Speech intelligibility:

A generalized latent variable approach on utterances' entropies

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Abstract

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1 Introduction

Intelligible spoken language requires all core components of speech perception, cognitive processing, linguistic knowledge, and articulation to be mastered (Freeman et al.; 2017). In that sense, its attainment carries an important societal value, as it is considered a milestone in children's language development; and more practically, it is qualified as the ultimate checkpoint for the success of speech therapy, and the "gold standard" for assessing the benefits of cochlear implantation (Chin et al.; 2012).

But what is speech intelligibility?. Intelligibility is usually conceptualized as the extent to which the elements in an acoustic signal generated by a speaker, e.g. phonemes or words, can be correctly recovered by a listener (Freeman et al.; 2017; Kent et al.; 1989; Munro and Tracey; 1999; van Heuven; 2008; Whitehill and Chau; 2004). The latter definition sets a clear contrast with comprehensibility, which involves the listener's ability to understand the sounds' message and its intent (Munro and Tracey; 1999; Smith and Nelson; 1985).

But the literature reveals that intelligibility is an intricate concept, with particular challenges to its assessment/measurement. The latter is because intelligibility can be affected by features of the communicative environment, such as noise (Munro; 1998); by features of the speaker, like speaking rate (Munro and Derwing; 1998) or accent (Jenkins; 2000; Ockey et al.; 2016); or features of the listener, like vocabulary mastery (Varonis and Susan; 1985). Moreover, this further emphasizes another aspect of the concept: its dynamic nature, where changes in intelligibility stem from the speaker's online adaptations to the listener and/or context.

Therefore, the literature suggests there are three aspects to the study of speech sounds, and therefore, three from which intelligibility can be asssessed: the acoustic, articulatory, and auditory aspects (Gudivada et al.; 2018). The first is focused on assessing the transmission and physical properties of speech sounds (Boonen et al.; 2020, 2021). The second is more concerned with the sounds' production (Rowe and Levine; 2018). While the last, center its attention on the speech sounds' perception, i.e. how the stimuli are perceived by a listener (Boonen et al.; 2020, 2021).

Focusing our attention on the last one, perceptual studies also use multiple approaches to measure intelligibility, but they can be largely grouped into two: subjective and objective ratings methods (Hustad et al.; 2020). In the former, listeners directly infer the intelligibility score of the speech samples through different procedures. While in the latter, listeners transcribe children's utterances orthographically (or phonetically), and use these as information to construct an entropy score that expresses the degree of (dis)agreement in the transcriptions (Boonen et al.; 2021; Shannon; 1948).

Consequently, objective ratings try to infer intelligibility from the extent to which a set of transcribers can identify the words contained in the utterances (Boonen et al.; 2021). While subjective ratings, try to directly produce a score based on a listener's perception of the sounds' intelligibility. In either case, the methods produce a proxy measure of the speaker's intelligibility as judged by a listener, a snapshot of his/her performance under a specific set of circumstances (Hustad et al.; 2020).

Moreover, the methods' validity, i.e. the extent to which scores are appropriate for their intended interpretation and use (Lesterhuis; 2018; Trochim; 2022), is founded on the idea that intelligibility is an intuitively understood notion, "something" that anyone can judge, but that can only be measured indirectly because of its entanglement with other features of the communication (Guilford; 1954; Stevens; 1946).

Recently in the literature, objective rating procedures applied on children's utterances recovered from spontaneous speech tasks have received special attention (Boonen et al.; 2021; Hustad et al.; 2020). The scores produced from these tasks are characterized by their clustered and bounded nature. The former happens because the data register multiple measurements per child; more specifically, one score per utterance, where multiple utterances are assessed. While the latter happens because the entropy score values are expresed in the continuum between zero and one (Shannon; 1948).

Although the literature has been clear on the aforementioned method benefits to (indirectly) quantify intelligibility (Boonen et al.; 2020, 2021; Hustad et al.; 2020), we notice the statistical procedures used to model such data have not been fully at par to the measurement procedure's sophistication.

First, previous research have dealt with the data clustering, but ignored its bounded nature. More specifically, Boonen et al. (2021) modeled and tested some research hypotheses of interest on similar data, through the use of multilevel linear models (MLM). To understand the importance of this decision, it is relevant to highlight why the use of such models is a requirement when the data is clustered.

When more than one observation arises from the same individual, location, or time, then traditional (single-level) statistical models may mislead us (McElreath; 2020). The reason for this, is that one of the main assumptions of these models gets violated: the independence of errors (Finch et al.; 2019).

The latter is easier to understand with a thought experiment. Consider the scenario hinted in previous paragraphs: we observe one entropy score per utterance, for a total of ten utterances per child. In this scenario, it would be reasonable to believe the ten entropy scores observed for the same child would be more similar with one another, than what they are, with the scores observed for other children. This within-child correlation would be due, for example, to having the same speech pattern, articulation, linguistic knowledge, among other reasons, perceived by the listener.

The presence and non-recognition of this within-child correlation in the data will, in turn, result in two know

statistical issues (Finch et al.; 2019). On the one hand, the inapropriate estimation of the standard error parameters of the model. This is important, as biased parameters might lead us to less appropriate statistical inferences, e.g. smaller standard error with larger t-statistics and smaller p-values, that lead to the rejection of a "true" null hypothesis (Type I error). On the other hand, if the multilevel structure of the data is ignored, we may miss important relationships involving each level in the data. Considering our thought experiment, it is easy to see the presence of two levels in our data: utterances (level 1) and children (level 2). Notice that we might have different information (variables) at each level that explains the data behavior, and by not appropriately including them, we will be suggesting the use of an incorrect model for understanding the outcome of interest.

Therefore, it is clear why modeling the data clustering is important from the statistical point of view. However, we argue that the latter practice is not sufficient, because it has not considered the bounded nature of the data, which might lead to a different set of statistical problems.

To understand the preceding statement, it is important to first highlight the main assumption of MLMs: normally distibuted errors (McCullagh and Nelder; 1983). But what the normality assumption implies?. First, it imply that we are assuming that our outcome of interest is, by extension, also normally distributed, i.e. the entropy scores and any transformation of them (e.g. its average) can take any value in the real line without constraint. And second, it implies that we are mainly interested on modeling the outcome's location (average), where the estimation of its spread (variance) takes a secondary role, only justified by the need of appropriate inferences.

It is clear from the entropy scores description, that the first implication of assuming normally distributed outcomes is not fulfilled. This is a problem because it implies that we might be allowing the final multilevel model to test hypotheses and produce predictions based on a modeling assumption that do not match the data reality, e.g. the model might produce negative entropy values (McElreath; 2020).

Moreover, a simple thought experiment can show us why ignoring the second implication can also mislead us. Consider children with three different patterns for ten entropy scores, all reporting the same entropy mean of 0.5. The patterns are: (a) scores closely agglomerated around 0.5, (b) scores loosely aglomerated around 0.5, and finally, (c) half of the scores agglomerated around 0.1 and the other half around 0.9. From the mean score we can say that the three children have an "average" level of intelligibility. However, from the spread of the scores we can notice that more uncertainty (to the asesssment of "average") should be assigned to child (c), followed by (b) and finally (a). This just mean that we can be more confident that child (a) has an "average" level of intelligibility, than in the other two cases, where (c) represent one extreme example of uncertainty.

In this sense, we notice that the need to model the distribution spread is no longer justified only by a demand of appropriate inferences, but also because it informs about the individual's intelligibility. Therefore, it is clear that more sophisticated statistical procedures are needed to model our data.

Second, although the literature suggest the entropy scores "captures" intelligibility, we can say that these scores are a coarse version of it, i.e. an uncertain manifestation of a child's intelligibility. Stated in other words, there is an unobserved (latent) intelligibility construct that is responsible for what it is observed on the entropy scores and their variation. Notice the previous can be stated because of two reasons. First, we observe multiple entropy scores per child. Second, the scores are entropy not "intelligibility" scores.

Therefore, if we hope to understand or intervene on the factors that drives speech intelligibility, first one needs to "construct" an intelligibility scale from the data (Carroll; 2006), allowing us to test our research hypotheses at the appropriate (children) level. Furthermore, the literature emphasize that failing to model this phenomena as a "latent construct" would also lead us to incorrect inferences (deHaan et al.; 2019).

In that sense, the aim of this research is to propose a novel analysis of the entropy data using a Bayesian implementation of the Generalized Linear Latent and Mixed Model (GLLAMM) (Rabe-Hesketh et al.; 2004a,c,b, 2012; Skrondal and Rabe-Hesketh; 2004). The statistical procedure offers four benefits. First, it allows to appropriately model the bounded nature of the entropy data. Second, it provides a way to "construct" the speaker's latent intelligibility scale. Third, it allow us to test our research hypothesis at the appropriate level. And fourth, as a result from the first two, we successfully avoid producing false confidence in the parameter estimates, which help us to produce better informed statistical inferences (McElreath; 2020).

We find that when the proposed method is used to investigate the speech intelligibility levels of normal hearing (NH) versus hearing-impaired children with cochlear implants (HI/CI), in a data composed of ten utterances recordings from thirty two NH and HI/CI children selected from a large corpus of spontaneously spoken speech collected by the CLiPS research center, it brings bring new insights about the use of replicated entropy scores to measure intelligibility. Furthermore, the method also provide a way to assess how some factors affect the (under)development of children's intelligibility.

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