How Optimal is Novel Word Recogntion Under Multimodal Uncertainty?

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Abstract

Identifying a spoken word in a referential context requires both the ability to integrate multimodal input and the ability to reason under uncertainty. How do these tasks interact with one another? We introduce a paradigm that allows us to examine how adults identify novel words under joint uncertainty in the auditory and visual modalities and propose an ideal observer model of how cues in these modalities are combined optimally. Model predictions are tested in three experiments where novel word recognition is made under two kinds of uncertainty: category ambiguity and perceptual noise. In all cases, the optimal model explains much of the variance in human mean judgments. When the signal is not distorted with noise, participants weight the auditory and visual cues optimally, that is, according to the relative reliability of each modality. But when one modality has noise added to it, human perceivers systematically prefer the unperturbed modality to a greater extent than the optimal model does. The study provides a formal framework which helps to quantify how word form and word meaning interact in word recognition under uncertainty. Moreover it offers a first step towards a model that accounts for form-meaning synergies in early word learning.

Keywords: Language understanding; audio-visual processing; word learning; speech perception; computational modeling.

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Introduction

Language uses symbols expressed in one modality – the auditory modality, in the case of speech – to communicate about the world, which we perceive through many different sensory modalities. Consider hearing someone yell "bee!" at a picnic, as a honey bee buzzes around the food. Identifying a word involves processing the auditory information as well as other perceptual signals (e.g., the visual image of the bee, the sound of its wings, the sensation of the bee flying by your arm). A word is successfully identified when information from these modalities provide convergent evidence. However, word identification takes place in a noisy world, and the cues received through each modality may not provide a definitive answer. On the auditory side, individual acoustic word tokens are almost always ambiguous with respect to the particular sequence of phonemes they represent, which is due to the inherent variability of how a phonetic category is realized acoustically (Hillenbrand, Getty, Clark, & Wheeler, 1995). And some tokens may be distorted additionally by mispronunciation or ambient noise. Perhaps the speaker was yelling "pea" and not "bee." Similarly, a sensory impression may not be enough to make a definitive identification of a visual category.[1] Perhaps the insect was a beetle or a fly instead. How does the listener deal with such multimodal uncertainty to recognize the speaker's intended word?

As a simplified case study of early word learning, the task of matching sounds to corresponding visual objects has been studied extensively in the developmental literature. For example, many studies focus on how children might succeed in this type of task despite

[1] In the general case, language can of course be visual as well as auditory, and object identification can be done through many modalities. For simplicity, we focus on audio-visual matching here.

referential ambiguity (Medina, Snedeker, Trueswell, & Gleitman, 2011; Pinker, 1989; Smith & Yu, 2008; Suanda, Mugwanya, & Namy, 2014; Vlach & Johnson, 2013; Vouloumanos, 2008; Yurovsky & Frank, 2015). However, even when they *know* the meanings of a word, listeners (both children and adults) often still find it challenging to recognize which word the speaker has uttered, especially under noise (Mattys, Davis, Bradlow, & Scott, 2012; Peelle, 2018). The purpose of the current study is thus to explore word recognition by adults under multimodal uncertainty. We focus on the special case where people have access to multimodal cues from the auditory speech and the visual referent. In the General Discussion, we return to the question of how these findings relate to questions about word learning.

One rigorous way to approach this question is through conducting an *ideal observer* analysis. This research strategy provides a characterization of the task/goal and shows what the optimal performance should be under this characterization.[2] When there is uncertainty in the input, the ideal observer performs an optimal probabilistic inference. For example, in order to recognize an ambiguous linguistic input, the model uses all available probabilistic knowledge in order to maximize the accuracy of this recognition. The ideal observer model can be seen as a theoretical upper limit on performance. It is not so much a realistic model of human performance, as much as a baseline against which human performance can be compared (Geisler, 2003; Rahnev & Denison, 2018). When there is a deviation from the ideal, it can reveal extra constraints on human cognition, such as limitations on the working memory or attentional resources. This approach has had a tremendous impact not only on speech-related research (Clayards, Tanenhaus, Aslin, & Jacobs, 2008; Feldman, Griffiths, & Morgan, 2009; Kleinschmidt & Jaeger, 2015; Norris & McQueen, 2008), but also on many other disciplines in the cognitive sciences (for reviews, see Chater & Manning, 2006; Knill & Pouget, 2004; Tenenbaum, Kemp, Griffiths, & Goodman, 2011)

[2] It is, thus, a general instance of the rational approach to cognition (Anderson, 1990), instantiating Marr's computational level of analysis (Marr, 1982).

Some prior ideal observer studies are closely related to the question we are addressing in the current work. For instance, Clayards et al. (2008) simulated auditory uncertainty by manipulating the probability distribution of a cue (Voice Onset Time) that differentiated similar words (e.g., “beach” and “peach”). They found that humans were sensitive to these probabilistic cues and their judgments closely reflected the optimal predictions. And Feldman et al. (2009) studied the perceptual magnet effect, a phenomenon that involves reduced discriminability near prototypical sounds in the native language (Kuhl, 1991), showing that this effect can be explained as the consequence of optimally solving the problem of perception under uncertainty.

Besides the acoustic cues explored in Clayards et al. (2008) and Feldman et al. (2009), there is extensive evidence that information from the visual modality, such as the speaker’s facial features, also influences speech understanding (see Campbell, 2008 for a review). Bejjanki, Clayards, Knill, and Aslin (2011) offered a mathematical characterization of how probabilistic cues from speech and lip movements can be optimally combined. They showed that human performance during audio-visual phonemic labeling was consistent (at least at the qualitative level) with the predictions of an ideal observer. This previous research did not, however, systematically study speech understanding when visual information was obtained through the referential context rather than through observation of speaker’s face. Although some experimental findings show that information about the identity of a referent can be integrated with linguistic information to resolve lexical and syntactic ambiguities in speech (e.g., Eberhard, Spivey-Knowlton, Sedivy, & Tanenhaus, 1995; Spivey, Tanenhaus, Eberhard, & Sedivy, 2002; Tanenhaus, Spivey-Knowlton, Eberhard, & Sedivy, 1995), to our knowledge no study has offered an ideal observer analysis of this task.

Combining information between words and visual referents might seem similar to audio-visual speech integration, but there are at least two fundamental differences between these two cases, and both can influence the way the auditory and visual cues are combined.

First, in the case of audio-visual speech, both modalities offer information about the same underlying speech category. They differ only in terms of their informational reliability. In a referential context, however, the auditory and visual modalities play different roles in the referential process – the auditory input represents the *symbol* whereas the visual input represents the *meaning* (and these differences are in addition to possible differences in informational reliability). Further, speech is claimed to have a privileged status compared to other sensory stimuli (Edmiston & Lupyan, 2015; Lupyan & Thompson-Schill, 2012; Vouloumanos & Waxman, 2014; Waxman & Gelman, 2009; Waxman & Markow, 1995), and that this privilege is suggested to be specifically related to the ability to refer (Waxman & Gelman, 2009).[3] Thus, in a referential context, it is possible that listeners do not treat the auditory and visual modalities as equivalent sources of information. Instead, there could be a sub-optimal bias for the auditory modality beyond what is expected from informational reliability alone.

Second, in the case of audio-visual speech, the auditory and visual stimuli are expected to be perceptually correlated. The expectation for this correlation is strong enough that when there is a mismatch between the auditory and visual input, they are still integrated into a unified (but illusory) percept (e.g., the McGurk Effect; McGurk & MacDonald, 1976). In the case of referential language, however, the multimodal association is by nature *arbitrary* (Greenberg, 1957; Saussure, 1916). For instance, there is no logical or perceptual connection between the sound "bee" and the corresponding insect. Moreover, variation in the way the sound "bee" is pronounced is generally not expected to correlate perceptually with variation in the shape (or any other visual property) in the category of bees. In sum,

[3]There is, however, a debate as to whether speech is privileged for children and adults for similar reasons. Whereas some researchers suggest that speech is privileged for both children and adults because of its ability to refer (e.g., Waxman & Gelman, 2009), others suggest that speech might *not* have a referential status from the start. Rather, speech might be preferred by children only because of a low level auditory "overshadowing" (e.g., Sloutsky & Napolitano, 2003).

cue combination in the case of arbitrary audio-visual associations (word-referent) is likely to be less automatic, more effortful, and therefore less conducive to optimal integration than it is in the case of perceptually correlated associations (as in audio-visual speech perception).

The current study

We investigate how cues from the auditory and the visual modality are combined in recognizing words in a referential context. In particular, we study how this combination is performed under various degrees of uncertainty in both the auditory and the visual modality. Imagine, for example, that someone is uncertain whether they heard "pea" or "bee." Does this uncertainty make them rely more on the referent (e.g., the object being pointed at)? Or, if they are not sure if they saw a bee or a fly, does this uncertainty make them rely more on the sound? More importantly, when input in both modalities is uncertain to varying degrees, do they weight each modality according to its relative reliability (the optimal strategy), or do they over-rely on a particular modality?

We begin by proposing an ideal observer model that performs the combination in an optimal fashion. We then compare the predictions of the optimal model to human responses. Humans can deviate from the ideal for several reasons. For instance, as mentioned above, a sub-optimality can be induced by the privileged status of a particular modality or by the arbitrariness of the referential association. In order to study possible patterns of sub-optimality, we compare the optimal model (which provides a normative benchmark) to a descriptive model (which is fit to human responses). Comparing parameter estimates between these two formulations allows us to quantify the degree of deviation from optimality.

We tested the ideal observer model's predictions in three behavioral experiments where we varied the source of uncertainty. In Experiment 1, audio-visual tokens were ambiguous with respect to their category membership only. In Experiment 2, we intervened by adding perceptual noise to the auditory modality, and in Experiment 3, we intervened by adding perceptual noise to the visual modality. In all experiments, participants were quantitatively near-optimal, though overall response precision was slightly lower than expected. In Experiment 1 – where neither of the modalities was perturbed with background noise – participants weighted auditory and visual cues according to the relative reliability predicted by the optimal model. However, in Experiment 2 and 3, participants over-relied on one modality when the other modality was perturbed with additional noise.

Paradigm and Models

In this section we first briefly introduce the multimodal combination task. Then we explain how behavior in this paradigm can be characterized optimally with an ideal observer model.

The Audio-Visual Word Recognition Task

We introduce a paradigm adapted from a task used by Sloutsky and Napolitano (2003). The original was used with both children and adults to probe audio-visual encoding (see Robinson & Sloutsky, 2010 for review). Here we use a slightly different version to test word recognition in a referential context. We use two visual categories (cat and dog) and two auditory categories (/b/ and /d/ embedded in the minimal pair /aba/-/ada/). For each participant, an arbitrary pairing is set between the auditory and the visual categories, leading to two audio-visual word categories (e.g., dog-/aba/, cat-/ada/). In each trial, participants are presented with an audio-visual target (the prototype of the target category), immediately followed by an audio-visual test stimulus (Figure 1). The test stimulus may differ from the target in both the auditory and the visual components. After these two presentations, participants press “same” or “different.”

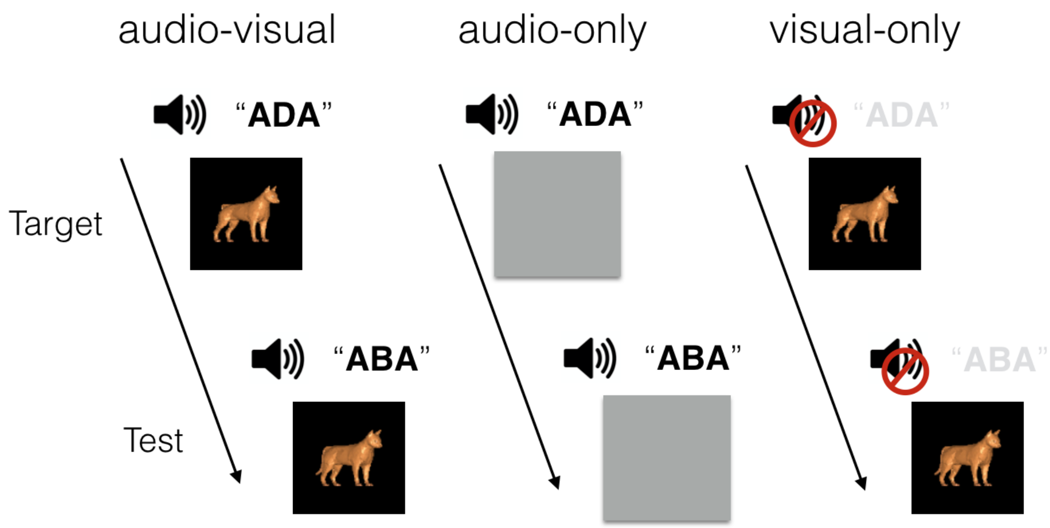

Figure 1. Overview of the task. In the audio-visual condition, participants are first presented with an audio-visual target (the prototype of the target category), immediately followed by an audio-visual test. The test may differ from the target in both the auditory and the visual components. After these two presentations, participants press 'same' (i.e., the same category as the target) or 'different' (not the same category). The auditory-only and visual-only conditions are similar to the audio-visual condition, except that only the sounds are heard, or only the pictures are shown, respectively.

In the testing phase of the original task (Sloutsky & Napolitano, 2003), participants were asked whether or not the two audio-visual presentations are *identical*. In the current study, we are interested, rather, in the categorization, i.e., determining whether or not two similar tokens are members of the same phonological/semantic category. Therefore, testing in our task is category-based: Participants are asked to press "same" if they think the second item (the test) belongs to the same category as the first (target) (e.g., dog-/aba/), even if there is a slight difference in the sound, in the referent, or in both. They are instructed to press "different" only if they think that the second stimulus was an instance of the other category (cat-/ada/). The task also includes trials where pictures are hidden (audio-only) or where sounds are muted (visual-only). These unimodal trials provide us with the participants' evaluation of the probabilistic information present in the auditory and visual categories. As we shall see, these unimodal distributions are used as inputs to the optimal cue combination model.

Optimal Model

We construct an ideal observer model that combines probabilistic information from the auditory and visual modalities. In contrast to the model used in most research on multisensory integration (e.g., Ernst & Banks, 2002), which typically studies continuous stimuli (e.g., size, location), the probabilistic information in our case cannot be characterized with *sensory noise* only. Since our task involves responses over categorical variables (phonemes and concepts), the optimal model should take into account not only the noise variability around an individual perceptual estimate but also its *categorical variability*, i.e., the uncertainty related to whether this perceptual estimate belongs to a given category (see also Bankieris, Bejjanki, & Aslin, 2017; Bejjanki et al., 2011). In what follows, we describe a model that accounts for both types of variability. First, we describe the model in the simplified case of categorical variability only. Second, we augment this simplified model to account for sensory noise.

Categorical variability. We assume that both the auditory categories (i.e., /aba/ and /ada/) and the visual categories (cat and dog) are distributed along a single acoustic and semantic dimension, respectively (Figure 2). Moreover, we assume that all categories are normally distributed. Formally speaking, if A denotes an auditory category (/ada/ or /aba/), then the probability that a point a along the acoustic dimension belongs to the category A is

$$p(a|A) \sim N(\mu_A, \sigma_A^2)$$

where μ_A and σ_A^2 are respectively the mean and the variance of the auditory category. Similarly, the probability that a point v along the visual dimension belongs to the category

V is

$$p(v|V) \sim N(\mu_V, \sigma_V^2)$$

where μ_V and σ_V^2 are the mean and the variance of the visual category. An audio-visual signal $w = (a, v)$ can be represented as a point in the audio-visual space. These audio-visual tokens define bivariate distributions in the bi-dimentional space. We call these bivariate distributions *Word categories*, noted W, and are distributed as follows:

$$p(w|W) \sim N(M_W, \Sigma_W)$$

where $M_W = (\mu_A, \mu_V)$ and Σ_W are the mean and the covariance matrix of the word category. The main assumption of the model is that the auditory and visual variables are independent (i.e., uncorrelated), so the covariance matrix is simply:

$$\Sigma_W = \begin{bmatrix} \sigma_A^2 & 0 \\ 0 & \sigma_V^2 \end{bmatrix}$$

This assumption says that, given a word-object mapping, e.g., $W =$(“cat”-CAT), variation in the way “cat” is pronounced does not correlate with changes in any visual property of the object CAT, which is a valid assumption in the context of our task.[4]

Now we turn to the crucial question of modeling how the optimal decision should proceed given the probabilistic (categorical) information in the auditory and the visual modalities, as characterized above. We have two word categories: dog-/aba/ (W_1) and cat-/ada/ (W_2).[5] When making decisions, participants can be understood as choosing one of these two word categories (Figure 2). For an ideal observer, the probability of choosing category 2 when presented with an audio-visual instance $w = (a, v)$ is the posterior

[4]Note that this assumptions is more adequate in the case of arbitrary associations such as ours, and less so in the case of redundant association such as audio-visual speech. In the latter, variation in the pronunciation is expected to correlate, at least to some extent, with lip movements.

[5]This mapping is randomized in the experiments.

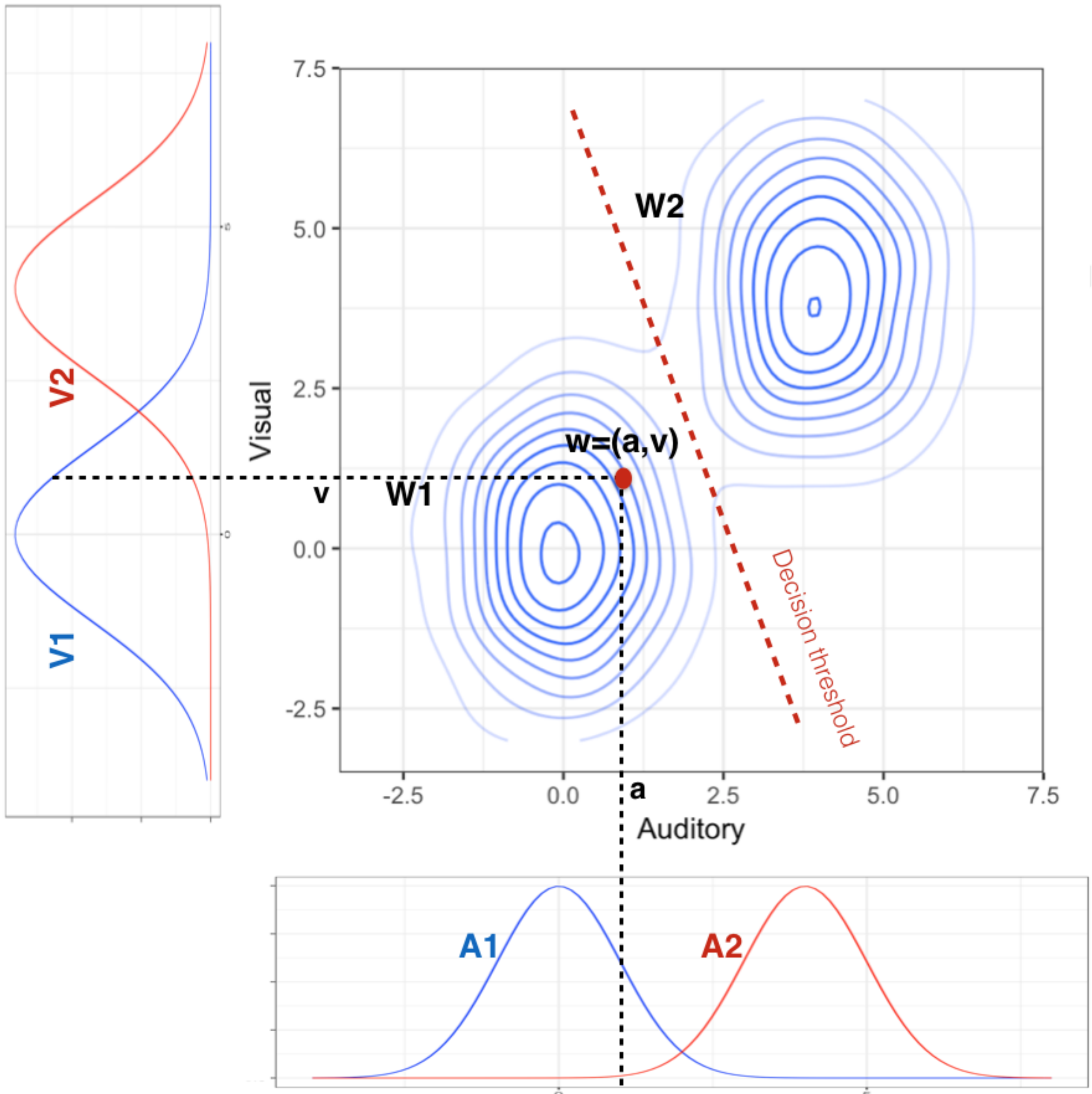

Figure 2. Illustration of the model using simulated data. A word category is defined as the joint bivariate distribution of an auditory category (horizontal, bottom panel) and a visual semantic category (vertical, left panel). Upon the presentation of a word token w, participants guess whether it is sampled from the word type W_1 or from the word type W_2. Decision threshold is where the guessing probability is 0.5.

222 probability of this category:

$$p(W_2|w) = \frac{p(w|W_2)p(W_2)}{p(w|W_2)p(W_2) + p(w|W_1)p(W_1)}$$

Using our assumption that the cues are uncorrelated, we have:

$$p(w|W) = p(a, v|W) = p(a|A)p(v|V)$$

Under this assumption, the posterior probability reduces to the following formula (see Appendix 1 for the details of the derivation):

$$p(W_2|w) = \frac{1}{1 + (1 + b)\exp(\beta_0 + \beta_a a + \beta_v v)} \tag{1}$$

where

$$1 + b = \frac{p(W_1)}{p(W_2)}$$
$$\beta_0 = \frac{\mu_{A2}^2 - \mu_{A1}^2}{2\sigma_A^2} + \frac{\mu_{V2}^2 - \mu_{V1}^2}{2\sigma_V^2}$$

$$\beta_a = \frac{\mu_{A1} - \mu_{A2}}{\sigma_A^2}$$
$$\beta_v = \frac{\mu_{V1} - \mu_{V2}}{\sigma_V^2}.$$

The parameter b represents the differential between the categories' prior probabilities. However, since the identity of word categories is randomized across participants, b measures, rather, a response bias to "same" if $b > 0$, and a response bias to "different" if $b < 0$. We expect a general bias towards answering "different" because of the categorical nature of our same-different task: When two items are ambiguous but perceptually different, participants might have a slight preference for "different" over "same". As for the means, their values are fixed, and they correspond to the most typical tokens in our stimuli. Finally, observations from each modality (a and v) are weighted in Equation 1 according to their reliability (that is, according to the *inverse* of their variance):

$$\beta_a \propto \frac{1}{\sigma_A^2}$$
$$\beta_v \propto \frac{1}{\sigma_V^2}.$$

Sensory variability. So far, we have only accounted for categorical variability, i.e., $\sigma_A^2 = \sigma_{A_C}^2$. For instance, if the speaker generates a target production a_t from an auditory category $p(a_t|A) \sim N(\mu_A, \sigma_{A_C}^2)$, the ideal model assumes that it has direct access to this production token (i.e., $a = a_t$), and that all uncertainty is about the category membership of this token. However, we might also want to account for internal noise in the brain and/or external noise in the environment. For example, the observer might not have access to the exact produced target, but only to the target perturbed by noise. If we assume this noise to be normally distributed, that is, $p(a|a_t) \sim N(a_t, \sigma_{A_N}^2)$, then integrating over a_t leads to this new expression of the probability distribution:

$$p(a|A) \sim N(\mu_A, \sigma_{A_C}^2 + \sigma_{A_N}^2)$$

Similarly, in the case of sensory noise in the visual modality, we get:

$$p(a|V) \sim N(\mu_V, \sigma_V^2 + \sigma_{V_N}^2)$$

Finally, using exactly the same derivation as above, we end up with the following multimodal weighting scheme in the optimal combination model (Equation 1) which takes into account both categorical and sensory variability:

$$\begin{aligned} \beta_a &\propto \frac{1}{\sigma_{A_C}^2 + \sigma_{A_N}^2} \\ \beta_v &\propto \frac{1}{\sigma_{V_C}^2 + \sigma_{V_N}^2}. \end{aligned}$$

Optimal cue combination. Equation 1 provides the optimal model's predictions for how probabilities that characterize uncertainty in the auditory and the visual modalities can be combined to make categorical decisions. Parameter estimates of the probability distributions in each modality are derived by fitting unimodal posteriors to the participants' responses in the unimodal conditions, i.e., the condition where only the sounds are heard or only the pictures are seen (Figure 1).[6] Using these derived parameters, the optimal model makes predictions about responses in the bimodal (i.e., audio-visual) condition where participants both hear the sounds and see the pictures.

Auditory and Visual baselines. The predictions of the optimal model will be compared to two baselines. The first baseline is a visual model which assumes that participants rely only on visual information, and an auditory model, which assumes that participants rely only on auditory information. More precisely, these baseline models assume that the participants' responses in the bimodal condition will not be different from their response in either the visual-only or the auditory-only condition. However, if the participants rely on both the auditory and the visual modalities to make decision in the bimodal condition, the optimal model would explain more variance in human responses than the visual or the auditory model do.

Descriptive model and analysis of (sub-)optimality

The optimal model (as well as the auditory and visual baselines) are *normative* models. Their predictions are made about human data in the bimodal condition, but their crucial parameters (i.e., variances associated with the visual and auditory modalities) are derived from data in the unimodal conditions. In addition to these normative models, we consider a *descriptive* model. It is formally identical to the normative optimal model (Equation 1), except that the parameters are fit to actual responses in the bimodal condition. If the referential task induces sub-optimality (due, for instance, to the arbitrary nature of the sound-object association), then the descriptive model should explain more variance than the optimal model does.

Comparison of the optimal and the descriptive models allows us, not only to quantify

[6] Further technical detail about model fitting in the unimodal conditions will be given in the method section of Experiment 1.

how much people deviate from optimality, but also to understand precisely the nature of this deviation. Let σ_A^2 and σ_V^2 be the values of the variances used in the optimal model (derived from the unimodal conditions), and σ_{Ab}^2 and σ_{Vb}^2 be the values observed through the descriptive model in the bimodal condition. Deviation from optimality is measured in two ways. First, we measure the change in the values of the variance specific to each modality, that is, how σ_A^2 compares to σ_{Ab}^2, and how σ_V^2 compares to σ_{Vb}^2. Second, we measure changes in the proportion of the visual and auditory variances, i.e., we examine how $\frac{\sigma_A^2}{\sigma_V^2}$ compares to $\frac{\sigma_{Ab}^2}{\sigma_{Vb}^2}$. The first measure allows us to test if response precision changes for each modality when we move from the unimodal to the bimodal conditions. The second allows us to test the extent to which the weighting scheme follows the prediction of the optimal model. The reason we used the proportion of the variances as a measure of cross-modal weighting is because this proportion corresponds to the slope[7] of the decision threshold in the audio-visual space (Figure 2). The decision threshold is defined as the set of values in this audio-visual space along which the posterior is equal to 0.5. Formally speaking, the decision threshold has the following form:

$$v = -\frac{\sigma_V^2}{\sigma_A^2} a + v_0$$

If the absolute value of the slope derived from the descriptive model is greater than that of the optimal model, the corresponding shift in the decision threshold indicates that participants have a preference for the auditory modality in the bimodal case. Similarly, a smaller absolute value of the slope would lead to a preference for the visual modality. The limit cases are when there is exclusive reliance on the auditory cue (a vertical line), and where there is exclusive reliance on the visual (a horizontal line).

There are three possible ways human responses can deviate from optimality. These

[7]Or more precisely the absolute value of the slope.

scenarios are illustrated in Figure 3, and are as follows:

1) Both variances may increase, but their proportion remains the same. That is, $\sigma^2_{Ab} \geqslant \sigma^2_A$ and $\sigma^2_{Vb} \geqslant \sigma^2_V$, but $\frac{\sigma^2_{Ab}}{\sigma^2_{Vb}} \approx \frac{\sigma^2_A}{\sigma^2_V}$. In this case, sub-optimality would be due to increased randomness in human responses in the bimodal condition. However, this randomness would not affect the relative weighting of both modalities, i.e., participants would still weigh modalities according to the relative reliability predicted by the optimal model.

2) The auditory variance increases at a higher rate. That is, $\sigma^2_{Ab} \gg \sigma^2_A$ and $\sigma^2_{Vb} \geqslant \sigma^2_V$, leading to $\frac{\sigma^2_{Ab}}{\sigma^2_{Vb}} > \frac{\sigma^2_A}{\sigma^2_V}$. In this case, sub-optimality would consist not only in participants being more random in the bimodal condition, but also in having a systematic preference for the visual modality, even after accounting for informational reliability.

3) The visual variance increases at a higher rate. That is, $\sigma^2_{Vb} \gg \sigma^2_V$, and $\sigma^2_{Ab} \geqslant \sigma^2_A$, leading to $\frac{\sigma^2_{Ab}}{\sigma^2_{Vb}} > \frac{\sigma^2_A}{\sigma^2_V}$. This case is the reverse of case 2, i.e., in addition to increased randomness in the bimodal condition, there is a systematic preference for the auditory modality, even after accounting for informational reliability.

We compared these models to human responses in three experiments. In Experiment 1, we studied the case where bimodal uncertainty was due to categorical variability, only. In Experiment 2 and 3 we added auditory and visual noise, respectively, on top of categorical variability.

Experiment 1

In this Experiment, we test the predictions of the model in the case where uncertainty is due to categorical variability (i.e., ambiguity in terms of category membership) and inherent sensory noise only. We do not add any external noise to the background. Thus, we use the following cue weighting scheme:

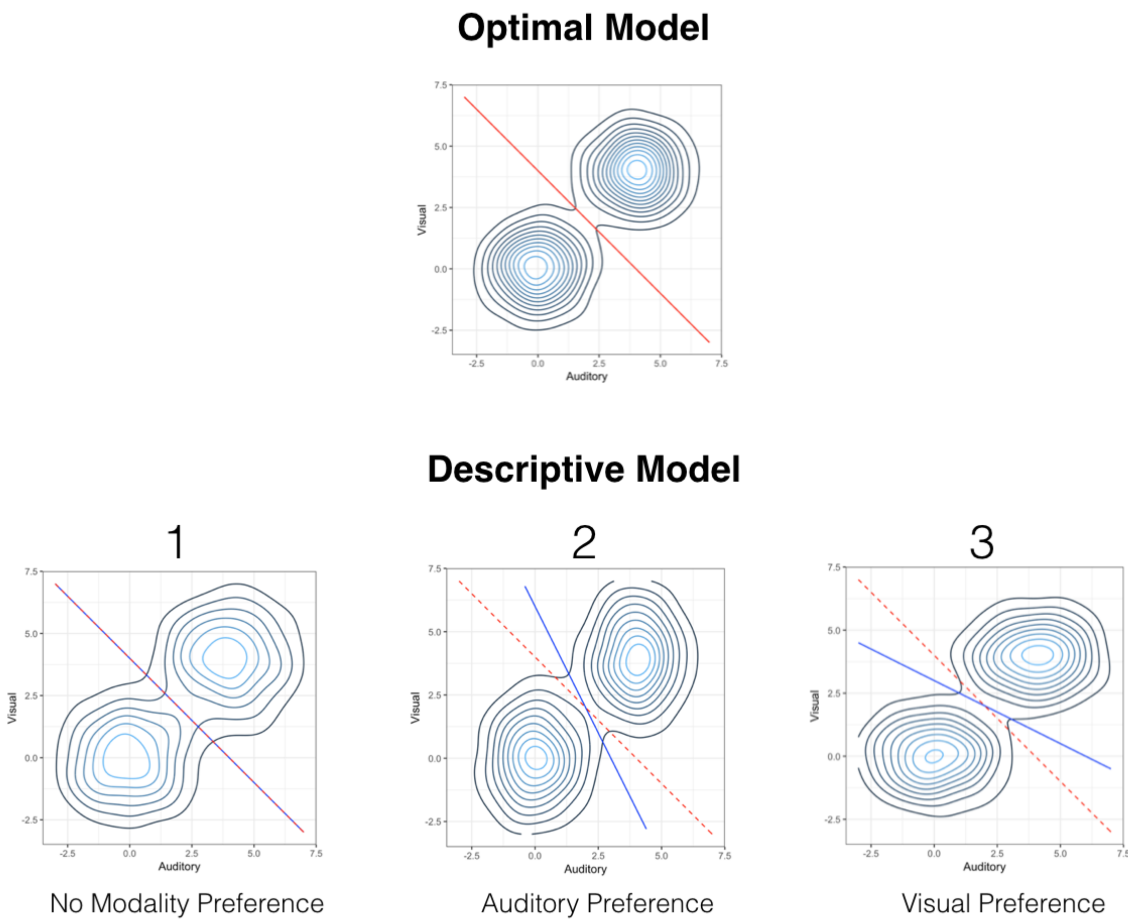

Figure 3. Illustration using simulated data showing the example of a prediction made by the optimal model (top), and the three possible ways human participants can deviate from this prediction (bottom). These cases are the following: 1) The variance increases equally for both modalities, but the weighting scheme (characterized by the decision threshold) is optimal, 2) The auditory variance increases at a higher rate, leading to a preference for the auditory modality, and 3) The visual variance increases at a higher rate, leading to a preference for the visual modality.

$$\beta_a \propto \frac{1}{\sigma_A^2} = \frac{1}{\sigma_{A_C}^2 + \sigma_{A_N}^2}$$

$$\beta_v \propto \frac{1}{\sigma_V^2} = \frac{1}{\sigma_{V_C}^2 + \sigma_{V_N}^2}.$$

Methods

Participants. We recruited a planned sample of 100 participants from Amazon Mechanical Turk. Only participants with US IP addresses and a task approval rate above 85% were allowed to participate. They were paid at an hourly rate of $6/hour. Participants were excluded if they reported having experienced a technical problem of any sort during the online experiment (N=14), or if they had less than 50% accurate responses on the unambiguous training trials (N=6). The final sample consisted of N = 80 participants. All participants provided informed consent before taking the experiment. [8]

Stimuli. For auditory stimuli, we used the continuum introduced in Vroomen, Linden, Keetels, Gelder, and Bertelson (2004), a 9-point /aba/–/ada/ speech continuum created by varying the frequency of the second (F2) formant in equal steps. We selected 5 equally spaced points from the original continuum by keeping the endpoints (prototypes) 1 and 9, as well as points 3, 5, and 7 along the continuum. For visual stimuli, we used a cat/dog morph continuum introduced in Freedman, Riesenhuber, Poggio, and Miller (2001). From the original 14 points, we selected 5 points as follows: we kept the item that seemed most ambiguous (point 8), the 2 preceding points (i.e., 7 and 6) and the 2 following points (i.e., 9 and 10). The 6 and 10 points along the morph were quite distinguishable, and we took them to be our prototypes.

Design and Procedure. We told participants that an alien was naming two objects: a dog, called “aba” in the alien language, and a cat, called “ada”. In each trial, we presented the first object (the target) on the left side of the screen simultaneously with the corresponding sound. For each participant, the target was always the same (e.g., dog-/aba/). The second sound-object pair (the test) followed on the other side of the screen after 500ms and varied in its category membership. For both the target and the test, visual stimuli were

[8] The sample size and exclusion criteria were specified in the pre-registration at https://osf.io/h7mzp/.

present for the duration of the sound clip ($\sim$ 800ms). We instructed participants to press "S" for same if they thought the alien was naming another dog-/aba/, and "D" for different if they thought the alien was naming a cat-/ada/. We randomized the sound-object mapping (e.g., dog-/aba/, cat-/ada/) as well as the identity of the target (dog or cat) across participants.

The first part of the experiment trained participants using only the prototype pictures and the prototype sounds (12 trials, 4 each from the bimodal, audio-only, and visual-only conditions). After completing training, we instructed participants on the structure of the task and encouraged them to base their answers on both the sounds and the pictures (in the bimodal condition). There were a total of 25 possible combinations in the bimodal condition, and 5 in each of the unimodal conditions. Each participant saw each possible trial twice, for a total of 70 trials/participant. Trials were blocked by condition and blocks were presented in random order. The experiment lasted around 15 minutes.[9]

Model fitting details.

Unimodal conditions.

Remember that data in these conditions allows us to derive the variances of both the auditory and the visual categories, and that these variances are used to make predictions about bimodal data (in the visual and auditory baselines as well as in the optimal model). These individual variances were derived as follows (we explain the derivation for the auditory-only case, but the same applies for the visual-only case). We use the same Bayesian reasoning as we did in the derivation of the bimodal model: When presented with an audio instance a, the probability of choosing the sound category 2 (that is, to answer "different") is the posterior probability of this category $p(A_2|a)$. If we assume that both sound categories

[9]The experiment can be accessed and played from the github repository: https://github.com/afourtassi/WordRec/

have equal variances, the posterior probability reduces to:

$$p(A_2|a) = \frac{1}{1 + (1 + b_A)\exp(\beta_{a0} + \beta_a a)}$$

with $\beta_a = \frac{\mu_{A_1} - \mu_{A_2}}{\sigma_A^2}$ and $\beta_{a0} = \frac{\mu_{A_2}^2 - \mu_{A_1}^2}{2\sigma_A^2}$. b_A is the response bias in the auditory-only condition. For this model (as well as all other models in this study), we fixed the values of the means to be the end-points of the corresponding continuum, since these points are the most typical instances in our stimuli. Thus, we have $\mu_{A1} = 0$ and $\mu_{A2} = 4$ (and similarly $\mu_{V1} = 0$, and $\mu_{V2} = 4$). This leaves us with two free parameters: the bias b_A and the variance σ_A^2. To determine the values of these parameters, we fit the unimodal posterior to human data in the unimodal case.

Bimodal condition.

In this condition, only the descriptive model is fit to the data, using the expression of the posterior (Equation 1). Since the values of the means are fixed, we have 3 free parameters: the variances for the visual and the auditory modalities, respectively, and b, the response bias. The visual and auditory baselines as well as the optimal model are not fit to the bimodal data, but their predictions are tested against these bimodal data. All these normative models use the variances derived from the unimodal data and the bias term derived from the fit to bimodal data.

Although the paradigm is within-subjects, we did not have enough statistical power to fit a different model for each individual participant (but see Experiment 4). Instead, models were constructed with data collapsed across all participants. The fit was done with a nonlinear least squares regression using the NLS package in R (Bates & Watts, 1988). We computed the values of the parameters, as well as their 95% confidence intervals, through non-parametric bootstrap (using 10000 iterations).

Table 1

Statistics for the dataset we used.

	Auditory		Visual		Bimodal		
Experiment	b_A	Var_A	b_V	Var_V	b_b	Var_{Ab}	Var_{Vb}
Experiment1	0.20	2.04	0.12	3.33	0.34	4.96	7.06
Experiment2	0.18	4.70	0.24	3.93	0.38	9.84	5.21
Experiment3	0.24	1.94	-0.11	13.00	0.35	3.00	39.42
Experiment4	0.40	1.92	0.22	3.24	0.42	4.17	7.28

Results and analysis

Unimodal conditions. Average categorization judgments and best fits are shown in Figure 4. The categorization function of the auditory condition was slightly steeper than that of the visual condition, meaning that participants perceived the sound tokens slightly more categorically and with higher certainty than they did with the visual tokens. The unimodal models' estimates are shown in Table 1.

Bimodal condition. Figure 5 compares the predictions of the normative and descriptive models against human responses. Remember that the normative models use the parameters estimated from the unimodal conditions (where people see input from only one modality) to predict behavior in the bimodal condition (where people see input from both modalities). The descriptive model has a similar structure than the optimal model, but is directly fit to human responses in the bimodal condition in order to allow us to assess deviation from optimaity.

We found, through comparing the correlation values, that the optimal model explained more variance than the visual and auditory models did. However, the optimal model was not perfect: It explained less variance than the descriptive model did, which indicates a

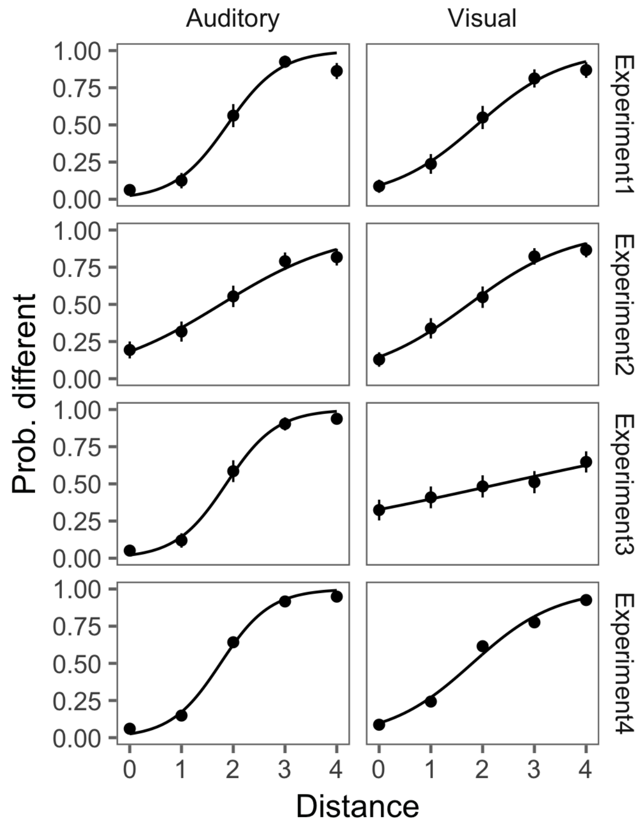

Figure 4. Human responses in the unimodal conditions across the three experiments. Points represent the proportion of ‘different’ to ‘same’ responses in the auditory-only condition (left), and visual-only condition (right). Error bars are 95% confidence intervals. Solid lines represent best unimodal posterior fits.

deviation from optimality. To investigate this deviation, we compare the parameter values of the optimal model to the values obtaied in the decriptive model (Table 1).[10]. We note an increase in *both* the auditory and visual variances. This increase in noise is compatible with the fact that human responses appear to be pulled towards chance (i.e., the value O.5) when compared to the optimal model (see 5). Below we investigate if this deviation from optimality can be related to the cue combination strategy.

[10]Note that the descriptive model explained almost all the variance in mean responses, which makes it a reasonble proxy for human real performance in the bimodal condition.

Cue combination. We analyzed if the cue combination was performed in an optimal way, or if there was a systematic preference for one modality when making decisions in the bimodal condition. As explained in 3, modality preference can be characterized formally as a deviation from the decision threshold predicted by the optimal model. The results in Figure 6 (top) show both the decision threshold derived from the descriptive model (in black) and the decision threshold predicted by the optimal model (in red). We found that the descriptive and optimal decision thresholds were almost identical. Indeed, non-parametric resampling of the data showed no evidence of a deviation from the optimal prediction (Figure 6, bottom).

Discussion

This experiment studied the way participants combine multimodal information to recognize novel words. We found that the optimal model explained more variance than the auditory or the visual models did, indicating that particiapants take into account both the auditory and visual cues when making a decision. That said, Figure 5 shows that the participants deviated slightly — but systematically— from the optimal prediction in that they were slightly pulled toward chance (i.e., the probability 0.5). This fact was captured by the increase in the value of the variance associated with each modality (as can be noted from Table 1). Note, however, that despite this increase response randomness in the bimodal condition, our analysis of modality preference showed that the *relative* values of these variances were not different (Figure 6), meaning that there was no evidence for a modality preference.

To sum up, 1) the participants used both the auditory and visual information, 2) they responded slightly more randomly that what was predicted, but 3) this increased randomness was general and did not influence the cue combination strategy, i.e., the participants still weighted modalities according to their relative reliability as predicted by the optimal model.

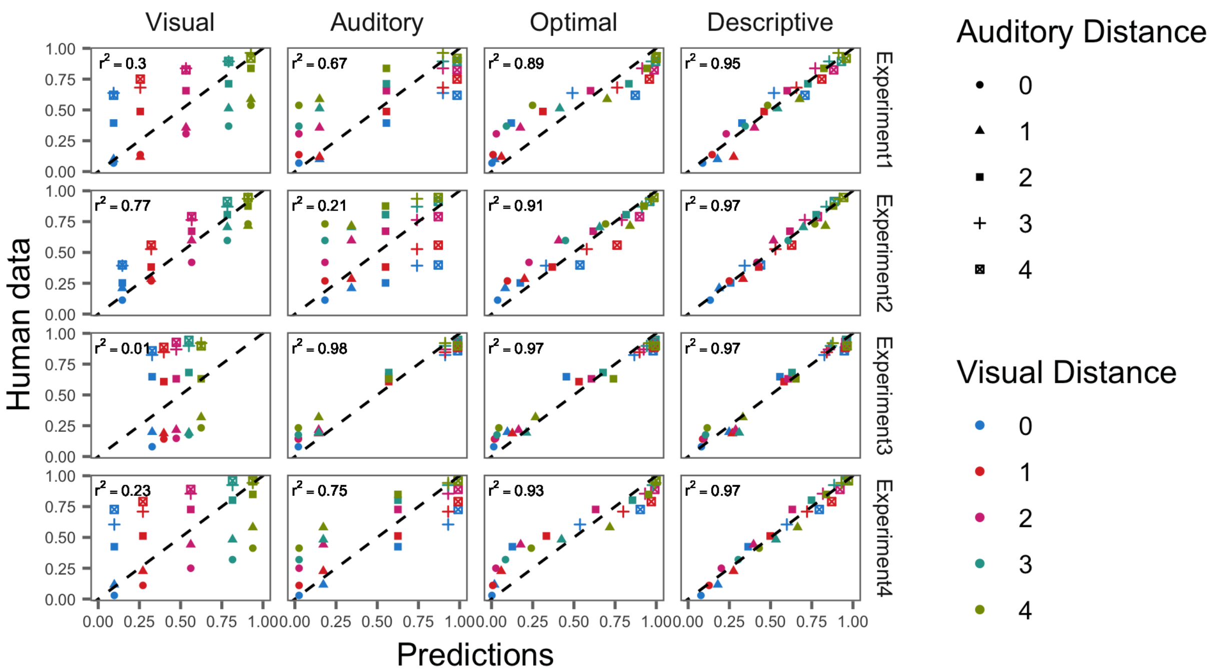

Figure 5. Human responses vs. Models' predictions in the bimodal condition across the three experiments. Each point represents data form a particular audio-visual matching (corresponding to an instance from the set of 5x5 possible matchings in the audio-visual space). Shape represents auditory distance from the target, and color represents visual distance from the target. Thus, each point is characterized by both shape and color.

This situation corresponds to the first case of sub-optimality described in Figure 3.

In Experiment 1, we tested word recognition when there was multimodal uncertainty in terms of category membership and inherent perceptual noise, only. In real life, however, both sound and visual tokens can undergo distortions due to noisy factors in the environment (e.g., car noise in the background, blurry vision in a foggy weather). In Experiment 2 and 3, we explore this additional level of uncertainty.

Experiment 2

In this Experiment, we explored the effect of added envirnonmental noise σ_E^2 on performance. We tested a case where the background noise was added to the auditory modality. We were interested to know if participants would treat this new source of uncertainty as predicted by the optimal model, that is, according to the following weighting scheme:

$$\beta_a \propto \frac{1}{\sigma_A^2} = \frac{1}{\sigma_{C_A}^2 + \sigma_{N_A}^2 + \sigma_{E_A}^2}$$
$$\beta_v \propto \frac{1}{\sigma_V^2} = \frac{1}{\sigma_{C_A}^2 + \sigma_{N_A}^2}.$$

The alternative hypothesis is that noise in one modality leads to a systematic preference for the non-noisy modality.

Methods

Participants. A sample of 100 participants was recruited online through Amazon Mechanical Turk. We used the same exclusion criteria as in Experiment 1. 7 participants were excluded because they had less than 50% accurate responses on the unambiguous training trials. The final sample consisted of N = 93 participants.

Stimuli and Procedure. We used the same visual stimuli as in Experiment 1. We also used the same auditory stimuli, but we convolved each item with Brown noise of amplitude 1 using the free sound editor Audacity (2.1.2). The average signal-to-noise ratio was - 4.4 dB. The procedure was exactly the same as in the previous experiment, except that the test stimuli (but not the target) were presented with the new noisy auditory stimuli.

Results

The analysis are similar to the analysis we did in Experiment 1.

Unimodal condition. We fit a model for each modality. Figure 4 shows human responses together with their best fits. The visual data is a replication of the visual data in Experiment 1. The auditory data, in contrast, were flatter, showing more uncertainty.

Bimodal condition. We used the values derived from the unimodal condition to construct the visual, auditory and optimal models. In addition, we fit a descriptive model which allowed us to assess real human performance in this condition. Figure 5 shows that, similar to Experiment 1, the optimal model explained more variance than the auditory and visual models did (note, however, that the visual model explained more variance than the auditory model did). Also similar to Exeperiment 1, the values of the variances increased in the bimodal condition (Table 1).

Cue combination. Here we investigated whethere the observed increase in the auditory and visual variances affected the relative weighting of the corresponding modalities. Figure 6 (top) shows that the participants' decision threshold deviated from optimality, and that this deviation was biased towards the visual modality (the non-noisy modality). Indeed non-parametric resampling of the data showed a decrease in the value of the slope in the descriptive model compared to the optimal model (Figure 6, bottom).

Discussion

Experiment 2 tested audi-visual combination in the case where the auditory input was noisy. We found, similar to Experiment 1, that the optimal model explained more variance than the auditory or the visual models did. In other words, despite additional noise, participants still used information from the noisy modality to recognize words. We also found a similar discrepancy between the descriptive and optimal models as response randomness increased along both the auditory and the visual modalities. As for the relative weighting, and contrary to Experiment 1 where modalities were weighted optimally, we found in this experiment that the visual modality had a greater weight than what was expected from its relative reliability. This situation corresponds to the second case of sub-optimality described in Figure 3.

Whereas in Experiment 2 we tested the case of added background noise to the auditory modality, in Experiment 3 we test the case of added noise to the visual modality.

Experiment 3

Similar to Experiment 2, we were interested to know if participants would treat additional uncertainty as predicted by the optimal model, that is, according to the following weighting scheme:

$$\beta_a \propto \frac{1}{\sigma_A^2} = \frac{1}{\sigma_{A_C}^2 + \sigma_{A_N}^2}$$
$$\beta_v \propto \frac{1}{\sigma_V^2} = \frac{1}{\sigma_{V_C}^2 + \sigma_{V_N}^2 + +\sigma_{V_E}^2}.$$

The alternative hypothesis is that noise in the visual modality would lead to a preference for the auditory input, just like noise in the auditory modality lead to a preference for the visual input in Experiment 2.

Methods

Participants. A planned sample of 100 participants was recruited online through Amazon Mechanical Turk. We used the same exclusion criteria as in both previous experiments. N=2 participants were excluded because they reported having a technical problem, and N=10 participants were excluded because they had less than 50% accurate responses on the unambiguous training trials. The final sample consisted of N = 88 participants.

Stimuli and Procedure. We used the same auditory stimuli as in Experiment 1. We also used the same visual stimuli, but we blurred the tokens using the free image editor GIMP (2.8.20). We used a Gaussian blur with a radius[11] of 10 pixels. The experimental procedure was exactly the same as in the previous Experiments.

Results

Unimodal conditions. Figure 4 shows responses in the unimodal conditions as well as the corresponding fits. The auditory data is a replication of the auditory data in Experiment 1. As for the visual data, we found that, in contrast to Experiment 1 and 2, responses were flatter, showing much more uncertainty.

Bimodal condition. Figure 5 shows that almost all the variance was captured by the auditory model alone, the addition of visual information in the optomal model did not improve the prediction of human responses. Similar to Exeperiment 1 and 2, the values of the variances increased in the bimodal condition (Table 1).

Cue Combination. Figure 6 indicates that the decision threshold was biased towards the auditory modality (the non-noisy modality). Indeed non-parametric resampling of the data showed an increase in the value of the slope in the descriptive model compared to the optimal model (Figure 6).

[11] A features that modulates the intensity of the blur.

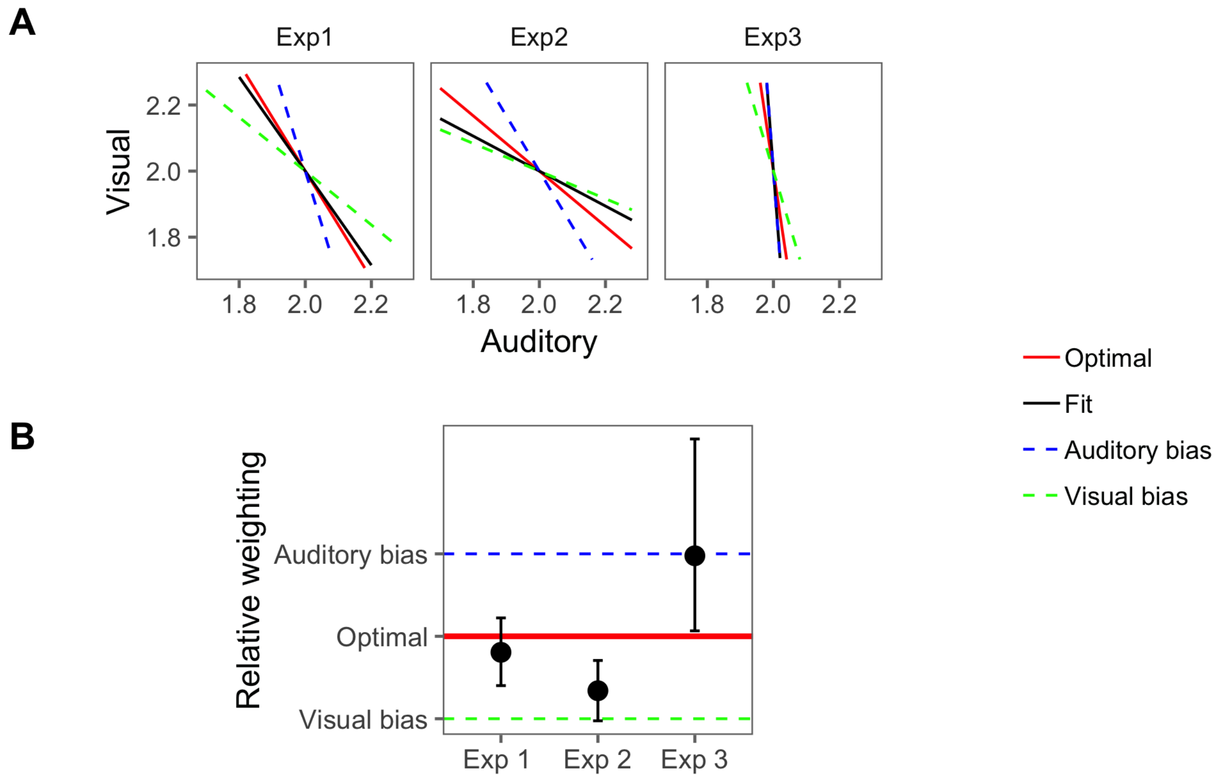

Figure 6. Modality preference is characterized as a deviation from the optimal decision threshold. A) The decision thresholds of both the optimal and the descriptive models (solid red and black lines, respectively). Deviation from optimality is compared to two hypothetical cases of modality preference. In these cases, deviation from optimality is due to over-lying on the visual or the auditory input by a factor of 2 (green and blue dotted lines, respectively). B) An alternative way to represent the same data. Each point represents the value of the decision threshold's slope derived from the descriptive model relative to that of the optimal model (log-scaled). The lines represent the optimal case as well as the two hypothetical cases of modality preference. Error bars represent 95% confidence intervals over the distribution obtained through non-parametric resampling.

Discussion

Experiment 3 tested audi-visual combination in the case where the visual input was noisy. Whereas in previous experiments the optimal model explained more variance than the auditory or the visual models did, here the auditory model alone explained almost all the variance. In other words, though participants were sensitive to variation in the noisy visual input when presented in isolation (as shown in Figure 4), they tended to ignore this information when the visual input was presented simultaneusel with the auditory input (i.e., in the bimodal condition). Instead, they relied almost exclusively on the non-noisy auditory modality.[12]

This finding corresponds to the third case of sub-optimality described in Figure 3. Indeed, precision dropped for both modalities in the bimodal condition compared to the unimodal condition. But the drop was much greater for the visual modality, resulting in a much lower weight assigned to it than what is expected from the optimal model. Therefore, just like participants over-relied on the visual modality when the auditory modality was noisy (Experiment 2), they also over-relied on the auditory modality when the visual modality was noisy (Experiment 3).

So far we have studied the problem of cue combination at the population level — the models were fit to the data aggregated across all participants. However, it is important to investigate individual variability, especially in Experiment 1 where we reported optimal cue combination. In fact, it is possible that a large part of the participants relied primarily on the visual modality and another part on the auditory modality. Such an extreme individual variability could possibly lead to an aggregate beahvior which appears optimal, but such optimality would be spurious. In order to rule out this extreme case, we need to examine the distribution of the specific cue combibination strategies followed by the participants.

[12]The reason why we saw this (floor) effect when we added noise to the visual modality (Experiment 3), and not when we added noise to the auditory modality (Experiment 2), is the fact that our visual stimuli were originally perceived less categorically and with less certainty than the auditory stimuli (see Experiment 1 in reffig:unimodal). This fact made it more likely for the visual categorization function to become flat and uninformative after a few drops in precision due to noise on the one had, and to the additional randomness induced by the bimodal presentation on the other hand.

Experiment 4

As we noted earlier, we did not have enough statistical power to fit a different model for each participant. Thus, in the current experiment, we re-ran Experiment 1 while extending its length, allowing us to collect the number of datapoints necessary to fit the models for each participant.

Participants. We recruited a planned sample of $N = 50$ participants from Amazon Mechanical Turk. Only participants with US IP addresses and a task approval rate above 99% were allowed to participate. They were paid at an hourly rate of $6/hour. Participants were excluded if they reported having experienced a technical problem of any sort during the online experiment ($N = 0$), or if they had less than 75% accurate responses on the unambiguous training trials ($N = 7$). The final sample consisted of $N = 43$ participants. All participants provided informed consent before taking the experiment.[13]

Stimuli. We used the same stimuli as in Experiment 1.

Design and Procedure. The design and procedure were similar to Experiment 1. There were, however, two differences: 1) We increased the number of responses elicited per subject from 70 to 300, and 2) we randomized the order of the three blocks (i.e., visual-only, auditory-only, and audio-visual) *within* subject: Each participant saw the 3 blocks exactly 6 times, covering all possible ordering combinations. Unlike the between-subjet randomzation in Experiment 1, this choices allowed us to avoid any confounding effects due to the order of exposure.

Results

[13]The sample size, exclusion criteria and the main analysese were pre-registered at https://osf.io/h7mzp/.

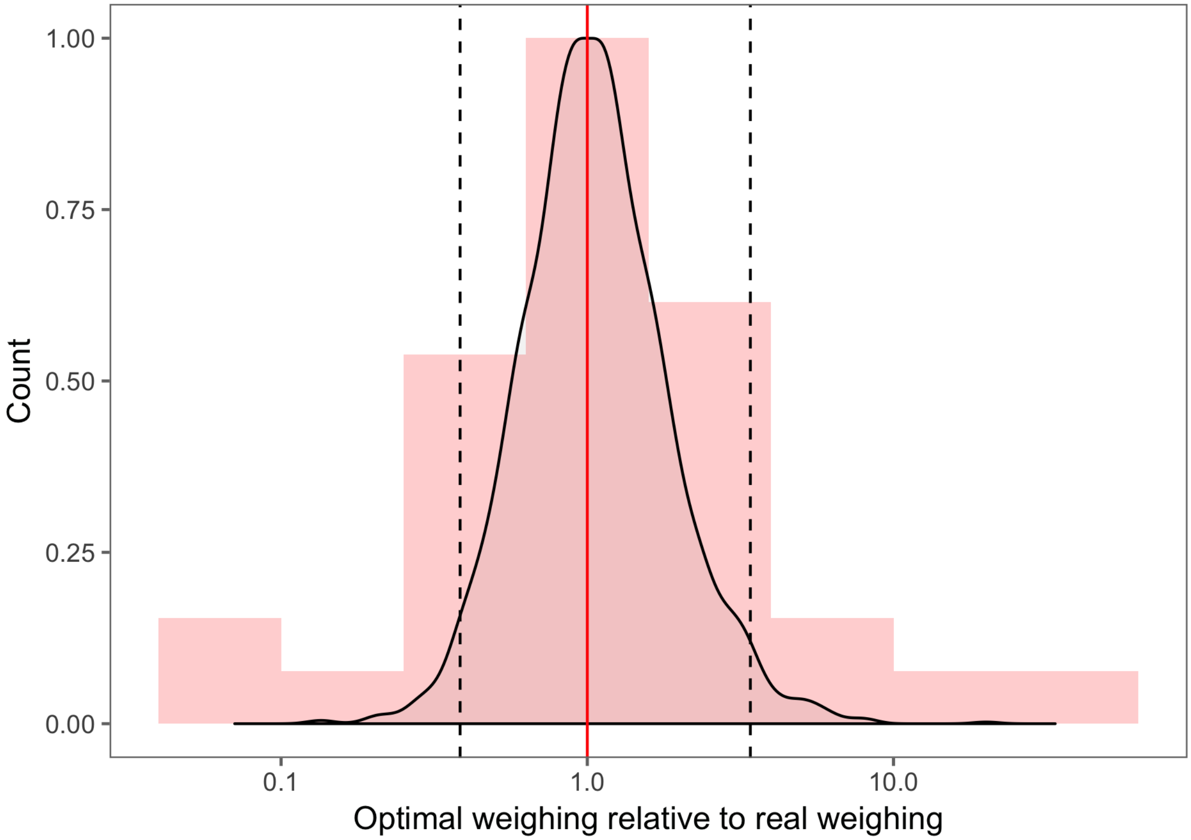

Figure 7. The histogram shows the distribution of the participants' optimal cue weighing relative the observed (i.e., descriptive) cue weigting (see Figure 3). Participant are optimal when this relative value is equal to 1 (red solid line). Values larger than 1 suggest over-reliance on the auditory modality whereas values lower than 1 suggest over-reliance on the visual modality. The density plot shows the distribution of simulated individual responses from the population-level probabilistic model. The dashed lines represent 95% confidence intreval on this simulated distribution. Participants that are outside this interval can be understood as over-relying on the auditory or visual modality in a non-random way (i.e., with $p < 0.05$).

Unimodal and Bimodal conditions. In order to replicate the analysis of Experiment 1, we started by fitting population-level models to the aggregated data. Indeed, we found that the results — as shown in Figure 4, Figure 5, and Table 1 — mirror closely the patterns obtained in Experiment 1.

Cue combinaton. We analyzed the cue combination strategies at the individual level. For each participant, we computed the optimal weighing, $\frac{\sigma_A^2}{\sigma_V^2}$, relative to the observed (i.e., descriptive) weighing, $\frac{\sigma_{Ab}^2}{\sigma_{Vb}^2}$. We show the resulting distribution in Figure 7. We note first that the distribution has a rather bimodal shape, centered around the optimal cue combination strategy. This finding rules out the hypotheis that optimality at the population level is a spurious finding, i.e., only obtained via aggregating over various sub-otimal strategies.

In addition, we asked whether the observed variance in the individual distribution was due to the randomness inherent to the process of sampling from a probabilsitic model or whether it corresponded to a real between-subject variability induced by different cue weighing strategies. We simulated responses through sampling from the population-level models and we computed the resuting distribution of cue weighing for each simulated indivudual leading to the density function in Figure 7. We can observe that most empirical values fall within the 95% confidence interval of the simulated density, showing that this part of the variance can be due to mere sampling randomness. However, a few participants had values outide this interval, indicating that they systematically over-relied on the visual modality ($N = 5$) or the auditory modality ($N = 6$) with p-value$ < 0.05$.

Discussion

This experiment was an extension to Experiment 1. Through collecting larger-size data per subject, we were able to analyze the cue combination optimality, not only at the population level, but also at the individual level. The population-level analysis replicated the results of Experiment 1. The individual-level analysis showed that the distribution of cue combination scores had a unimodal shape centered around the optimal combination, thus reflecting geuine cue combination at the individual level. That said, the variance of this distribution indicates that a few participants tended to over-rely on the auditory modality and others tended to over-rely on the visual modality beyond sampling errors.

General Discussion

In the current paper, we explored word identification under uncertainty about both words and their referents. We conducted an ideal observer analysis of this task whereby a model provided predictions about how information from each modality should be combined in an optimal fashion. The predictions of the model were tested in a series of four experiments where instances of both the form and the meaning were ambiguous with respect to their category membership only (Experiment 1 and 4), when instances of the form were perturbed with additional background noise (Experiment 2), and when instances of the referent were perturbed with additional visual noise (Experiment 3). We discuss the findings of these studies first with respect to our ideal observer model and inferences about optimality and second with respect to their implications for word identification more generally.

Patterns of optimality and sub-optimality

In all of our experiments, and when compared to the predictions of the visual or the auditory models, participants generally relied on both modalities to make their decisions in the bimodal condition. Indeed, in Experiment 1 and 2, the optimal model accounted for more variance in mean responses than the auditory or the visual models did. In Experiment 3, participants appeared to rely on one modality, but this was likely a floor effect, due to the fact that noise made the visual input barely perceptible. Further, in Experiment 1 and 4, which did not involve background noise, participants not only relied on both modalities, but generally weighted these modalities according to the predictions of the optimal model, that is, according to their relative reliability. At the individual level, Experiment 4 showed that most participant were near-optimal. Only a few subjects over-relied on the auditory or visual modalities beyond sampling errors.

More generally, the idea is that it is easier to integrate correlated, redundant cues (e.g., the size of a an object based on both visual and haptic information) into a unified percept, than it is to combine perceptually uncorrelated cues to make a categorization judgement ,e.g., recognizing a freshly learned object category based on its distinctive features such as shape and color. We argue that our task — which consists in combining perceptually uncorrelated cues from the auditory and visual modalities to recognize a novel word — is more similar to the second case.

Despite this overall pattern, we documented two major cases of sub-optimality. First, in all experiments, the variance associated with each modality increased in the bimodal condition compared to the unimodal conditions. Participants responded slightly more randomly in the bimodal condition than they did in the unimodal conditions. This finding contrasts with research on multisensory integration where associations tend to lead to a higher precision (e.g., Ernst & Banks, 2002). Nevertheless, research on multisensory integration has typically dealt with a special case involving correlated, redundant multimodal cues, e.g., determining the size of an object based on visual and haptic information. Another possible case of multisensory integration involves perceptually uncorrelated cues, e.g., recognizing a novel category based on some features such as shape and color (e.g., Bankieris et al., 2017) or, in our case, recognizing novel words cues based on phonological and semantic cues. Perhaps it is harder to integrate uncorreated cues because information form these cues must be encoded separately through the decision making process. In fact, retaining two separate cues at the same time instead of forming one unified percept (as in multisensory integration of redundant cues), or instead of retaining only one cue (as in the unimodal case), is likely to place extra demands on cognitive resources, which, in turn, could cause general performance to drop. Indeed, there is evidence that cognitive load due to divided attention (e.g., when performing two tasks at the same time) has a detrimental effect on word recognition (Mattys & Wiget, 2011).

Some previous research bas found similar cases of suboptimal behavior. For instance, studies that have explored the identification of ambiguous, newly learned pairs of word-referent associations have reported what appears to be a decrease in speech perception acuity in both children (Stager & Werker, 1997) and adults (Pajak, Creel, & Levy, 2016). Recently, Hofer and Levy (2017) provided a probabilistic model of this phenomenon. In agreement with the findings of our study, Hofer and Levy (2017) characterized the apparent reduction in perceptual acuity as an increase in the noise variance of the auditory modality. Our findings, besides providing more evidence to this documented fact, suggest that the reduction in perceptual acuity may occur simultaneously in both the auditory *and* the visual modalities.

The second case of sub-optimality is related to how participants weighted the cues from the visual and the auditory modalities in a noisy context. In contrast to Experiment 1 adn 4 where the combination was indistinguishable from the optimal prediction, results of Experiment 2 and 3 suggested that participants had a systematic preference for the other (non-noisy) modality. This finding aligns with previous work that suggests that when the auditory signal is degraded, participants compensate by relying more on other sources of information such as the accompanying visual cues, the semantic/syntactic context, or the top-down expectations. This kind of compensation has been observed with adults (Mattys et al., 2012; Tanenhaus et al., 1995), and recent evidence suggests that it starts in childhood (K. MacDonald, Marchman, Fernald, & Frank, 2018; Yurovsky, Case, & Frank, 2017). Generally speaking, previous experimental studies have not differentiated between an optimal compensatory strategy (i.e., relying more on the alternative source while using all information still available in the distorted signal), and a sub-optimal strategy (i.e., relying more on the alternative source while ignoring at least some of the information still available in the distorted signal), however. The formal approach followed in this paper allowed us to tease apart these two possibilities, and our analysis supports the sub-optimal compensatory strategy: The preference for the non-noisy modality is above and beyond what can be explained by the relative reliability alone, meaning that the participants tend to ignore at least part of the information still available in the noisy modality.

This second case of sub-optimal behavior may be related to the fact that language understanding under degraded conditions is cognitively more taxing than language understanding under normal conditions (Mattys et al., 2012; Peelle, 2018; Rönnberg, Rudner, Lunner, Zekveld, & others, 2010). Perhaps these demands lead to sub-optimal behavior (i.e., over-reliance on the less noisy cue) as participants seek to minimized cognitive effort. One could also explain this phenomenon in terms of the metacognitive experience about the fluency with which information is processed. The perceived perceptual fluency (e.g., the ease with which a stimulus' physical identity can be identified) can affect a wide variety of human judgements (see Schwarz, 2004 for a review). In particular, variables that improve fluency tend to increase liking/preference (Reber, Winkielman, & Schwarz, 1998). In our case, the subjective experience of lower fluency in the noisy modality might cause people to underestimate information that can be extracted from this modality, especially when presented simultaneously with a higher fluency alternative.

Word recognition in the wild

An important question to ask is how the combination mechanism — as revealed in our controlled study — scales up to real life situations. Note that in order to test audio-visual cue combination under uncertainty, we had to use a case of double ambiguity, that is, a case where both the word forms ("ada"–"aba") and the referents (cat–dog) were similar and, thus, confusable. However, to what extent does such a case occur in real languages?
Cross-linguistic corpus analyses suggest that lexical encoding tends, surprisingly, towards double ambiguity in many languages (Dautriche, Mahowald, Gibson, & Piantadosi, 2017; Monaghan, Shillcock, Christiansen, & Kirby, 2014; Tamariz, 2008). For instance, Dautriche et al. (2017) analyzed 100 languages and found that words that are similar phonologically

tend to be similar semantically as well. These studies suggest that the case of double uncertainty, though perhaps not pervasive, could be a real issue in language as it increase the probability of confusability for many words. That said, the inferences discussed here might play a more significant role in naturalistic language comprehension when ambiguity in both the form and/or the referent is induced by an *external* noisy context — e.g., a very noisy party or a far away referent — even when these forms and referents are not confusable in normal situations.

Though we only studied adult performance in this paper, the problem of word recognition under uncertainty is likely more pressing for children. In fact, children have greater difficulties differentiating the meanings of novel similar-sounding words (e.g., “bin” vs. “din”), even when these words are uttered very clearly (Creel, 2012; Merriman & Schuster, 1991; Stager & Werker, 1997; Swingley, 2016; White & Morgan, 2008). Such similar-sounding words can be shown to be differentiated by infants in simplified experimental settings (e.g., Yoshida, Fennell, Swingley, & Werker, 2009). Nevertheless, Swingley (2007) suggested that the ability to make this differentiation is likely not mature in early childhood; children’s representations are almost certainly noisier than the adults’ representations and may also be encoded with lower confidence. Thus, children even more than adults might benefit from additional disambiguating cues during new word-referent encoding and recognition.

A multi-modal cue combination strategy might help children not only recognize words, but also refine their underlying phonological and semantic representations in the process. Previous research in early word learning has – whether implicitly or explicitly – largely treated the process of refining the word form and of refining the word meaning as following a linear timeline. However, developmental data reveal that children do not wait to have complete acquisition of word forms before they start learning their meanings (Bergelson & Swingley, 2012; Tincoff & Jusczyk, 1999). Rather, both form and meaning representations develop in a parallel fashion. A few studies have already suggested the possibility of an interaction between sound and meaning in early acquisition. For instance, Waxman and Markow (1995) showed that labeling various objects with the same name helps infants form the underlying semantic category (but see Sloutsky & Napolitano, 2003). And in the opposite direction, Yeung and Werker (2009) showed that pairing similar sounds with different objects can helps infants enhance their sensitivity to subtle phonological contrasts in their native language. The present study proposes a first step towards a formal framework where these sorts of sound-meaning interactions in development can be unified and further explored.

One salient limitation of our current work is that we used a restricted and highly simplified stimulus set. For the auditory modality, we used speech categories that varied along a single acoustic dimension. While this dimension might be sufficient to recognize words in our specific case, in general the speech signal is far more complex, varying along several acoustic/phonetic dimensions. Additionally, these dimensions may be highly variable due to various kinds of speaker and context differences.

As for the visual modality, simulating meaningful variability is a more difficult task. Indeed, parameterizing the semantic space has been a notoriously hard problem and thus requires more simplifying assumptions. Following previous studies (Freedman et al., 2001; Havy & Waxman, 2016; Sloutsky & Fisher, 2004), we used a visual continuum along a one-dimensional morph. This choice was motivated by the need to construct a multimodal input where the auditory and visual components are parametrized in a symmetrical fashion, allowing us to compare graded effects of auditory and visual information on categorical judgment. Though such a visual variability is clearly artificial (one does not encounters in real life an animal that is, e.g., 30 % dog and 70 % cat), we assume that the induced uncertainty form this visual stimuli has a similar effect on word recognition as the uncertainty induced by more naturalistic semantic variability.

It is an open question whether people use the same strategy in controlled laboratory conditions and more naturalistic settings where they have to deal with various levels of variability. An answer to this question is likely to involve a multifaceted research approach that goes beyond controlled experimentation. We believe that one fruitful approach is to test computational mechanisms with an input that more accurately represents the full extent of multimodal variability in the learning environment (Dupoux, 2018; Fourtassi, Schatz, Varadarajan, & Dupoux, 2014; Harwath, Torralba, & Glass, 2016; B. C. Roy, Frank, DeCamp, & Roy, 2015).

Conclusions

Our work provides a formal framework where old and new questions about word recognition as well as other categorical tasks involving uncorrelated cues can be given a precise formulation. We used a novel method which enabled us not only to test for optimality as in prevous studies (e.g., Bankieris et al., 2017; Bejjanki et al., 2011), but also to examine systamtically how and by how much people deviate from optimality in their combination strategies. This exploration is important bla bla Rahnev and Denison (2018)

While we focused on the case of arbitrary associations in novel word recognition, it is possible to use the same framework to study, for instance, the case of *iconicity*, that is, when there is a resemblance between the sound of a word and its referent. Previous work has suggested that iconicity, among other things, helps with learning (and generalizing the meaning of) new words (see Dingemanse, Blasi, Lupyan, Christiansen, & Monaghan, 2015 for a review). Using the research strategy in this paper, we can, for example, test whether iconicity has such an advantage because it mitigates the sub-optimal patterns observed with more arbitrary pairings.

Finally, though the current framework only characterizes adult word recognition, it provides a first step towards a model where developmental questions can also be investigated. For instance, future work should explore whether children, like adults, use probabilistic cues from both the auditory and the visual input to recognize ambiguous words, the extent to which they combine these cues in an optimal fashion, and whether this cue combination help them to refine their early phonological and semantic representations.

All data and code for these analyses are available at https://github.com/afourtassi/WordRec

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Appendix 1: derivation of the posterior (Equation 1)

For an ideal observer, the probability of choosing category 2 when presented with an audio-visual instance $w = (a, v)$ is the posterior probability of this category:

$$p(W_2|w) = \frac{p(w|W_2)p(W_2)}{p(w|W_2)p(W_2) + p(w|W_1)p(W_1)}$$

Which reduces to:

$$p(W_2|w) = \frac{1}{1 + \frac{p(w|W_1)}{p(w|W_2)}\frac{p(W_1)}{p(W_2)}}$$

In order to further simplify the quantity $\frac{p(w|W_1)}{p(w|W_2)}$, we use our assumption that the cues are uncorrelated:

$$p(w|W) = p(a, v|W) = p(a|A)p(v|V)$$

Using the log transformation, we get:

$$\ln(\frac{p(w|W_1)}{p(w|W_2)}) = \ln(\frac{p(a|W_1)}{p(a|W_2)}) + \ln(\frac{p(v|W_1)}{p(v|W_2)})$$

Under the assumption that the categories are normally distributed and that, within each modality, the categories have equal variances, we get (after simplification):

$$\ln(\frac{p(a|W_1)}{p(a|W_2)}) = \frac{\mu_{A1} - \mu_{A2}}{\sigma_A^2} \times a + \frac{\mu_{A2}^2 - \mu_{A1}^2}{2\sigma_A^2}$$

and similarly:

$$\ln(\frac{p(v|W_1)}{p(v|W_2)}) = \frac{\mu_{V1} - \mu_{V2}}{\sigma_V^2} \times v + \frac{\mu_{V2}^2 - \mu_{V1}^2}{2\sigma_V^2}$$

When putting all these terms together, we obtain this final expression for the posterior:

$$p(W_2|w) = \frac{1}{1 + (1 + b)\exp(\beta_0 + \beta_a a + \beta_v v)}$$

where

$$1 + b = \frac{p(W_1)}{p(W_2)}$$

$$\beta_0 = \frac{\mu_{A2}^2 - \mu_{A1}^2}{2\sigma_A^2} + \frac{\mu_{V2}^2 - \mu_{V1}^2}{2\sigma_V^2}$$

$$\beta_a = \frac{\mu_{A1} - \mu_{A2}}{\sigma_A^2}$$

$$\beta_v = \frac{\mu_{V1} - \mu_{V2}}{\sigma_V^2}.$$

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