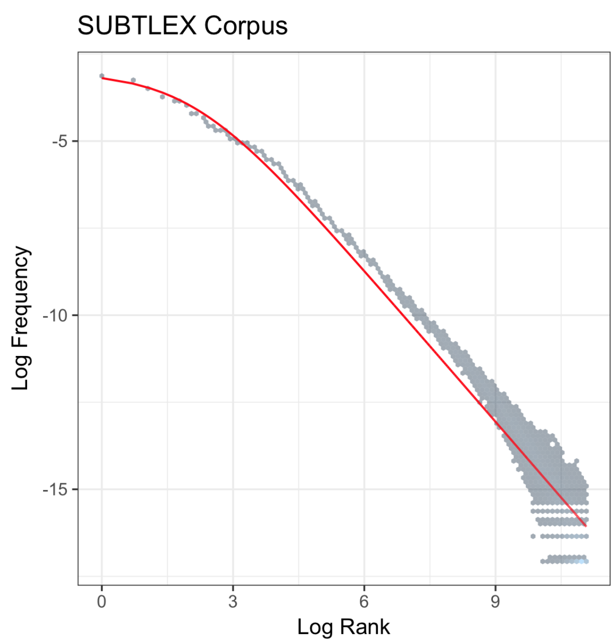

Figure 1. Following Piantadosi (2014), we independently estimate frequency and rank on a split-half SUBTLEX corpus. The points represent density, and the red line is the maximum-likelihood fit Mandelbrot equation.

Another framing of this observation is that the log rank of a word's frequency and its log frequency are linearly related. Mandelbrot (1953) modified this proposal to slightly rank-shift the distribution for a better empirical fit and so gave perhaps the best known

[2]This section draws on the discussion in Piantadosi (2014), which treats these issues in more detail.

quantitative account of Zipf's law:

$$f(r) \propto \frac{1}{(r+\beta)^{\alpha}} \tag{1}$$

where α is approximately 1 and β is around 2.7.

Empirical studies, across languages, show that the actual frequency distribution of words in a language is somewhat more complex than a simple power law, but that the broad strokes of Zipf's observation are robust. Baayen (2001) explores a variety of proposed distributions (e.g., log-normal, generalized inverse Gauss-Poisson, generalized Z-distribution) and shows that no proposed distribution perfectly captures the empirical pattern of results across all corpora and that some corpora seem to fit better with some distributions than others. Yu, Xu, and Liu (2018) show that, across 50 languages, the rank-frequency distribution can be divided into three segments of low, medium, and high frequency.

The emergence of Zipfian (or near-Zipfian) distributions is not limited to just large-scale lexical features. Piantadosi (2014) shows that near-Zipfian distributions emerge within a wide variety of semantic classes, such as for number words and taboo words. Moreover, in the absence of any semantic information at all, near-Zipfian distributions emerge: Piantadosi asked participants to generate novel stories using nonce words and found that even these nonce words follow a near-Zipfian distribution.

In addition to discussion of the precise mathematical form of these distributions, there has been some debate as to what gives rise to these distributions of words across lexicons and whether they are particularly meaningful. The situation is complicated by two factors. First, it can be difficult to distinguish power law behavior from other long-tailed distributions, like the various flavors of exponential distributions (Clauset, Shalizi, & Newman, 2009). Second, as we discuss below, there are many proposed mechanisms that can give rise to the observe distributions, and the mechanism that causes these patterns to emerge in natural language are less clear.

To that end, there remain some puzzles as to why all natural languages show the Zipfian frequency distribution. Miller (1957) and Conrad and Mitzenmacher (2004), among others, have argued that Zipfian distributions can arise as a result of random natural processes. For instance, if one imagines a bunch of monkeys randomly typing on a keyboard (or simulates this by generating random letters), a Zipfian frequency distribution will be observed. But random-typing models are bad scientific models of how languages could actually give rise to Zipfian distributions since, unlike in random typing models, people store and re-use words as units (Ferrer-i-Cancho & Elvevåg, 2010; Piantadosi, 2014). The scientific fact that needs to be accounted for is not that certain words occur disproportionately often by random drift but that, in the presence of rich semantic information, words are stored and re-used in a way that generates the characteristic distribution. Furthermore, in addition to not being a realistic model of word generation, random typing models do not fully capture the distributions observed (Ferrer-i-Cancho & Elvevåg, 2010).

So what does give rise to Zipfian frequency distributions in natural language? Could it just arise from the nature of the world? That is, is there something about the distribution of objects in the world that causes humans to want to talk in such a way that gives rise to a Zipfian distribution (Ferrer-i-Cancho & Solé, 2003; Manin, 2008)? For instance, even naturally constrained kinds, like the planets and the elements, seem to follow a Zipfian frequency distribution when counted up in an English language corpus (Piantadosi, 2014). But Piantadosi (2014) argues that this cannot be the whole picture since, even when people are asked to tell a story using made-up words (e.g., *Blicket*, *Fark*, etc.), the distribution of those nonce words will be Zipfian. Simon (1955), among others, propose stochastic accounts, which claim that Zipfian distributions arise from preferential re-use. If you use a word in some text, you are more likely to use it again. This "the rich get richer" scheme is known to give rise to power law distributions in a wide variety of contexts. Ferrer-i-Cancho and others have proposed communicative accounts

(Ferrer-i-Cancho, 2005; Ferrer-i-Cancho & Solé, 2003), suggesting that Zipfian distributions enable more efficient communication and can arise from pressures towards optimal communication and a minimization of effort by the speaker and listener (Ferrer-i-Cancho, 2016). Manin (2008) also argued that speaker cost is minimized when a Zipfian distribution is used. And a Zipfian distribution benefits word segmentation, of the sort required for learning language (Kurumada, Meylan, & Frank, 2013). Pagel, Beaumont, Meade, Verkerk, and Calude (2019) used data from surveys to suggest that humans have a preference to converge on the same word for a given meaning by preferring words that are most commonly used by others.

Given the vast array of competing explanations offered, we will not settle the question here of why natural languages, at various scales, converge on similar Zipfian distributions of word frequencies. But, in the next section, we will explore how individual semantic spaces are carved up in efficient ways that strongly suggest a communicative aspect to the structure of lexical space.

2.2 Distribution of words in more specialized semantic spaces

To get a better sense of how principles of communicative efficiency structure the distribution of words in the semantic space, it is helpful to consider a line of work exploring how semantic spaces are broken into meaningful linguistic units. In the general case, where the lexicon is studied as a whole, it is difficult to identify independent communicative goals about how often certain meanings should be conveyed. But it becomes more straightforward in these restricted domains, which has led to fruitful work on how communicative efficiency leads to lexical structure within semantic spaces, such as color words, kinship terms, and naming systems.

Consider the color system. Languages vary widely in how many color words they have–that is, in how they divide up the visual color space into discrete semantic units. What would an optimal lexicon do? Would it have 11 basic color words, like in English, or just five color words that everyone knows, as in Berinmo (Davidoff, Davies, & Roberson, 1999)?

One answer is that it depends on the communicative needs of the language users, an insight that can be formalized using information theory (Gibson et al., 2017; Regier, Kemp, & Kay, 2015). Imagine playing the following game. You and a partner are given a set of 100 colored boxes, such that each box is a different color and the colors of the boxes are even spread throughout the color space visible to the human visual system. You are secretly shown that one randomly selected box contains a prize, but your partner does not know which one it is. Your goal is to get your partner to correctly identify the prize-containing box but you can say only one color word. Your partner guesses and is told whether they are right. If they are wrong, they guess again.

Imagine that 3 of the boxes are what you would call "red" but 20 of the boxes are what you would call "blue". If your partner guesses randomly among the red boxes, on their first guess they have a decent change (1/3) of getting it right. But if it's a blue box and you say "blue," they have a 1/20 chance. Therefore, the task is easier in this scenario when the box in question is red.

On average, the number of guesses it would take your partner to find the correct box is related to the amount of information in your language's color system. If you had a maximally informative color system such that you had a unique color word for each of the 100 boxes, you could communicate the key box to your partner in just one round. But this comes at a cost, in that it requires a significant amount of effort for a society to learn and maintain so many color words. At the other extreme, a color system that has only 2 words would be easy to learn. But it would require many more guesses for your partner to find the right box.

Using a task not unlike the game described (where speakers are asked to name the colors of each of the chips on a Munsell grid–a grid of colors organized to be roughly equally spaced in human perceptual space), researchers have run this task and analyzed the data in an information-theoretic framework in order to measure the information in a color system (Gibson et al., 2017; Lindsey, Brown, Brainard, & Apicella, 2015; Regier et al., 2015) . The information in a color system is given by the surprisal of a particular color (here defined as a particular color chip), averaged over all color chips. To compute the surprisal of a particular chip, one can estimate the negative log of the probability of a chip given a color word weighted, by the probability of a word given a chip.

In the equation below, we compute the surprisal of a single chip $S(c)$ by summing up the weighted log probability of the chip c given a word w, where weighting is over the probability of use of a word w given a chip c.

$$S(c) = -\sum_{w} P(w|c) \log(P(c|w)) \tag{2}$$

Surprisal, averaged over the probability of a particular chip, is used to compute the information in the color system, as in Eq. 3.

$$\sum_{c} P(c) * S(c) \tag{3}$$

Following this procedure and using World Color Survey data, which includes color naming data from a wide variety of world cultures, it has been observed that more industrialized cultures have more information in the color system. Gibson et al. (2017), for instance, uses the Tsimane' culture, a relatively isolated Amazon group, as a test case alongside English and Spanish.The result of this analysis, when applied to data from English, Spanish, and Tsimane', is that the English and Spanish color systems have significantly more information (or less entropy) than the Tsimane' color system. The hypothesized reason for this asymmetry is that the Tsimane' have less need for a highly informative color system since they are less likely to differentiate objects based on color (Gibson et al., 2017).

There is also evidence that the distribution of information within the color word system is meaningful. Specifically, salient foreground objects are more likely to have warm colors (reds, yellows) whereas backgrounds are more likely to have cool colors (blues, greens). People are more likely to talk about foreground objects, so an efficient color system should have more information in warm colors. And indeed, across languages, there is more information in the warm color space (reds, yellows, browns) than in the cool color spaces (blues, greens).

Both of these observations–that industrialized cultures have more information in the color system and that there tends to be more information in warm colors than cool colors–give evidence for the idea that color words are adapted to the needs of the speakers. If there is a need for more information in the color system, there are likely to be more color words, and those color words are likely to have boundaries that are more widely agreed on by speakers. As it is, languages seem to trade off optimally between the complexity of the system and its informativity (Zaslavsky, Kemp, Tishby, & Regier, 2019; Zaslavsky, Regier, Tishby, & Kemp, 2019).

Moreover, while the above analysis relates to color words (part of our lexicon for describing visual experiences), Winter, Perlman, and Majid (2018) show that, at a higher level, the lexicon is optimally distributed such that the space of visual words is overrepresented in English. That is, compared to the number of words in the language for describing auditory or olfactory experience, English has a greater number of words for describing visual experience and those words have higher token frequency. This follows from the fact that we more often want to speak about visual experience than about other sensory domains.

Similar ideas have been applied to other semantic domains, outside the senses. For instance, Kemp and Regier (2012) showed that kinship terms are structured along an efficient frontier. Some languages have more kinship terms than others. For instance, Old English had distinct words for paternal uncles and aunts (as distinguished from maternal uncles and aunts)–a distinction lost in modern English. Imagine the same sort of game described above for color words but where, instead of hiding a prize in one of the colored boxes, I hide the prize with a random relative and am allowed to give a kinship term (i.e., aunt, cousin, grandmother, etc.) as a clue. For instance, if you have 3 aunts and I give you the clue "aunt," you now have a 1/3 chance of guessing which family member has the prize. A language with more kinship terms will make it easier for you to guess who has the prize. That is, if you have 1 paternal aunt and 2 maternal aunts and we speak a language with separate terms for those, I could instead give the clue "paternal aunt" and you would know exactly who has the prize. The trade-off is complexity: it's more complex to have to learn more kinship terms. Crucially, from an information-theoretic perspective, there do not appear to be languages that have extra complexity without a subsequent increase in informativity or vice versa (Kemp & Regier, 2012), which means that languages seem to exist approximately along a Pareto-optimal frontier (meaning that you cannot improve informativity without increasing complexity, and you cannot reduce complexity without decreasing informativity).

This approach has been applied in a number of diverse domains from numeral systems (Xu, Liu, & Regier, 2020) to animals (Zaslavsky, Regier, et al., 2019). It even appears that, according to an analysis that combines climate data and linguistic data, speakers develop optimal season naming conventions for their local environment in order to trade off the informativity of season words (e.g., given that it is "summer," how much does that tell you about today's temperature and expected rainfall) against the season system's overall complexity (Kemp, Gaby, & Regier, 2019).

Applying information-theoretic ideas to human names, a system that (unlike color words and kinship terms) does not appear to be semantically constrained, Ramscar (2019) found that the structure of human naming systems show patterns consistent with predictions from communication theory. In particular, in a society with relatively few people (like many small-group societies before the Industrial Revolution), people use only first names and these first names are sufficient for picking out individuals in a population.

But, as populations grow, cultures independently have converged on compound naming systems.

This body of work, as a whole, suggests that individual semantic spaces are largely efficiently structured along an optimal frontier (Kemp, Xu, & Regier, 2018; Zaslavsky, Regier, et al., 2019). It is not a coincidence that the domains chosen (color words, kinship terms, names) are ones in which it is particularly easy to quantify the space of real-world referents. That is, work in visual perception has made it relatively straightforward to categorize the human color space and words that map onto it. Kinship terms correspond to a set of real-world relations that are relatively easy to compute. Formulating these sorts of analyses for other, less mathematically precise domains is more difficult. But the work, taken as a whole, is suggestive that we should expect the lexicon to display efficient structure across domains.

3 Which words should be frequent?

In the previous section, we saw that natural languages settle on a lexical distribution such that the most frequent words are much more frequent than less frequent words, and that individual semantic spaces are largely efficiently structured.

But we have not yet considered the question of which strings should be assigned to which meanings. Would the English lexicon be just as effective if the word that corresponds to our concept of RED were called "cerulean" and the concept of CERULEAN were called "red"? Or would it be onerous to have to say a long word like "cerulean" to refer to a frequently used concept, like RED. In this section, we will focus on the relationship between frequency and other lexical properties to argue that the answer is no: re-shuffling the mapping between color names and their referents (or between any set of words and their referents) would lead to sub-optimal design because the lexicon is already optimized such that frequent words have a particular set of desirable properties.

3.1 Word length and word frequency

In addition to observing the power law distribution for word lengths, Zipf also observed that the most frequent words tend to be short.The reason for the correlation between length and frequently is seemingly obvious: it would be onerous if you had to say something like "thessaloniki" every time you wanted to use the article "the" or if you had to say "antediluvian" every time you wanted to use the article "an." Zipf called this the Principle of Least Effort (Zipf, 1949), and the relationship between length and frequency in language is often referred to as Zipf's Law of Abbreviation.

The actual distribution of word lengths in languages is not as simple to characterize as the distribution of word frequencies. Sigurd, Eeg-Olofsson, and van de Weijer (2004) showed that, in Swedish and English, a gamma distribution can be used to characterize the word length distributions, with a peak of tokens occurring at length 3. Extending the observation to more languages, Bentz and Ferrer-i-Cancho (2016) showed that the relationship between frequency and length holds across a wide variety of languages and linguistic contexts. For a summary of the distribution of word lengths across languages and models used to explain them, see Grzybek (2015).

But using frequency alone to predict word length ignores the important contribution of context. In fact, information theory tells us that to construct an optimal code (one that is short as possible while still being robust), word lengths should be proportional not to frequency but to predictability in context. Let's go back to the color game we described in the previous section, where you have a set of colored boxes and a prize hidden randomly inside one of them. You know the location of the prize, but your partner does not. You can use one color word to try to get your partner to identify the correct box, but you lose points for every character you use. If your lexicon is well designed, the boxes with colors which you are more likely to discuss will have shorter color names.

But there is a further prediction that can be made using information theory. With our colored boxes, imagine that the color word you are transmitting to your partner is transmitted over a noisy channel but that you get help from the context. Namely, your partner knows that if the prize is in a red box, all the red boxes will light up. In this case, you might wonder if you even need to say the word red since context (the light) has already done all the work. The same might hold for language: if context is highly informative, the next word can be short or even sometimes elided. If the preceding context is not informative or the upcoming word is surprising, you might want it to be long. Consistent with this account, it has been repeatedly observed that people will take longer to pronounce a word that is difficult or not predictable from context (Arnon & Cohen Priva, 2013; Aylett & Turk, 2004; Bell et al., 2003; Fox Tree & Clark, 1997; Watson, Buxó-Lugo, & Simmons, 2015).

Piantadosi, Tily, and Gibson (2011) used this observation to test the idea that a measure of predictability that uses local n-gram context could better explain word lengths than frequency alone. The n-gram context, in this case, means that predictability is computed for a word w_n by using the $n-1$ words that precede it. Using Google n-gram corpora from 10 languages, they use the local context to estimate the average predictability of words in context and find that, in general, there is a higher correlation between length and average surprisal (the predictability of a word in context) than between length and frequency.

Indeed, the information-theoretic underpinnings of Zipf's Law of Abbreviation may follow from very general cognitive principles towards compression and simplicity (Chater & Vitányi, 2003). For instance, see Ferrer-i-Cancho, Betnz, and Seguin (2020), Ferrer-i-Cancho et al. (2013) for an information-theoretic explanation of Zipf's Law of Abbreviation, which covers both human language and animal communication systems (such as calls from dolphins, macacques, and other animals). They show that the drive towards compression seems to be a general property of such systems, and that it can be derived by a pressure towards compression in the signal.

As with the Zipfian rank-frequency distribution, there has been some question whether the observed length/frequency correlation effect is a statistical artifact. Miller (1957) argued that monkeys typing on a keyboard (with a space bar) would produce text where the shorter words are typically more frequent than longer words. The intuition is that a string like "fep<SPACE>" is far more likely to be re-sampled than a string like "fepalopolis<SPACE>".

This line of criticism, namely that the correlation between word length and frequency/informativity may be spurious because it can be generated by chance, has been made in various forms since. Ferrer-i-Cancho and del Prado Martin (2011) argued that the word length and frequency/informativity effect can arise as a result of random typing. But the random-typing models rely on the idea that all meanings are equally likely to be conveyed, which is not true. Furthermore, the random-typing model does not capture the fact that words are stored and re-used and is thus a realistic model of real language use (Ferrer-i-Cancho & Elvevåg, 2010; Kanwal, Smith, Culbertson, & Kirby, 2017; Piantadosi et al., 2011). See also Richie (2016) for a discussion of these issues.

Caplan, Kodner, and Yang (2019) have challenged this work and argue for an updated model of Miller's random-typing monkeys that account for phonotactics. Specifically, they argue against the claim that there is special communicative optimization in the fact that more frequent and phonotactically probable words tend to have more homophones and meanings, as argued by Piantadosi, Tily, and Gibson (2012). Instead, they claim that, under certain phonotactic assumptions, random models generate lexicons in which common and probable words have more homophones and meanings. Similarly, Trott and Bergen (2020) find that real lexicons have fewer homophones than one might expect by chance.

Criticisms from the perspective of random typing models towards the efficient structure of the lexicon have, in part, led to work exploring the mechanism by which optimal word length distributions actually emerge in the lexicon. Mahowald, Fedorenko, Piantadosi, and Gibson (2013), for instance, explicitly tested the idea that words shorten after informative contexts. To do so, they selected words that had been shortened in the extant lexicon, such as *chimp* from *chimpanzee*. Using the Google Books corpus, they found that these shortenings are more likely to occur after predictive n-gram contexts. They also ran a behavioral experiment in which participants were asked to choose a short or long form of a word (*chimp* of *chimpanzee*) after either a supportive context ("Susan loves the apes at the zoo, and she even has a favorite... ") or a neutral context("During a game of charades, Susan was too embarrassed to act like a..."). People were more likely to choose a short form after a predictive context, as shown in Figure 2.

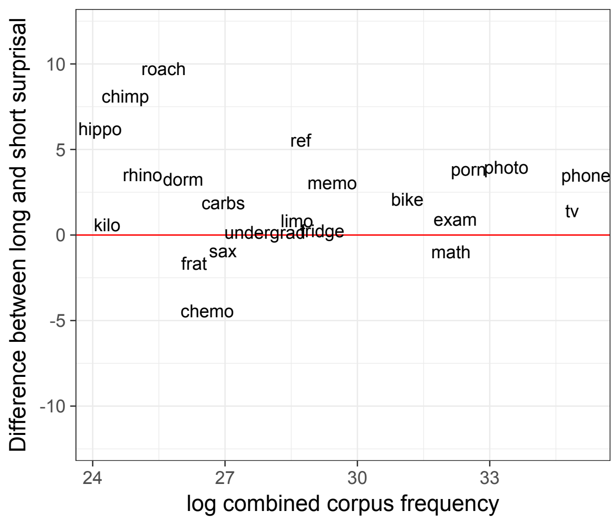

Figure 2. From Mahowald, et al. (2013): the y-axis shows the difference between the log surprisal of the long form and the log surprisal of the short form (estimated from Google Books) for the short words forms shown on the plot. Words above the line show the predicted effect whereby the long form surprisal is greater than the short form surprisal.

Kanwal et al. (2017) pursued this line of inquiry by running artificial language experiments. They showed that, if people are pressured to be both accurate and efficient (but not if they are pressured to be only one or the other), the length/frequency effect will emerge spontaneously during the task. Interestingly, when there was no penalty for inefficient speaking, the effect did not emerge. Similarly, Chaabouni, Kharitonov, Dupoux, and Baroni (2019) found that, in an emergent language simulation using artificial neural agents, there was actually an an *anti-efficient* relationship between length and frequency unless there was an explicit penalty for long utterances. In effect, without that penalty, the system optimized itself to ease the confusability burden on the listener.

Indeed, besides frequency and informativity, other work has shown that word lengths (and people's expectations about them) vary in expected ways based on factors directly related to a word's meaning, such that communicative cost is higher when a more complicated or weighty meaning is needed. To that end, Lewis and Frank (2016) showed that the complexity of an object is related to its length, and Bennett and Goodman (2018) showed that more extreme intensifiers tend to be longer (and therefore costlier) than less extreme intensifiers. In that sense, a speaker has to pay a cost in order to use a more extreme intensifier. Furthermore, Tauzin (2019) showed that people's expectations about the frequency of reference objects influences how long they expect words to be.

These behavioral studies, which rely on semantic representations being linked to expectations about word length, are difficult to account for under the random-typing models. Under the random-typing models, there is no notion of a word that can be stored and re-used and so there is no way for semantic effects to act systematically on word length. Therefore, taken together, all of the results that show systematic relationships between word length and frequency argue against the random typing account for the relationship between word length and word frequency. Rather, the length of words is intimately tied to a word's semantics and to the real-world meanings it conveys.

3.2 Phonotactics and word frequency

Another degree of freedom lexicons have regarding word frequency is how to distribute the phonological characteristics of words across the frequency spectrum. As with many aspects of the functional lexicon, Zipf had something to say on this topic. Just as he said that frequent words should be short, he also stated that languages should preferentially re-use easy-to-articulate sounds. To take this one step further, we might expect that spoken languages should prefer *phonotactically probable* words–that is, sequences which are likely under that particular language's sound structure. In English, a word like *cat* is phonotactcially quite probable whereas a word like *tzatziki*, with its unusual onset, is less probable.

How does this prediction play out in lexical structure? Landauer and Streeter (1973) showed a correlation between phonotactic probability and frequency for English, and Frauenfelder et al. (1993) found a similar result for English and Dutch. Across 96 written languages tested using corpora from Wikipedia entries in those languages, the most frequent words tend to be more orthographically probable than less frequent words, where orthographic probability is measured using an n-letter model trained over types and where orthographic probability is taken as a stand-in for phonotactic probability–a defensible assumption at the large scale used in that work (Mahowald, Dautriche, Gibson, & Piantadosi, 2018). Meylan and Griffiths (2017) made a similar argument across 13 languages, showing that phonological surprisal is correlated with frequency.

There are a few possible reasons for this pattern to emerge across languages. First, consistent with Zipf's Principle of Least Effort, it is preferable to be able to re-use phonotactically probable sequences, which have been shown to be easier to process and understand (Vitevitch & Luce, 1998; Vitevitch & Sommers, 2003). Second, just as it has been argued that long words are preferable in unpredictable (i.e., high information) contexts because they are more robust to being understood, so too might it be the case that it is preferable for less frequent words to have more information in their phonetic content.

Arguing along these lines, King and Wedel (2020) show that words which are less probable (i.e., less frequent) contain more disambiguating sounds in general (i.e., are less phonotactically probable). Because word beginnings are particularly important for disambiguation, they also explore how this plays out over the course of words and find that information is frontloaded: the beginnings of improbable words contain more disambiguating information early on.

There is also an intriguing relationship between phonemic information and word length. Words with more contrastive segments tend to be shorter (Nettle, 1995), and languages with more complex syllables have fewer syllables and more polysemy (Fenk-Oczlon & Fenk, 2008). Adopting an information-theoretic approach, Pimentel, Roark, and Cotterell (2020) use a phonotactic model to quantify the bits per phoneme across languages and find a negative correlation with word length, suggesting a complexity tradeoff such that long words have, on average, less information per phoneme. The implication is that there may be a relatively constant amount of information delivered per word.

While there are compelling information-theoretic reasons for a lexicon to prefer a structure with highly frequent words that are also highly phonotactically probable, this necessarily leads to words that are closer together in phonetic space. That is, words like *run*, *fun*, and *sun* are all minimal pairs and frequent, whereas less frequent words tend to be longer, more phonotactically unusual, and therefore have fewer neighbors (nothing rhymes with "abecedarian").

Because of the increased confusibility of short words in dense phonetic neighborhoods, there is a competing communicative pressure which says that words should be spread out in phonetic space. If we attempt to control for these phonotactic effects, do words cluster in phonetic space? Dautriche, Mahowald, Gibson, Christophe, and Piantadosi (2017) asked this question and showed that, relative to various statistical baselines, real lexicons are clumpy. Specifically, across lexicons from English, Dutch, German, and French, they use statistical models (such as n-gram models over phonemes) to construct "null lexicons," which can be compared to real lexicons on various properties such as number of minimal pairs. Compared to these baselines, real lexicons have more neighbors and minimal pairs than one would expect by chance.

Lexical ambiguity can, in a sense, be thought of as an extreme form of lexical clustering. Just as languages tend to favor lexicons with many minimal pairs ("cat", "bat", "hat"), another ubiquitous feature of language is the re-use of not just a neighboring wordform for a new meaning but the very same wordform. That is, in English, "bat" can be the flying mammal or the piece of baseball equipment. Piantadosi et al. (2012) argued that, although this may appear confusing, the ambiguity of individual lexical items is typically not a problem in everyday contexts and that ambiguity is actually efficient. It enables the re-use of short, probable words. Moreover, frequent words tend to have more meanings (Ferrer-i-Cancho & Vitevitch, 2018), and those meanings tend to be cognitively related (Xu, Duong, Malt, Jiang, & Srinivasan, 2020).

Thus, there is good evidence that suggests that perhaps potential confusability is not *the* predominant driving force in the lexicon. That is not to say, however, that there is no pressure in the lexicon to avoid confusion. Indeed, there is some evidence that, when the confusability of phonemes is considered, there are indeed lexical dispersion effects. For instance, whereas many large-scale lexical studies treat phonemes as equidistant, King (2018) present a lexical analysis suggesting that, when phonetic confusability is considered, words are structured to avoid confusabililty. This line of evidence is broadly consistent with the observation that phonological systems are structured to minimize confusion (Boersma & Hamann, 2009; Flemming, 2004; Graff, 2012; Wedel, 2011), and that these effects can be exaggerated through speech (Buxó-Lugo, Jacobs, & Watson, 2020; Gahl, 2008; Gahl & Strand, 2016; Gahl, Yao, & Johnson, 2012; Jacobs, Yiu, Watson, & Dell, 2015; Lindblom, 1990; Meinhardt, Bakovic, & Bergen, 2020).The importance of these phonemic considerations suggests that different perceptual considerations may affect the frequency of words in speech as compared to writing (Lau, Huang, Ferreira, & Vul, 2019).

4 Which meanings should be assigned to which wordforms?

If you were designing a lexicon from scratch, you might consider structuring it so that the form of a word told you something about its meaning. For instance, all the words having to do with the concept of a CAT could be similar to each other, or "cat-like" in some way.

Instead, most lexicons have largely arbitrary relationships between word forms and word meanings. The sequence of sounds /kæt/, for instance, has nothing to do with the real-world entity CAT. As a matter of fact, different languages pick different sequence of sounds to refer to these small furry pets. This arbitrariness of the sign, where the form of the word is not systematically related to its meaning, is a well established property of the world's lexicons (Hockett, 1960; Saussure, 1916).

A closer look at languages, however, reveals plenty of exceptions to the arbitrariness of the sign. One often-cited form of non-arbitrariness is iconicity (Perniss, Thompson, & Vigliocco, 2010), whereby certain acoustic properties resemble aspects of meanings within spoken languages or certain signs reflect aspects of their meanings within signed languages (Orlansky & Bonvillian, 1984; Perlman, Little, Thompson, & Thompson, 2018; Perniss, Lu, Morgan, & Vigliocco, 2018; Slonimska et al., 2020; Wilcox, 2004). For instance, onomatopoeic words such as French "miaou" or English "mew" offer straightforward examples where languages imitate some aspects of the referent (here cat vocalizations) with the imposed constraints of their phonology.

Another class of iconic words are ideophones, which recruit other aspects of the signal to imitate their meaning (Hinton, Nichols, & Ohala, 2006). For instance, contrasts in vowels have been shown to correspond to contrasts in magnitude (Dingemanse, 2012) and reduplicated words convey often plurality or repetition. It has also been shown that, cross-linguistically, people prefer to give rounded, smooth objects names with labial consonants and open vowels (e.g., "bouba"), whereas spiky, sharp objects are more likely to have sounds with closed vowels (e.g., "kiki"). This is the so-called "bouba-kiki" effect that has been observed many times in a variety of contexts (Bremner et al., 2013; Köhler, 1970; A. Nielsen & Rendall, 2011) and in ways that extend to a variety of phonetic properties (D'Onofrio, 2014), but in a way that is heavily influenced by the phonetic properties of the linguistic system (Shang & Styles, 2017). The effect has also been observed in children (Fort et al., 2018; Maurer, Pathman, & Mondloch, 2006). And there seems to be some ability to generalize semantic features across languages (Tzeng, Nygaard, & Namy, 2017).

Another form of non-arbitrariness is systematicity, which refers to statistical regularities between forms and their usage within a specific language. For instance, grammatical classes, such as nouns vs. verbs or open- vs. close-class words, share certain phonological and prosodic properties (Kelly, 1992; Monaghan, Chater, & Christiansen, 2005) and phonesthemes, such as word-initial "fl-" in English (e.g., flap, fly, flutter, flicker), suggest a certain meaning (in this case, verbs related to movement; Bergen, 2004; Marchand, 1959).

Availability of large spoken and written corpora, and advances in natural languages processing techniques and statistical analyses, have enabled large-scale analyses of the lexicons to quantify the degree of non-arbitrariness present across languages. These studies reveal a systematic positive correlation between the phonological similarity of word forms (i.e the number of phonemes they share) and the semantic similarity of their meanings (i.e., the distance between their vector-based representations) significantly above what would be expected under random form-meaning re-assignment, in a variety of typologically unrelated languages (Blasi, Wichmann, Hammarström, Stadler, & Christiansen, 2016; Dautriche, Mahowald, Gibson, Christophe, & Piantadosi, 2017; Monaghan, Shillcock, Christiansen, & Kirby, 2014; Pimentel, McCarthy, Blasi, Roark, & Cotterell, 2019; Tamariz, 2008). Importantly, these correlations are not driven by regions of iconic words present in the vocabulary, but rather seem to be a feature of the lexicon as a whole, even when controlling for the etymology of words or the morphological structure of the lexicon (Monaghan et al., 2014). In sum, while the lexicon is indeed arbitrary in the sense there is no straightforward mapping from form to meaning, there is still some substantial, albeit subtle, systematicity between word forms and their meanings.

What are the possible advantages of a non-arbitrary lexicon? One of the tasks faced by children learning their language is to link the form of a word to one of the many plausible meanings available to them (Quine, 1960). A fully arbitrary lexicon may be challenging for learners as they would need to put greater resources in learning the form-meaning mappings of their language than if they could simply deduce the meaning of a word from its phonology. Non-arbitrariness may thus convey several learning advantages to help learners bootstrap their way into language (Imai & Kita, 2014; A. K. Nielsen & Dingemanse, 2018). Several studies have shown that adults and children as young as 14 months find it easier to learn iconic form-meaning mappings than arbitrary mappings (Asano et al., 2015; Imai, Kita, Nagumo, & Okada, 2008; Imai et al., 2015; Maurer et al., 2006). The literature on iconicity in signed language acquisition in children is mixed, with some suggesting that iconicity is a major factor driving acquisition of signed languages and others suggesting it is not (Konstantareas, Oxman, & Webster, 1978; Orlansky & Bonvillian, 1984).

Congruent with the idea that iconicity facilitates word learning, corpus analyses have demonstrated that the words that are acquired the earliest are the most iconic (Laing, 2014; Monaghan et al., 2014; Perry et al., 2015) and that adults use more iconic words when speaking to children than to other adults (Perry, Perlman, Winter, Massaro, & Lupyan, 2018). Another important challenge for children is to learn how to use words in sentences depending on their grammatical class. It has been shown that children learn nouns and verbs better if there is a systematic correspondence between their sounds and their grammatical classes (Fitneva, Christiansen, & Monaghan, 2009; Kelly, 1992; Nygaard, Cook, & Namy, 2009). Thus, systematicity in vocabulary may support categorical generalization to novel words.

Similarly one may wonder about the possible advantages of an *arbitrary* lexicon. Arbitrariness is advantageous for speakers as it allows them to communicate about anything, beyond what could be referred to iconically (A. Clark, 1998). It is also critical for communication as it minimizes confusion between words with similar meaning, which in a systematic system would be expressed in a similar way. This is supported by experimental studies showing that arbitrary form-meaning mappings facilitate the distinction between referents, which is hindered by systematic mappings (Monaghan, Christiansen, & Fitneva, 2011).

Arbitrary and non-arbitrary form-meaning mappings each bring their own selective advantages and disadvantages. Over generations of learners, such advantages and disadvantages, will shape the lexicon's structure, influencing the presence and the distribution of (non-)arbitrary form-meaning mappings within and across languages. This process can be tested in the laboratory: Iterated learning provides a framework to study the emergence of a lexicon through this repeated cycle of learning and use. Iterated learning is the process by which individuals learn a language produced by a previous individual, who learned it in the same way (Kirby et al., 2008; Smith, Kirby, & Brighton, 2003) and can be simulated using computational models or experiments with human participants in the lab. These experiments show, among other things, that arbitrary signals can be turned into systematic ones after repeated episodes of language transmission (Kirby, Tamariz, Cornish, & Smith, 2015; Silvey, Kirby, & Smith, 2015; Verhoef, Roberts, & Dingemanse, 2015).

The arbitrariness of the sign, previously proposed as a "design feature" of language (Hockett, 1960), is broadly correct in the sense that the vast majority of words do not have meanings that can be straightforwardly referred from their referred. But it does seem to be an oversimplification in the light of recent quantitative research revealing a substantial and meaningful systematicity of the vocabulary across languages.

5 How should the lexicon be designed to make it learnable by children?

In the preceding section, we discussed one aspect of the lexicon that helps children learn it, namely the presence of some degree of iconicity – or other forms of non-arbitrariness – in the form-meaning mapping. What other aspects of lexical design might be related to considerations of learnability?

A basic constraint that infants bring to the language learning problem is the limited repertoire of sounds they can produce. Their lives would therefore be much more convenient if the words they needed to express earliest were easy to say. One way that this desideratum does in fact appear to be borne out is the fact that across the world's languages, even entirely unrelated ones, child words for "mother" tend to resemble /mama/ and child words for "father" tend to resemble /papa/ or /baba/. This reason for this widespread phonological confluence, as formulated by Jakobson (1962), is thought to be that the sounds in these words – /m/, /p/, /b/, /a/ – are the sounds that are easiest for infants to produce, and so are likely to make up the earliest word-like sequences that emerge from infant babbling. Parents then interpret these sequences as referring to themselves and encourage their repetition. Under this account, infants and parents effectively co-create the earliest slice of the lexicon to best facilitate infants' earliest communicative needs, thus shaping it to be near-universal cross-linguistically.

Of course, beyond these earliest few words, the lexicons of the world's languages diverge dramatically. What properties might lexicons share that ensure their learnability? One way of gaining traction on the question is through a related question – what influence do lexical properties have on the course of early word learning? A body of research has explored this question by using corpus and survey data to estimate the age at which each of a large set of words is learned, and then finding properties of words' meaning or linguistic environment that predict those ages.

Within a lexical category (e.g., nouns, verbs), English words that are more frequent in speech to children are likely to be learned earlier (J. C. Goodman et al., 2008). Further studies (also in English) have found evidence that age of acquisition is likely to be earlier for words that have more phonological neighbors (e.g., Storkel, 2004, 2001, 2004; Stokes, 2010; Jones and Brandt, 2019; but see Swingley and Aslin, 2007; Stager and Werker, 1997); words that share more associations with other words in the learning environment (Fourtassi, Bian, & Frank, 2018; Hills et al., 2009); words that occur more often in isolation (Brent & Siskind, 2001; Swingley & Humphrey, 2018); words whose meanings are more concrete (Gentner, 1978, 1981, 1982; L. R. Gleitman & Gleitman, 1997; Swingley & Humphrey, 2018); words that are rated more iconic and/or more associated with babies (e.g., such as "choo-choo" or "doggy", Massaro & Perlman, 2017; Perry et al., 2015; Thompson, Vinson, Woll, & Vigliocco, 2012); words which have sound symbolism (even in a different langauge, as in Kantartzis, Imai, & Kita, 2011) and words that occur in more distinctive spacial, temporal, and linguistic contexts (E. V. Clark, 1987; Ferrer-i-Cancho, 2013; Roy et al., 2015; Trueswell et al., 2016). For more on this domain, see Swinglely, this volume.

Building on this body of work, Braginsky et al. (2019) conducted a large-scale analysis of the predictors of early word learning across languages. They found a much greater degree of consistency in these predictors than would be expected by chance. Across 10 languages (Croatian, Danish, English, French, Italian, Norwegian, Russian, Spanish, Swedish, and Turkish), words are more likely to be learned earlier if they are (in order of largest to smallest effect size) more frequent, shorter, more concrete, more frequently the only word in an utterance, more likely to appear in shorter utterances, more associated with babies, and more frequently the final word in an utterance.

Additionally, these effects differ by lexical category: for content words (nouns, adjectives, and verbs) being more concrete and more frequent affect their learning the most, while for function words, being shorter and appearing in shorter sentences affect their learning the most. These patterns are supportive of the hypothesis that different word classes are learned in different ways, or at least that the bottleneck on learning tends to be different, leading to different information sources being more or less important across categories (L. R. Gleitman et al., 2005). For work on vocabulary growth differences across individuals, see Potter Lew-Williams, this volume.

Taken together, these results paint a picture of what sort of lexicon may be most conducive to early word learning. In many ways, that ideal lexicon has properties that resemble the real-world lexical features discussed throughout this chapter. For instance, an ideal lexicon might have relatively high levels of phonological and associative density and, indeed, much evidence suggests that lexicons tend to be highly clustered in phonetic space

(Dautriche, Mahowald, Gibson, Christophe, & Piantadosi, 2017). A lexicon that is good for learning might also have a non-negligible set of words exhibiting iconicity: this too is a property we have seen across a variety of lexicons (Dautriche, Mahowald, Gibson, & Piantadosi, 2017; Monaghan et al., 2014). Finally, lexicons that are well-suited for learning should have a tendency for words that are of communicative import for infants and toddlers to be relatively short, frequent, and amenable to appearing in supportive environments like shorter sentences and distinctive linguistic contexts (see Dautriche, Fibla, Fievet, & Christophe, 2018; Dautriche et al., 2015, for the role of contextual usage).

In sum, the learnability advantages described here translate into the overall structure of the lexicon. In some sense, this is deeply unsurprising: the words that survive in languages are necessarily those that can be learned by children.

6 Conclusion

By combining insights from communication theory, observations in functional linguistics, and results from cognitive science, we can see that the lexicon shows a number of efficient design properties that make it tractable and efficient for human language use.

Specifically, the body of evidence presented here suggests that, to design an optimal lexicon for human language use and acquisition, one should do the following:

1. Structure the lexicon such that the words follow a near-Zipfian distribution.

2. Structure semantic spaces along a Pareto-optimal frontier, trading off complexity against the information in the system according to the communicative needs of the speakers.

3. Make the words that are easiest to predict in context short. Make words that are hard to predict by context long.

4. Make frequent words phonotactically probable, even if it means that frequent words will be more easily confused phonetically.

5. While the mapping between form and meaning is arbitrary, build a lexicon with

some correlation between form and meaning.

Throughout this chapter, which depends on the notion of a lexicon that is pressured towards efficiency, we keep in mind criticism along the lines of Marcus and Davis (2013), who have argued that care should be taken when making claims about optimality in human cognition. A danger in this work is making optimality–or efficiency–a moving goalpost such that any behavior observed is defined as optimal. One advantage of working in language and specifically on the lexicon, however, is that communication theory provides a mathematically precise and rigorous definition of efficient behavior under different assumptions. And experiments and modeling work in developmental psychology give clear guidance as to what makes linguistic systems easier or harder to learn. Given that the lexicon is largely arbitrary and has a high number of degrees of freedom, it is an ideal place for exploring these pressures because the lexicon is flexible enough, and free enough, to adapt and change in response to different communicative pressures. Consider, for instance, the explosion in use of word shortenings that emerged as a result of the rise of texting (which, due to the tininess of phones and the largeness of thumbs, penalizes long words more strongly than other forms of communication): "ttyl", "lol", "imho", and so on.

Of course, no language will ever have a perfectly efficient lexicon because there are many competing demands in language, e.g. efficiency in syntactic space and the sometimes contradictory pressures for learnability on the one hand and efficiency on the other. To that end, work purporting to show efficiency in the lexicon needs to always ask the question "efficient relative to what baseline?" Indeed, the use of baseline can affect the strength of the claims made.

Moreover, the communicative needs of any individual speaker in any individual context are likely unique, and it is impractical to have a unique lexicon for every conversation and context–although note that any specialized context quickly develops its own vocabulary with its own shortenings and jargon. Rather, the lexicon of a language needs to be general enough to function in a wide variety of contexts.

Nonetheless, it is noteworthy how many principles of efficient communication can be observed by measuring large-scale statistical properties both within and across languages. Some of the statistical properties reported in work here are straightforward: it is certainly not surprising that short words tend to be more frequent than long words. But much of the statistical work discussed here–and much of the statistical work on the lexicon in recent years–has formalized and quantified the statistical structure of various aspects of the lexicon. In doing so, doors have opened towards establishing newer and more detailed principles that guide how words and languages evolve to satisfy language users' needs.

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