Title: Prosody leaks into the memories of words
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ABSTRACT

The average predictability (aka informativity) of a word in context has been shown to condition word duration (Seyfarth, 2014). All else being equal, words that tend to occur in more predictable environments are shorter than words that tend to occur in less predictable environments. One account of the informativity effect on duration is that the acoustic details of word reduction are stored as part of a word’s representation. Other research has argued that predictability effects are tied to prosodic structure in integral ways. With the aim of assessing a potential prosodic basis for informativity effects in speech production, this study extends past work in two directions; it investigated informativity effects in another large language, Mandarin Chinese, and broadened the study beyond word duration to additional acoustic dimensions, pitch and intensity, known to index prosodic prominence. The acoustic information of content words was extracted from a large telephone conversation speech corpus with over 400,000 tokens and 6,000 word types spoken by 1,655 individuals and analyzed for the effect of informativity using frequency statistics estimated from a 431 million word subtitle corpus. Results indicated that words with low informativity have shorter durations, replicating the effect found in English. In addition, informativity had significant effects on maximum pitch and intensity, two phonetic dimensions related to prosodic prominence. Extending this interpretation, these results suggest that informativity is closely linked to prosodic prominence, and that lexical representation of a word includes phonetic details associated with its prosodic prominence. In other words, the lexicon absorbs prosodic influences on speech production.

Keywords: probabilistic reduction, prosody prominence, lexical representation, speech production, predictability, informativity

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1 Introduction

The process of speech production leaves a phonetic imprint on words that reflects the particular communicative ecology of the speech act, including who’s talking, who’s listening, the common ground in the conversation, etc. If the product of the moment-by-moment influences on speech are stored in memory (i.e., lexicalized) and then accessed as targets for subsequent productions, word forms can drift in the direction of common influences on that word’s production. In this way, words come to take on the phonetic characteristics of their typical usage contexts.

A key result in this vein is that the average contextual predictability of a word, i.e., the “informativity”, predicts both word length (Plantadosi, Tily, & Gibson, 2011) and word duration (Seyfarth, 2014). This result builds on the well-established observation that word length and also word duration both vary with predictability. Frequently occurring words tend to have fewer segments than rarer words (Zipf, 1936). Even when the number of segments is held constant, word frequency negatively correlates with word duration, i.e., the millisecond duration of spoken words; frequent words tend to be shorter in duration than less frequent words (Bell et al., 2003; Jurafsky, Bell, Gregory, & Raymond, 2001). This type of probabilistic reduction of predictable words has been established in numerous languages, e.g., English (e.g., Bell, Brenier, Gregory, Girand, & Jurafsky, 2009), Dutch (Kuperman, Pluymaekers, Ernestus, & Baayen, 2007; Pluymaekers, Ernestus, & Harald Baayen, 2005a, 2005b), French (Bürki, Ernestus, Gendrot, Fougeron, & Frauenfelder, 2011; Pellegrino, Coupé, & Marsico, 2011; Torreira & Ernestus, 2011), Italian (Pellegrino et al., 2011), Spanish (Torreira & Ernestus, 2012), and Kaqchikel (Tang & Bennett, 2018). In contrast, the results showing effects of informativity (i.e., average predictability) on word duration are relatively new and are available only for English (Seyfarth, 2014).

That “on average” predictable words in English tend to be shorter than less predictable words, even in locally unpredictable contexts, may implicate phonetically detailed representations of words as well as a process of lexicalization (see, e.g., Bybee, 2001). A feedback loop, through which speaker productions are stored as phonetically detailed episodic memories, or “exemplars”, can, over time, bias lexical representations in the direction of production constraints (e.g., Wedel, 2007).

There are two main aims of this paper. The first is to examine whether the effect of informativity on word duration extends to Mandarin Chinese, a typologically different language from English. Replicating this result in another language is important because of the implications that it has for the nature of lexical representations. The second aim is to evaluate whether the effect of informativity generalizes beyond word duration to other phonetic parameters, specifically pitch and intensity. This investigation is motivated by the hypothesis that probabilistic reduction in predictable environments may reflect the structuring of language in terms of prominence and grouping, i.e., prosodic structure (Ladd 1986; Jun 2014).

Prosody is universal in the sense that all languages structure words into prosodic phrases of varying sizes and exhibit variation in word prominence. Prosodic structure has a substantial influence on the phonetic form of words, including their duration (e.g., Turk & Shattuck-Hufnagel, 2000). There is emerging evidence that the phonological properties of words are molded in part by the broader pragmatic goals of speech embodied in prosody (Roettger & Grice, 2019). Words produced at prosodic boundaries, under prosodic focus, or sentential stress are systematically enhanced, often produced with greater duration, intensity and pitch excursions than words in less prominent positions. The assignment of prosodic structure to speech varies according to a number of linguistic and para-linguistic factors and in language-specific ways. Notably, the perception of prosodic prominence is conditioned by the frequency of a word (Baumann 2014; Cole et al. 2010; Cole et al. 2017; Nenkova
et al., 2007) and also by informativity (Antilla et al., 2018). These results are consistent with the possibility that predictability conditions the assignment of prosodic structure and, by extension, that informativity (or average predictability) reflects average prosodic prominence.

On this hypothesis, more informative words are longer because they attract a higher level of average prosodic prominence. As far as we know, this hypothesis has never been tested. If informativity is picking up on (lexicalized) prosodic prominence, then informativity should predict not just word duration but also other phonetic reflexes of prosodic prominence, particularly intensity and pitch. We test this prediction in a series of studies on Mandarin Chinese.

In what follows, we describe four corpus studies of Mandarin Chinese. In each case, we fit linear mixed effects models to phonetic parameters related to prosodic prominence: duration, pitch, and intensity. Through a combination of fixed and random effects, we investigate the influence of frequency, contextual predictability and informativity while controlling for as many additional factors known to influence these variables as possible. The first three studies investigate word duration, pitch and intensity, respectively. The fourth study is a mediation analysis. We investigate whether effects of informativity on pitch and intensity are mediated by duration.

2 Materials and Methods

2.1 Acoustic corpus

Acoustic measurements were extracted from the HKUST Mandarin Telephone Speech, Part 1 corpus developed by Hong Kong University of Science and Technology (HKUST) (Fung, Huang, & Graff, 2005). The corpus is a collection of 150 hours of Mandarin Chinese conversational telephone speech from Mandarin speakers in mainland China. 1,793 speakers were recruited from several cities across mainland China. Most of the speakers did not know each other. Two speakers were connected by a telephone operator and they were assigned a specific topic from 40 topics to encourage a more meaningful conversation. Each call was capped at 10 minutes and the majority of the calls reached this limit. All but one speaker spoke only in one call. In total, 897 ten-minute long calls, each with two speakers having a conversation on an assigned topic, were recorded. Each side of a call was recorded in two separate files. Some demographic information of the speakers was available, such as age, gender and phone type (a fixed landline connection or a mobile connection).

The corpus contains the audio recordings and their corresponding orthographic transcriptions using Chinese characters with utterance-level timestamps. In addition, the transcriptions contain a range of annotations concerning disfluent speech (e.g., partial words, restarts, filled pause), speaker noise (e.g., laughers, coughs), background noise, hard to understand speech regions, and use of foreign (non-Chinese) languages.

To obtain the acoustic measurements, the corpus needed to be forced aligned. At the time of writing, the authors were not aware of any available forced aligner for Mandarin Chinese, with the exception of SPPAS (Bigi, 2015), since the alignment quality of SPPAS was unacceptable, we therefore decided to train our own aligner using the Montreal Forced Aligner (MFA, version 1.0) (McAuliffe, Socolof, Mihuc, Wagner, & Sondergagge, 2017).

2.1.1 Corpus segmentation

The audio recordings were segmented into chunks based on the annotators’ segmentation. The annotators segmented the speech files into conversational turns at natural boundaries; each conversational turn was permitted to be maximally 10 seconds long (Y. Liu et al., 2006). In total, 203,594 speech chunks were segmented. Johnson, Di Paolo, & Bell (2018) found that when training
an aligner, the alignment quality can be affected by the amount of environmental noise in the training data. We therefore excluded a number of utterances based on a set of criteria concerning their noise level.

2.1.2 Data filtering

Firstly, the speech chunks from speakers who used a mobile device were excluded. We assume that these speakers would be more likely be located outdoors and/or physically move around while they were speaking, therefore these utterances might contain more environmental noise than utterances from landline speakers. The data from 138 speakers (15,634 speech chunks) were removed and this exclusion reduced the whole dataset by 7.6%.

Secondly, speech chunks with a low Signal-to-Noise ratio (SNR) were excluded. Two algorithms for estimating the SNR of a signal without a reference noise file were used, 1) Waveform Amplitude Distribution Analysis (WADA-SNR) (Kim & Stern, 2008) and 2) NIST’s SNR algorithm (National Institute of Standards and Technology, n.d.). We used the Matlab implementation of these algorithms by Ellis (2011) to conduct the SNR estimation. The estimated SNR values can only be interpreted in relative, not absolute, terms, therefore the two sets of estimated SNR values were z-score transformed. The WADA-SNR values exhibited a bimodal distribution with some utterances estimated to have the maximum SNR value of 100. We excluded these files from the z-transformation of the WADA-SNR values for the remaining files to avoid skewing the z-scores. We then manually inspected samples of the speech chunks at various combinations of the two SNR z-scores to establish a few cut-off levels. We excluded any chunk that has:

a) both an NIST-SNR z-score above 2.5 and a WADA-SNR value of 100. While they have high SNR values, manual inspections of these speech chunks revealed that they were actually non-speech files containing pure tones.

b) both an NIST-SNR z-score below -1 and a WADA-SNR below -1. These files were judged by the first author to be significantly noisy.

Thirdly, speech chunks that contain words that were labelled as being masked by noise or unclear (the annotator transcribed the speech but was uncertain), or contain stretches of noise and stretches of untranscribable speech.

Together, these filters reduced the total number of speech chunks to 161,891 by 1,655 speakers.

2.1.3 Word segmentation and Part of Speech tagging

Since written Mandarin Chinese does not have word delimiters between words, word segmentation was required to parse the orthographic transcriptions into word units. The NLPIR Institute of Computing Technology, Chinese Lexical Analysis System (ICTCLAS) (version: 2016) (Zhang, 2016; Zhang, Yu, Xiong, & Liu, 2003) was used to perform the word segmentation via the PyNLPIR library (Roten, 2017). Each segmented word was also Part of Speech (POS) tagged by the ICTCLAS. The POS tag set, ICTPOS3.0 (Qun, Hua-Ping, & Hao, 2004), was used.

2.1.4 Pronunciation dictionary

To train the aligner, we needed to convert orthographic words into pronunciations. The CC-CEDICT dictionary (Denisowski, 2018) was used as the main source of pronunciation. The release on 2018-12-10 contains 116,646 word entries completed with pronunciation in pinyin.

When given multiple pronunciations, forced aligners have the ability to select the pronunciation that matches the acoustic signal best. Allowing for pronunciation variations that are likely to exist in the acoustic signals can further improve alignment quality. To ensure the pronunciations were appropriate
for our speakers, all the entries in CC-CEDICT that are tagged as Taiwan Mandarin were removed, since the speakers in the acoustic corpus are Mainland China Mandarin speakers.

Two high frequency pronouns, 那 “that” and 这 “this”, have two common pronunciations when they precede a classifier; 那 can be realised (in pinyin) as ‘na4’ and ‘nei4’ and 这 can be realised (in pinyin) as ‘zhe4’ and ‘zhei4’. All the CC-CEDICT entries containing either of these characters were manually coded by a native speaker for whether they can be realized with both pronunciations and the missing alternative pronunciations were added. The resultant dictionary contains only Mainland Mandarin pronunciations, enriched with alternative pronunciations entries containing the two pronouns preceding a classifier.

Pinyin transcriptions of the words in the corpus were extracted directly from this processed pronunciation dictionary. If they were not listed there, they were constructed by means of a grapheme-to-phoneme model that was trained on the processed pronunciation dictionary using phonetisaurus (Novak, Minematsu, & Hirose, 2016). The automatically transcribed entries that contain either 那 “that” or 这 “this” characters were manually checked for alternative pronunciations which were added if needed.

The standard practice for forced alignment is to align phones, therefore the pinyin transcriptions were converted to IPA using the pinyin-IPA mapping table in Duanmu (2007, pp. 319–329). The surface phone set described in Duanmu (2007) was chosen over the underlying phone set to enable the aligner to train more accurate acoustic models at the expense of a larger phone set. Each syllable was coded using the template [Onset, Nucleus+Tone, Coda] which uses onset, nucleus and coda phones with tone being part of the nucleus\(^1\).

The remaining out-of-vocabulary words were exclusively foreign words from English. They were manually transcribed using the surface phone set of Mandarin assuming a Mandarin accented pronunciation of English. While these foreign words were not analyzed, their inclusion in the dictionary allowed the surrounding Chinese words to be aligned. It is worth noting that the number of foreign words amounts to only 467 word tokens (out of 1.2 million tokens), therefore transcribing them using the Mandarin phone set should only have a negligible negative effect on the quality of the acoustic models.

2.1.5 Forced alignment training

The speech chunks, their corresponding word segmented orthographic transcriptions and the orthography-to-IPA pronunciation dictionary were used to train the aligner. The default parameters were used. The speaker-specific alignment training function was enabled, because preliminary studies have found that this consistently improved alignment quality (Peters & Tse, 2016; Wilbanks, 2015).

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\(^1\) There are alternative ways of coding the Mandarin syllables. Firstly, each syllable can be divided into an onset and a rime, following the tradition of Chinese phonology. Secondly, the tone of each syllable can be coded as part of the syllable, the rime (or the nucleus and the coda). The coding theme for the tone is related to the question of what constitutes the tone-bearing unit (TBU). However, given that there is no general consensus in the literature (see Duanmu, 2007, pp. 233–235, for a review) concerning the TBU for Mandarin Chinese, we decided to code the tone with the nucleus, since it is arguably the most conservative scheme.
17 of the 161,891 files failed to be aligned leaving 161,874 aligned speech chunks. No hand correction was made to the automatic alignment.

2.1.6 Acoustic estimates

Using the word alignment, three acoustic dimensions of each word were estimated -- duration, intensity (maximum, minimum) and pitch (maximum, minimum). Duration was extracted directly from the textgrids. Intensity and pitch measurements were made using Praat (Boersma & Weenink, 2019). An intensity object was created using the function ‘To Intensity…’ with the default parameters (Minimum pitch was set as 100.0 Hz and the time step was computed as one quarter of the effective window length). A pitch object was created using the function ‘To Pitch…’ with the default parameters (pitch floor was set to 75 Hz, pitch ceiling was set to 600 Hz and time step was 0.75 / pitch floor). The maximum and minimum intensity and pitch were extracted after a parabolic interpolation. For each word, we obtained five acoustic variables -- duration, maximum intensity, intensity range (maximum intensity minus minimum intensity), maximum pitch and pitch range (maximum pitch minus minimum pitch).

2.2 Lexical corpus

In order to examine the effect of word probabilities, a speech-like written corpus of Mandarin Chinese (Tang & Mandera, In preparation) was used to estimate word frequency, contextual predictability and informativity. The corpus consists of 431 million word tokens from TV/film subtitle texts of Mandarin Chinese. The written corpus was word segmented and POS tagged using ICTCLAS just as the transcriptions of the acoustic corpus. This corpus was chosen for a number of reasons.

Firstly, previous work has shown that frequency estimates derived from subtitle texts consistently outperform those from non-speech like genres (such as newspaper texts) in explaining behavioural data, such as reaction time in lexical decision tasks and word naming tasks (Brysbaert & Boris New, 2009; Cai & Brysbaert, 2010; Keuleers, Brysbaert, & Boris New, 2010; van Heuven, Mandera, Keuleers, & Brysbaert, 2014). This is even the case when the non-speech-like corpora are larger in size than the corresponding subtitle corpus.

Secondly, subtitle texts are a better genre-of-speech match with the telephone conversational speech compared to newspaper texts in terms of their levels of formality and the fact that subtitle texts consist primarily of dialogues.

Thirdly, its large corpus size improves the representativeness of the corpus (Biber, 1993), under the typical assumption that the larger your corpus the more representative it is as the average linguistic experience of the language users.

Finally and most importantly, informativity computed using a large corpus will reduce the chance of frequency falsely capturing effects that should be attributed to informativity. In a simulation study, Cohen Priva and Jaeger (2018) investigated whether the size of the lexical corpus could create spurious frequency and predictability effects. First, they created lexical corpora of various sizes sampled from a bigger corpus which they assumed to represent the “true” experience of the language users. Second, they computed frequency, contextual predictability and informativity using each of these sampled corpora as well as the “true” corpus. Finally, they correlated the three estimated predictability variables computed using the sub corpora with each of the predictability variables computed using the “true” corpus. They reported that even for a sampled lexical corpus of 10 million words, they found the estimated frequency variable would still spuriously correlate with the “true” informativity variable. While the study did not report the minimum lexical corpus size required to avoid or mediate a spurious frequency effect, it is nonetheless clear that our corpus of over 400 million
words is a substantial methodological improvement compared to the 12 million word corpus used by other studies on word informativity (Seyfarth, 2014). This is particularly true, considering that a) Mandarin Chinese has relatively poor morphology compared to English, so the inter-word probability estimates (bigrams) should be even better in Mandarin Chinese, and b) the 12 million word corpus in English was already sufficient to reveal an informativity effect.

2.2.1 Probability estimates

The three word probability measures are described below.

**Word frequency** is the total number of times a word appears in the lexical corpus.

**Contextual predictability** is the conditional probability of a word given its context as formulated in equation 1, where \( c \) is the context which is operationalized as the preceding or following word in an utterance and \( w \) is the target word.

Equation 1: \( P_r(W = w | C = c) \)

**Informativity** is the negative log average contextual predictability of a word in every context in which it appears in, weighted by the contextual predictability of the contexts given the word, as formulated in equation 2.

Equation 2: \( - \sum_c P_r(C = c | W = w) \log_2 P_r(W = w | C = c) \)

Unlike Seyfarth (2014), contextual predictability was computed directly from bigram token frequencies without any additional smoothing because we would like to avoid increasing researcher degrees of freedom. A review of the predictability effect on phonetic duration (Daland & Zuraw, 2018) suggests that the details of a study matter for whether a particular predictability estimate has an effect. While smoothing techniques could estimate the spoken words in contexts that are unattested bigrams in the lexical corpus, the probability estimates of attested and unattested bigrams would differ, depending on the chosen smoothing technique and the associated parameters. Given our large corpus size, we believe that the increase in researcher degrees of freedom outweighs the limited benefit of having potentially better probability estimates and not having to lose acoustic data due to data sparsity.

2.3 Variables

Words in the acoustic corpus were annotated based on the lexical corpus and the acoustic corpus for a range of type-level and token-level variables. They are described below for dependent variables and predictor variables separately. Besides the informativity variables, the rest of the predictor variables were reported to have an effect on duration in previous literature (e.g., Seyfarth 2014; Gahl 2008).

2.3.1 Dependent variables

**Duration:** word duration (in ms) was extracted using the word-level timestamps. It is a continuous variable and log-transformed (base 10).

**Maximum intensity:** maximum intensity (in dB) was extracted from the intensity contour of each word. It is a continuous variable. No log-transformation was needed because the decibel is already on a log scale.
Intensity range: intensity range (in dB) was computed using the maximum intensity and minimum intensity. It is a continuous variable with no additional log-transformation.

Maximum pitch: maximum pitch (in Hz) was extracted from the pitch contour of each word. It is a continuous variable. It was log-transformed (base 10).

Pitch range: pitch range (in Hz) was computed using the maximum pitch and minimum pitch. It is a continuous variable. It was log-transformed (base 10).

2.3.2 Predictor variables

Token frequency: the number of times a word appears in the lexical corpus were counted, log-transformed (base 2) and then z-transformed.

Contextual predictability: two variables of contextual predictability were estimated using the lexical corpus using equation 1 -- a) the conditional probability of a word given the previous word (forward predictability) and b) the conditional probability of a word given the following word (backward predictability); log-transformed (base 2) and then z-transformed.

Informativity: two variables of informativity were estimated using the lexical corpus according to equation 2 -- a) the informativity of a word given the previous word (forward informativity) and b) the informativity of a word given the following word (backward informativity); log-transformed (base 2) and then z-transformed.

Word length: the number of segments in the word transcription was counted and then z-transformed. Word length serves as a direct control for word duration, the more segments a word has, the longer its duration. The effect of word length on intensity and pitch is less clear. It is possible that longer words are more likely to have high intensity/pitch as there would be more time to achieve high intensity and pitch targets.

Disfluency: two binary variables of disfluency were estimated using the annotation of the acoustic corpus, preceding disfluency and following disfluency. The variables indicate whether the word is immediately a) preceded and b) followed by a non-silence disfluency, namely laughter, sneezes, coughs, lip smacks and filled pauses; sum-coded with ‘not disfluent’ being the reference level.

Pause duration: two continuous variables of pausal duration were estimated using the alignment of the acoustic corpus using short pauses detected automatically by the trained aligner as well as the duration of annotated-then-aligned breath units -- preceding pause duration and following pause duration. The variables are the duration of a pause immediately a) preceding the word and b) following a word respectively. The duration variables (in ms) were Laplace transformed (add one), log-transformed (base 10) and then z-transformed.

Pause duration is used as an approximation to determining phrasal position and boundary strength. Previous work on word duration found that words before a pause have longer word duration, which suggests phrase-final lengthening. Rather than coding pauses as a binary variable, as was done, for example, in Gahl (2008) with an arbitrary cut-off duration of 0.5 second, we coded it as a gradient variable to provide a more accurate estimate for phrasal positional effects, since boundary strength as estimated with pause duration has been shown to predict the rate of segment deletion (Tanner, Sonderegger, & Wagner, 2017). Following the practice of Tanner et al. (2017), force-aligned pauses of less than 30 ms were set to have a duration of 0 ms because they are likely to be aligner errors or due to low amplitude signals (such as stop closures).

Speech rate: Speech rate was estimated as the number of syllables per second (de Jong & Wempe, 2009). Following the practice of Gahl (2008) and Seyfarth (2014), for the purpose of computing
speech rate, an utterance is defined as a stretch of speech within a conversational turn (which has a maximum duration of 10 seconds as defined by the corpus developers) that are marked by pauses, disfluencies, and other interruptions that are longer or equal to 0.5 second or by the conversational turn boundaries. Two continuous variables of speech rate were computed, preceding speech rate and following speech rate. They are the speech rate on either a) the left or b) the right of the utterance. They were computed using the number of syllables before/after the target word itself, divided by the duration of that region, and then z-transformed.

**Previous mention:** Previous work (Fowler, 1988; Fowler & Housum, 1987) has shown that words which are repeated in a spoken discourse are sometimes reduced in production compared to previous mentions of those words. Repetitions were coded separately for the previous mention of a word from the same speaker and those from another speaker within the dialogue, since it has been shown that these two types of repetitions can have different effect sizes on acoustic reduction (Tron, 2008). Two binary variables were computed, self-mention and cross-speaker mention; sum-coded with ‘no previous mention’ as the reference level.

**Syntactic category:** the syntactic category of the words was coded using the main tags in the ICTPOS 3.0 tag set. After excluding certain categories (as outlined in Section 2.4 -- Exclusion criteria), nine categories remained. This variable was coded using the target encoding (also called mean encoding) scheme (Micci-Barreca, 2001), which takes the mean of the dependent variable for each category which yields a single continuous variable. This variable was then z-transformed. The target encoding scheme was chosen over the usual contrast coding schemes, because, firstly it greatly reduces the number of predictors needed to code a nine-level categorical variable from eight predictors (N-1) to just one; secondly, it does not sacrifice any details of the nine categories; and finally, it performs similarly to or better than contrast coding schemes in regression and classification models (Cerda, Varoquaux, & Kégl, 2018).

**Age:** the age of the speaker was included to capture potential social factors. The age variable was in years and z-transformed.

**Gender:** similar to age, the gender of the speaker was included to capture potential social factors. The gender variable was binary and sum-coded with ‘Female’ as the reference level.

### 2.4 Exclusion criteria

After the acoustic estimates and the probability estimates were computed, certain acoustic word tokens were excluded given a number of criteria as outlined below. The final dataset consists of 436,390 words.

1. Words for which we cannot compute all of the acoustic estimates (44,875 words). Specifically, Praat failed to compute the intensity and pitch values in these cases.

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2 Cross-speaker-mention was computed differently from self-mention. Recall that some conversational turns were not aligned due to their inherent noise or the speaker’s phone type. We, therefore, cannot always use the word-level timestamps to check if a word produced by one speaker was previously mentioned by the other speaker. We opted for a conservative coding scheme, such that a word by the other speaker is only counted as mentioned if its conversational-turn-level offset timestamp comes before the word-level onset timestamp of the target word by the speaker. Note that this means some cross-speaker previous mentions could have been missed out in cases of cross-talk.
b) Words that have impossible acoustic values such as a negative intensity values\(^3\) (7 words).

c) Words that cannot be part-of-speech tagged by the ICTCLAS tagger (755 words).

d) Words that are tagged as being proper names (22,261 words) and other miscellaneous tags (6,270 words) such as onomatopoeia. Proper names have been shown to process differently from typical nouns and how their probabilistic estimates are speaker dependent (Bredart, 2002; Cohen & Burke, 1993; Nomi & Cleary, 2008).

e) Words that are tagged as function words such as pronouns, classifiers, prepositions and others (537,815 words). Function words were not analysed in this study, since it has been shown that predictability has different effects on the duration of function words and content words (Bell et al., 2009; Tang & Bennett, 2018).

f) Words that are annotated as being produced only partially (15,370 words) or mispronounced (654 words). These words were excluded because their acoustic details are shown to differ from typically produced words. Partially produced words have shorter segmental content and acoustic details that differ from their fully produced forms (Howell & Vause, 1986; Howell & Williams, 1992). Words that are mispronounced have shown to have both categorical and gradient acoustic errors (Frisch & Wright, 2002; Goldrick, Keshet, Gustafson, Heller, & Needle, 2016).

g) Words that are filled pause words (23,302 words), acronyms (2,056 words) or foreign words (467 words).

h) Words that appear in the corpus only once. This improves the interpretation of the statistical models, since our models have random intercepts of word types and random effects, which are best used for repeated levels.

i) Words that are at the start or at the end of a conversational turn (as previously mentioned in Section 2.1.1 Corpus segmentation), since contextual predictability and speech rate cannot be computed.

j) Words that are at the start or at the end of an utterance (as previously defined in Section 2.3.1 Dependent variables for computing speech rate), since speech rate cannot be computed.

### 2.5 Model procedure

Linear mixed-effects models were fit to the acoustic data conducted using the \texttt{lme4} package in R (Bates, Mächler, Bolker, & Walker, 2015; R Core Team, 2013). For each of the five dependent variables (one duration, two intensity, and two pitch variables), a model was fitted with the predictor variables outlined in Section 2.3.1 Dependent variables as fixed effects. These models were fitted with a number of random effects.

As is typical of psycholinguistic research, per-word random intercepts and per-speaker random intercepts were included to allow for idiosyncrasies of individual speakers (1,655 speakers) and word types (6,347 word types). Furthermore, tones are known to condition syllable duration (Yang, Zhang, Li, & Xu, 2017) and intensity (Liu & Samuel, 2004; Whalen & Xu, 1992) and, by definition, pitch. The tone sequence of each word was, therefore, included as random intercepts (176 tone sequence types). In addition to these random intercepts, two correlated per-speaker slopes of backward informativity and forward informativity were fitted to allow for the informativity effects to vary by speaker. P-values for each effect were calculated using the normal approximation to the \(t\)-statistic.

\(^3\) Manual inspections revealed that these negative intensity values are due to the signal consists of mainly silence.
While it is not as ideal as using the Satterthwaite approximation (Luke, 2017), given our large sample size (>400,000 tokens), the p-values should not be particularly anti-conservative (Barr, Levy, Scheepers, & Tily, 2013).

The structure of the models is given below in the syntax of lmer.

**Dependent variable (either Duration, Maximum intensity, Intensity range, Maximum pitch or Pitch range) ~ Frequency + Forward predictability + Backward predictability + Forward informativity + Backward informativity + Word length + Preceding disfluency + Following disfluency + Preceding pause duration + Following pause duration + Preceding speech rate + Following speech rate + Previous self-mention + Previous cross-speaker mention + Age + Gender + Syntactic category + (1 | Word type) + (1 | Tone sequence) + (1 + Forward informativity + Backward informativity | Speaker)**

In addition to these models, a series of mediation analyses was conducted to examine whether the effects of informativity, if any, found in one model for a dependent variable can be explained by another dependent variable. This was particularly important for the two acoustic dimensions, pitch and intensity, that were not previously examined for informativity. Should there be an informativity effect found for duration and also for pitch and/or intensity, we would need to rule out duration being a mediator that underlies the observed relationship between pitch/intensity and informativity. For completeness, such mediation analyses were also conducted for duration with pitch and/or intensity being the mediator(s). These analyses were done by adding the mediator variable as an additional fixed effect.

All models underwent the process of model criticism. For each model, the residuals were extracted and data points that were 2.5 standard deviations above or below the mean residual value were excluded. No more than 4% of the data points were excluded in any of the models.

Table 1 summarizes the distribution of the variables (both dependent variables and the predictors). The tables show the mean, standard deviation, interquartile range and range (max-min) for the continuous variables and count information for the categorical variables.

| Variable                   | Mean  | SD    | IQR  | Range  |
|----------------------------|-------|-------|------|--------|
| Word duration (log10, ms)  | 2.3274| 0.2153| 0.3152| 1.4244 |
| Maximum Pitch (log10, hz) | 2.3344| 0.1717| 0.2539| 0.9319 |
| Maximum Intensity (dB)    | 70.8120| 8.1587| 11.2336| 64.8949 |
| Pitch range (log10, hz)   | 1.4912| 0.4911| 0.6110| 2.7344 |

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4 Owing to the size of our models, we were unable to compute the Satterthwaite approximation (Luke, 2017) to get approximate degrees of freedom as implemented in the lmerTest library (Kuznetsova, Brockhoff, & Christensen, 2017).
|                        |       |       |       |       |
|------------------------|-------|-------|-------|-------|
| Intensity range (dB)   | 18.2478 | 11.0847 | 16.8048 | 61.6008 |
| Frequency (log2)       | 18.5713 | 3.3258 | 5.0989 | 20.6272 |
| Forward predictability (log2) | -8.5494 | 3.7905 | 5.4577 | 23.1329 |
| Backward predictability (log2) | -8.5857 | 3.9606 | 5.9200 | 23.3191 |
| Forward informativity (log2) | 7.8706 | 2.7495 | 4.1630 | 18.8828 |
| Backward informativity (log2) | 7.7266 | 2.9244 | 4.3457 | 20.8744 |
| Word length            | 3.1680 | 1.3401 | 2.0000 | 11.0000 |
| Preceding pause duration (log10, ms) | 0.2016 | 0.6357 | 0.0000 | 2.6911 |
| Following pause duration (log10, ms) | 0.2026 | 0.6589 | 0.0000 | 3.4971 |
| Preceding speech rate  | 5.5960 | 1.8950 | 2.3188 | 32.9710 |
| Following speech rate  | 5.2539 | 1.6933 | 2.0395 | 33.1040 |
| Age                    | 27.4332 | 4.7825 | 6.0000 | 41.0000 |
| Syntactic category (target coded to word duration) | 2.3275 | 0.0865 | 0.0729 | 0.3501 |
| Syntactic category (target coded to maximum pitch) | 2.3345 | 0.0097 | 0.0114 | 0.0695 |
| Syntactic category (target coded to maximum intensity) | 70.8121 | 1.1530 | 0.6817 | 4.7107 |
| Syntactic category (target coded to pitch range) | 1.4913 | 0.0893 | 0.1354 | 0.4406 |
| Syntactic category (target coded to intensity range) | 18.2479 | 1.9531 | 3.7755 | 10.7913 |
| Preceding disfluency   | True: 5,412, False: 430,978 |
|                          | True: 2,549, False: 433,841 |
|--------------------------|-----------------------------|
| Following disfluency     |                             |
| Previous self-mention    | True: 281,255, False: 155,135 |
| Previous cross-speaker mention | True: 238,610, False: 197,780 |
| Gender                   | Male: 221,508, Female: 214,882 |

Table 1: Descriptive statistics of variables

3 Results

Before examining the effect of informativity on acoustic prominence, we conducted a correlation analysis between the five acoustic variables (after transformation) as shown in table 2. This will allow us to better understand if any informativity effect found for a given acoustic variable is likely to be a spill over effect from another correlated acoustic variable.

All correlations were statistically significant due to the large amount of data. Duration was most correlated with intensity range (R=0.56) and pitch range (R=0.49), c.f., maximum intensity (R=0.23) and max pitch (R=0.14). Maximum pitch and maximum intensity were weakly correlated at 0.12. These correlational relationships suggest that the effect of informativity on prominence would be most conclusive if the informativity effect were found with duration, maximum intensity and maximum pitch, because they are least correlated with each other. For this reason, we focus on these three dependent measures.

Four studies were conducted. Study I focuses on the effect of informativity on word duration, replicating Seyfarth (2014) in a new language, Mandarin Chinese. Study II extends the effect to pitch (maximum pitch) which is another phonetic cue to prosodic prominence in Mandarin Chinese. Study III investigates intensity (maximum intensity), another cue to prosodic prominence in Mandarin Chinese. Study IV seeks to further disassociate the relationship between word duration and the maximum pitch/intensity by conducting a series of mediation analyses by including word duration as a fixed effect in Study II and Study III and by including maximum pitch/intensity as a fixed effect in Study I.

|               | Duration | Max. Intensity | Intensity Range | Max. Pitch | Pitch Range |
|---------------|----------|----------------|-----------------|------------|-------------|
| Duration      | -        | 0.23           | 0.56            | 0.14       | 0.49        |
| Max. Intensity| -        | -              | 0.28            | 0.12       | 0.18        |
| Intensity Range| -        | -              | -               | 0.16       | 0.3         |
| Max. Pitch    | -        | -              | -               | -          | 0.64        |
3.1 Study 1 -- Duration

The final fixed and random effects estimates for the duration model are summarized in table 3 and table 4. All predictors except one (Age, $p = 0.5184$) were statistically significant. Crucially, both of the informativity predictors were associated with word duration in the expected direction (forward informativity: $\beta = 0.0099$, $t = 7.0700$, $p < 0.0001$; backward informativity: $\beta = 0.0059$, $t = 4.4836$, $p < 0.0001$). The higher the informativity of a word, the longer the word duration.

We now examine the control variables. Most of the variables were associated with word duration in the expected direction. Shorter word durations were associated with higher forward and backward predictability, faster speech rate (preceding and following), words that were previously mentioned (self-mention and cross-speaker mention). Longer word durations were associated with longer word length, neighbouring disfluencies (preceding and following) and following pause duration. Male speakers produced shorter word durations. Syntactic category was associated positively with word duration which is unsurprising because it was target coded which uses the mean value of the dependent variable as a predicting value for each category (see Section 2.3.2: Predictor variables).

Two variables were associated with word duration in an unexpected direction: preceding pause duration and word frequency. Unlike English, preceding pause duration was negatively associated with word duration ($\beta = -0.0021$, $t = -11.0986$, $p < 0.0001$), suggesting a phrasal-initial shortening effect. Phrasal-initial shortening has been previously reported for Mandarin in broadcast news speech data (Liberman, 2014; Yuan, Ryant, & Liberman, 2014) without adjusting for other factors such as word type and tone content. This suggests that our effect is unlikely to be a statistical accident, since it is robust with or without adjusting for other factors and across two speech genres. However, in experimental studies, the phrase-initial shortening is less consistent (Tseng, Pin, Lee, Wang, & Chen, 2005; Xu & Wang, 2009; Yang 2011; Yang 2016).

While word frequency has a positive coefficient ($\beta = 0.0095$, $t = 5.1712$, $p < 0.0001$), it does not mean that the more frequent the word is, the longer it is, but rather it is a suppressor effect due to informativity being correlated with word frequency (forward informativity: $R = -0.933$, backward informativity: $R = -0.929$). Figure 1 illustrates the relationship between word frequency and informativity. Two lexical items with similar frequency but different informativity were specifically highlighted in the figure. This suppressor effect of word frequency was similarly found in the English study of informativity by Seyfarth (2014) (see references therein).
Figure 1: An illustration of the difference between frequency and informativity given the following word in Mandarin Chinese, modelled after Seyfarth (2014)’s illustration on English words. Sample of 200 word types that were observed in the acoustic data at least 10 times. Dotted line indicates the trend between frequency and informativity for the sampled words. Two specific words with similar frequency but different informativity (商业 ‘business’ and 根据 ‘according to’) were highlighted using a larger font size.

|                      | β     | SE   | t     | p      |
|----------------------|-------|------|-------|--------|
| Intercept            | 2.5504| 0.0069| 368.9001| < 0.0001|
| Frequency            | 0.0095| 0.0018| 5.1712| < 0.0001|
| Forward predictability| -0.0169 | 0.0003| -57.5467| < 0.0001|
| Backward predictability| -0.0188 | 0.0003| -60.5199| < 0.0001|
| Forward informativity| 0.0099 | 0.0014| 7.0700| < 0.0001|
|                                    | Estimate | SE   | z     | p     |
|------------------------------------|----------|------|-------|-------|
| Backward informativity             | 0.0059   | 0.0013 | 4.4836 | < 0.0001 |
| Word length                        | 0.0359   | 0.0012 | 29.3871 | < 0.0001 |
| Preceding disfluency = Yes         | 0.0571   | 0.0017 | 34.3589 | < 0.0001 |
| Following disfluency = Yes         | 0.0760   | 0.0025 | 30.8858 | < 0.0001 |
| Preceding pause duration           | -0.0021  | 0.0002 | -11.0986 | < 0.0001 |
| Following pause duration           | 0.0432   | 0.0002 | 220.1911 | < 0.0001 |
| Preceding speech rate              | -0.0112  | 0.0002 | -56.5481 | < 0.0001 |
| Following speech rate              | -0.0111  | 0.0002 | -56.6389 | < 0.0001 |
| Previous self-mention = True      | -0.0117  | 0.0005 | -25.5572 | < 0.0001 |
| Previous cross-speaker mention = True | -0.0030 | 0.0005 | -6.5749 | < 0.0001 |
| Age                                | 0.0005   | 0.0008 | 0.6458 | 0.5184 |
| Gender = Male                      | -0.0260  | 0.0017 | -15.5798 | < 0.0001 |
| Syntactic category                 | 0.0111   | 0.0006 | 18.3594 | < 0.0001 |

Table 3: Fixed effect summary for the duration model
### Table 4: Random effect summary for the duration model

|                          | SD       | Correlation |
|--------------------------|----------|-------------|
| Word (intercept)         | 0.03661  | -           |
| Speaker (intercept)      | 0.03343  | -           |
| Speaker (forward informativity) | 0.01220  | -0.31       |
| Speaker (backward informativity) | 0.01158  | 0.16        |
| Tone sequence (intercept) | 0.05747  | -           |
| Residual                 | 0.11619  | -           |

3.2 Study 2 -- Pitch

The final fixed and random effects estimates for the maximum pitch model are summarized in table 5 and table 6. All except two predictors (Frequency, $p = 0.1161$; Following disfluency, $p = 0.2813$) were statistically significant. Like Study 1, forward informativity was associated with maximum pitch in the expected direction ($\text{forward informativity}: \beta = 0.0040, \ t = 4.5129, p < 0.0001$). However, backward informativity has an opposite effect on maximum pitch ($\beta = -0.0028, \ t = -3.2460, p = 0.0012$). This is a surprising finding because it would suggest that the two informativity predictors are in opposition in their effects on maximum pitch. While it is unclear why backward informativity acts in a different direction, the effect sizes of the two informativity predictors (0.0040 and -0.0028) would suggest that there is still an overall positive effect of informativity on maximum pitch.

We now examine the control variables. All of the variables were associated with maximum pitch in the expected direction. Lower maximum pitch values were associated with higher forward and backward predictability, faster speech rate (preceding and following), words that were previously mentioned (self-mention and cross-speaker mention). Higher maximum pitch values were associated with longer word length and preceding disfluencies. The two pause duration variables, preceding pause duration with a positive coefficient and following pause duration with a negative coefficient, suggest that maximum pitch is higher phrase-initially and lower phrase-finally (Xu & Wang, 2009). Male speakers and older speakers produced lower maximum pitch. Just as Study 1, syntactic category was unsurprisingly associated positively with maximum pitch since it was target coded.
|                                | β      | SE     | t     | p       |
|--------------------------------|--------|--------|-------|---------|
| Intercept                      | 2.3408 | 0.0038 | 619.3450 | < 0.0001 |
| Frequency                      | 0.0019 | 0.0012 | 1.5712 | 0.1161  |
| Forward predictability         | -0.0054 | 0.0002 | -25.9537 | < 0.0001 |
| Backward predictability        | -0.0007 | 0.0002 | -3.1559 | 0.0016  |
| Forward informativity          | 0.0040 | 0.0009 | 4.5129 | < 0.0001 |
| Backward informativity         | -0.0028 | 0.0009 | -3.2460 | 0.0012  |
| Word length                    | 0.0017 | 0.0008 | 2.1460 | 0.0319  |
| Preceding disfluency = Yes     | 0.0060 | 0.0012 | 5.1589 | < 0.0001 |
| Following disfluency = Yes     | 0.0019 | 0.0017 | 1.0774 | 0.2813  |
| Preceding pause duration       | 0.0013 | 0.0001 | 9.2459 | < 0.0001 |
| Following pause duration       | -0.0010 | 0.0001 | -6.9972 | < 0.0001 |
| Preceding speech rate          | -0.0030 | 0.0001 | -21.7587 | < 0.0001 |
| Following speech rate          | -0.0011 | 0.0001 | -7.7405 | < 0.0001 |
| Previous self-mention = True   | -0.0048 | 0.0003 | -14.9362 | < 0.0001 |
| Previous cross-speaker mention = True | -0.0015 | 0.0003 | -4.7142 | < 0.0001 |
| Age                            | -0.0032 | 0.0015 | -2.0791 | 0.0376  |
| Gender = Male                  | -0.2372 | 0.0031 | -77.1714 | < 0.0001 |
| Syntactic category             | 0.0015 | 0.0004 | 3.6626 | 0.0002  |

Table 5: Fixed effect summary for the maximum pitch model
|                          | SD       | Correlation |
|--------------------------|----------|-------------|
| Word (intercept)         | 0.022527 | -           |
| Speaker (intercept)      | 0.061875 | -           |
| Speaker (forward informativity) | 0.006097 | 0.08        |
| Speaker (backward informativity) | 0.005779 | -0.11       | -0.65      |
| Tone sequence (intercept) | 0.021502 | -           |
| Residual                 | 0.074251 | -           |

Table 6: Random effect summary for the maximum pitch model

3.3 Study 3 -- Intensity

The final fixed and random effects estimates for the maximum intensity model are summarized in table 7 and table 8. All except four predictors (Backward informativity, p = 0.2225; Word length, p = 0.53; Gender, p = 0.0506; Syntactic category, p = 0.075) were statistically significant. While backward informativity did not reach significance, forward informativity was associated with maximum intensity in the expected direction ($\beta = 0.4043$, $t = 5.8113$, $p < 0.0001$). The higher the forward informativity of a word, the higher the maximum intensity.

We now examine the control variables. Lower maximum intensity values were associated with higher forward and backward predictability, faster speech rate (preceding and following), words that were previously mentioned (self-mention and cross-speaker mention). Higher maximum intensity values were associated with neighbouring disfluencies. The two pause duration variables, preceding pause duration with a positive coefficient and following pause duration with a negative coefficient, suggest that maximum intensity is higher phrase-initially and lower phrase-finally. Older speakers produced higher maximum intensity.

|       | $\beta$  | SE     | t       | p       |
|-------|----------|--------|---------|---------|
| Intercept | 72.215   | 0.2675 | 269.9803| < 0.0001|
|                         | SD   | Correlation |
|-------------------------|------|-------------|
| Word (intercept)        | 2.4250 |             |

Table 7: Fixed effect summary for the maximum intensity model
3.4 Study 4 -- Mediation analysis

We have shown that there is an effect of informativity on duration, pitch and intensity in the last three studies. However, it is possible that these apparent effects could be explained by only one of these dependent variables, specifically the informativity effects on duration, as it is most widely reported, could explain the effects on pitch and intensity.

To evaluate whether the effects of informativity on pitch and intensity could be explained by duration, we conducted mediation analyses by adding duration as a fixed effect to the pitch and intensity models. For completeness, we also fitted the duration model with pitch or intensity as a fixed effect. These mediation analyses are summarized in Table 9. The analyses showed that the two informativity effects remain the same across the three acoustic dimensions even when mediated.

| Mediator                      | Duration | Maximum Pitch | Maximum Intensity |
|-------------------------------|----------|---------------|-------------------|
|                               | β        | SE            |       | β        | SE            |       | β        | SE            |       |
| Forward informativity        | 0.0099   | 0.0014        | 7.07  | 0.0095   | 0.0014        | 6.91  | 0.0082   | 0.0014        | 5.90  |
|                               | 0.0040   | 0.0009        | 4.51  | 0.0037   | 0.0009        | 4.19  | 0.4043   | 0.0696        | 5.81  |
|                               | 0.3497   | 0.0684        | 5.11  | 0.0684   | 0.0655        |       |          |               |      |
| Backward informativity       | 0.0059   | 0.0013        |       | 0.0058   | 0.0013        |       | -0.0028  | 0.0009        |       |
|                               | -0.0034  | -0.0034       |       | 0.0813   | 0.0667        |       | 0.0417   | 0.0655        |       |

Table 9: Mediation analyses summary for the maximum intensity model.
Table 9: Summary of Informativity effects on duration, maximum pitch and maximum intensity

|                | Duration | Maximum Pitch | Maximum Intensity |
|----------------|----------|---------------|-------------------|
|                | \( \beta \) | SE | \( t \) | \( \beta \) | SE | \( t \) | \( \beta \) | SE | \( t \) |
| Forward informativity | 0.0099 | 0.0014 | 7.0700 | 0.0039 | 0.0008 | 4.6575 | 0.4043 | 0.0696 | 5.8113 |
| Backward informativity | 0.0059 | 0.0013 | 4.4836 | -0.0034 | 0.0008 | -4.2165 | 0.0813 | 0.0667 | 1.2198 |

Table 10: Informativity summary of duration, maximum pitch and maximum intensity

4 Discussion

Our main result is that informativity, operationalized as the average bigram predictability of a word, influences three phonetic dimensions associated with prosodic prominence in Mandarin Chinese: word duration, maximum pitch and maximum intensity.

Our choice to investigate Mandarin was motivated by several considerations. Importantly, the phonetic characteristics of prosodic prominence are well-known in this language. Another consideration was the general underrepresentation of non-Indo-European languages in research on probabilistic reduction at the phonetic level. The majority of existing research on probabilistic reduction comes from English (e.g., Bell, Brenier, Gregory, Girand, & Jurafsky, 2009), Dutch (Kuperman, Pluymaekers, Ernestus, & Baayen, 2007; Pluymaekers, Ernestus, & Harald Baayen, 2005a, 2005b), French (Bürki, Ernestus, Gendrot, Fougeron, & Frauenfelder, 2011; Pellegrino, Coupé, & Marsico, 2011; Torreira & Ernestus, 2011), Italian (Pellegrino et al., 2011) and Spanish (Torreira & Ernestus, 2012), while there is only a small number of comparable studies on non-Indo-European languages, such as Cantonese (Zhao & Jurafsky, 2009), Japanese (Sano, 2018; Shaw & Kawahara, 2019; Shaw & Kawahara, 2018), and Kaqchikel (Tang & Bennett, 2018). Our results on Mandarin Chinese make a typological contribution to the investigation of probabilistic reduction in
the Sino-Tibetan language family. Notably, they come from a language that has lexical tone. Even though pitch is lexically contrastive in Mandarin, we still found significant variation in pitch dictated by predictability and also by informativity.

We interpret these results as resulting from lexicalization of phonetic details associated with prosodic prominence. In the remainder of this discussion, we motivate the close connection that we have assumed between predictability and prosodic prominence (4.1). We then explain how the effect of informativity, a word-level variable, relates to lexicalization (4.2). Lastly, we discuss the relative strength of forward informativity and backwards informativity in the context of cognitive mechanisms proposed to account for the relation between predictability and word duration more broadly (4.3).

4.1 The connection between predictability and prosodic prominence

A key assumption behind our interpretation of the results is that predictability conditions prosodic prominence. Here we draw on connections between a few lines of research. The first is prosodic focus, which refers to the emphasis given to words often because they introduce new information to the discourse (Bolinger, 1958) or alternatives to the truth propositional content of an utterance (Rooth, 1992). In Mandarin Chinese (as well as English and many other languages), any number of content words in a sentence can receive prosodic focus, marked phonetically by local increases in maximum pitch, pitch range, duration, intensity, and post-focal compression of intensity and pitch range (e.g., Breen et al. 2010; Cao 2012; Chao 1968; Chen 2006; Chen and Gussenhoven 2008; Chen et al. 2014; Cooper et al. 1985; Ito and Speer 2006; Robert Ladd 2008; Lee et al. 2015; Lieberman 1960; Liu and Xu 2005; Ouyang and Kaiser 2015; Pierrehumbert and Beckman 1988; Xu 1999; Xu and Xu 2005; Xu et al. 2012; Wang and Xu 2011; Yuan 2004). Focused items tend also to be less predictable, as contextual unpredictability is a natural consequence of presenting new information or an item from a set of alternatives. There is a natural link between low predictability and prosodic prominence in focused words. All else equal, new information in a discourse context is likely to receive increased prosodic prominence, as measured in the phonetic signal (e.g., Calhoun, 2010). It is also the case that listeners judge less predictable words to be more prominent, even when bottom-up factors in the speech signal have been controlled for (Cole, Mo, & Hasegawa-Johnson 2010; Bishop, Kuo and Kim (to appear)). In studies of prosodic prominence, both word frequency (Baumann 2014; Cole et al. 2010; Cole et al. 2017; Nenkova et al. 2007) and informativity (Antilla et al., 2018) have been shown to influence prominence perception. This indicates that the connection between predictability and prominence may constitute part and parcel of tacit linguistic knowledge. Taken together, these findings serve to motivate our investigation of predictability, as measured in our study, on phonetic dimensions associated with prosodic prominence.

The link between predictability and prosodic prominence is closely related to the Uniform Information Density (UID) hypothesis (Jaeger, 2010) and the Smooth Signal Redundancy (SSR) hypothesis (Turk, 2010). We discuss each of these hypotheses in turn.

The UID proposes that predictability influences selection between grammatically available variants at all levels of linguistic structure. When a choice is made available by the grammar, speakers choose variants that maintain uniform distribution of information across some dimension (time, linear order of words, effort, etc.). Prosody, as a level of linguistic structure, would presumably fall within the scope of the UID as proposed by Jaeger (2010). Our hypothesis could therefore be viewed as a specific application of UID to prosodic structure; that is, prosodic structure, including phrasing and levels of prominence, are selected to distribute information uniformly across time. This proposal refers to a specific level of linguistic structure, prosody, and a specific dimension, time, over which information is distributed uniformly. The general version of UID does not commit to time as the dimension over
which information is uniformly distributed. For example, the UID is consistent as well with production effort as the dimension that trades off with information. Speech could be varied so that information is distributed across speaker effort. Xu & Promon (2019) provide a critical evaluation of the “effort” hypothesis, arguing that, time, not energy, is the most valuable resource for speech production; on their proposal, the amount of time allocated to each linguistic unit is a function of its importance. This predicts the relation between predictability and duration found in our study, but it does not necessarily predict effects of predictability on pitch and intensity, unless of course they are mediated by variation in duration. As words get shorter, the time required to achieve a pitch target could be reduced to the point that that the target is not achieved, i.e., target undershoot (Lindblom 1963). Crucially, our mediation analysis in section 4.3 shows that the influences that informativity has on pitch and intensity are not mediated by duration.

The Smooth Signal Redundancy (SSR) hypothesis states that prosody modulates the speech signal to maintain stable word recognition probability over time (Aylett & Turk, 2004; Turk, 2010). Part of recognition probability comes from predictability, or language redundancy; part comes from the speech signal. The connection between predictability and prosodic prominence discussed above is highly consistent with the SSR. The SSR dictates that predictability (as an index of language redundancy) trades off with signal enhancement, which includes prosodic prominence. Thus, the key prediction of our hypothesis is one that is shared by SSR—phonetic dimensions under prosodic control are precisely those that are influenced by contextual probability.

To summarize, the preceding discussion motivates a connection between prosody and predictability. Since prosodic phrasing and prominence affects not only the phonetic dimension of word duration but also pitch and intensity, we explored whether effects of predictability found on duration in past studies would generalize beyond word duration to pitch and intensity, a prediction that was confirmed in our data.

4.2 Reflections of prosodic prominence in the lexicon

In addition to the effects of predictability, we also found significant influences of the average predictability of a word -- informativity -- on word duration, pitch and intensity. It is on the basis of this result that we make our second claim, that prosodic influences on words are absorbed into the lexicon. Informativity, as it has been computed in this study and elsewhere, is a word-level variable. Each word has a unique set of contexts in which it occurs. Within these contexts, a word can be more or less predictable. Our results show that each word also has a characteristic prosodic profile, represented by combinations of duration, pitch, and intensity. Crucially, a word’s prosodic profile is systematically related to the contexts in which it occurs. This was captured in our models through the effect of informativity on word duration, pitch, and intensity.

The most general version of our claim is that words come to take on the phonetic characteristics of the prosodic contexts in which they are typically produced. Words that typically occur in prosodically prominent positions are correspondingly produced with greater duration, pitch and intensity. We view this second claim as compatible with a range of perspectives on the lexicon. Minimally, it requires that phonetic representations associated with words can change over time, a fact that is well-established, including, famously, in the case of the Queen of England (Harrington et al., 2001). Theories that adopt a lexicon of phonetically-detailed episodic memories capture changes in the lexicon over time rather directly, through combinations of memory trace decay and the addition of new exemplars (Goldinger, 1998; e.g., Johnson, 1997; Pierrehumbert, 2001; Foulkes & Docherty, 2006). In these theories, change in the speech community over time is directly encoded in the lexicon, at least to the extent that the dimensions of variation are encoded veridically (Foulkes & Docherty
2006). Accordingly, the prosodic prominence with which a word is produced will come to shape the long term representation of that word alongside other aspects of a word’s context, including the typical location that it was produced (Hay et al. 2017) and the speech characteristics of typical users of a word (Walker & Hay 2011).

Lexical representations that are somewhat more abstract in that they disentangle various influences on the speech signal can also be seen to make the same prediction. This is because listener attribution of the source of phonetic variation is often imperfect. Consider for example a word produced in a low predictability context with a correspondingly high degree of phonetic prominence. A listener may attribute some degree of prominence to the particular context in which the word was produced, and represent only residual phonetic details as associated with the lexical item. This process involves some degree of abstraction in that the details of the word’s pronunciation are abstracted away from the particular context. However, on this account, prosodic prominence can still influence the long-term representation of words. This is because listener compensation for contextual effects is typically imperfect. A well-studied case is compensation for coarticulation. Listeners routinely attribute some aspects of the phonetic signal associated with a speech segment to the coarticulatory context in which it was produced (e.g., Beddor et al., 2003); however, such compensation is typically incomplete (Cole et al., 2011) and varies in degree across listeners (Yu et al., 2015), a set of facts which has also received a rational analysis (Sonderegger and Yu, 2010). Incomplete compensation for the influence of prosodic prominence on word forms makes the same prediction as “pure” episodic representation of words. Over time, the lexicon will come to reflect the prosodic ecology of language use. This basic idea is broadly compatible with different conceptualizations of the mental lexicon.

Words that are typically produced in prominent environments will come to take on the phonetic characteristics of prominent environments, even when produced in prosodically weak positions. To the extent that predictability drives prosodic prominence, an assumption we motivated in 4.1, this prediction is borne out in the data as a significant effect of informativity on the phonetic dimensions of prosodic prominence in Mandarin Chinese: pitch, duration and intensity.

There is already some evidence for the lexical encoding of prosodic patterns coming from studies on German and English, languages in which pitch patterns (or tunes) are assigned at the phrasal level (Calhoun & Schweitzer, 2012; Schweitzer et al., 2015). Schweitzer et al. showed that f0 contours are more stable in predictable collocations than in unpredictable collocations, suggesting a possible lexicalization of intonation. In a study predicting the presence/absence of a phrasal pitch accent in a manually labelled portion of the Switchboard corpus, Nenkova et al. (2007) showed that a lexical property, the probability of particular lexical items to bear accent, was by far the best predictor (explaining 75.59% of the data). Anttila et al. (to appear) examined a finer-grained annotation of English prominence. Their corpus was hand-annotated for metrical grids encoding gradient levels of sentence prominence. Results revealed that nouns had much higher levels of prominence than verbs and function words and that informativity was a significant predictor of prominence judgments even after grammatical factors, e.g., Nuclear Stress Rule (Chomsky & Halle, 1968), had been taken into account. These results are consistent with the view that sentence-level prominence may be a driving force in shaping word-level stress (Anttila, Dozat, Galbraith, & Shapiro, to appear).

In sum, prosody leaves its imprint on the phonetic form of words; the mental lexicon reflects the typical prosodic contexts in which words are produced.

4.3 The broader context of our proposal and relation to other accounts

One empirical contribution of the current paper is that we show that predictability and informativity influence pitch and intensity, in addition to duration, and that the effects of informativity on pitch and
intensity are not mediated by duration. This is theoretically significant in part because it narrows the range of possible accounts to eliminate those that predict only effects of information on duration.

There is a substantial body of work exposing systematic relations between “speech rate”, as quantified by the duration of linguistic units, e.g., segments, syllables, words, and the information contained in those units (Arnon & Cohen Priva, 2015; Arnon & Priva, 2013; Arnon & Snider, 2010; Aylett & Turk, 2004, 2006; Bell et al., 2009; Jurafsky et al., 2001; Priva, 2015; Shaw & Kawahara, 2019; Tang & Bennett, 2018). This work points to a tradeoff between time and information -- linguistic units carrying more information tend to take more time to produce. Another dimension of variation is vowel and syllable reduction (e.g., Jurafsky et al. 2001; Aylett & Turk, 2004), although it is also the case that shorter vowel durations can condition vowel reduction—as the movement of speech organs may fail to achieve their targets under time pressure, i.e., “target undershoot” (Lindlom 1963; Lindblom & Moon, 1993). Thus, the empirical basis of much of the existing theorizing about predictability in speech is based on duration or potentially duration-mediated factors, such as vowel reduction. Notable exceptions include Watson et al. (2008), who evaluate effects of predictability and context importance on duration, intensity and pitch in an experimental game-like setting and Fitzroy and Breen (2020) who compare effects of predictability on intensity with previous results on duration (Breen 2020). Both of these studies reveal differential effects of predictability on duration and other dimensions of prosodic prominence.

Focusing just on duration patterns, relatively consistent information rates -- achieved by trading off time-per-unit with information-per-unit -- have been observed across languages (Coupé, Oh, Dediu, & Pellegrino, 2019), across speakers of the same language (Cohen Priva, 2017), and within speakers in different situations (Arnold, Bennetto, & Diehl, 2009; Buz, Tanenhaus, & Florian Jaeger, 2016; Kitamura, 2014; Maniwa, Jongman, & Wade, 2008; Raveh, Steiner, Siegert, Gessinger, & Möbius, 2019; Schertz, 2013). The ubiquity of this pattern across these levels of description suggests a cognitive basis for the behavior. That is, the production mechanism at the level of the individual constrains speech to adhere to relatively stable information rates. Consequently, the same patterns found within the individual can be found on average within a speech community and across speech communities.

To the extent that these patterns are ubiquitous across languages, including observance at the level of individual speakers, an account rooted in fundamental aspects of human language, as embodied in the mind/brain, is justified. “Efficient communication” is often evoked in this context as a universal functional constraint on language. Languages, sitting at the intersection of biology, ecology and culture, have in common that they evolve to serve a communicative function (Gibson et al., 2019; Winter & Christiansen, 2012). However, functional pressures on the development of the system are distinct from the internal workings. Cognitive mechanisms that have been proposed to explain stable information rates include those that are largely situated within the speech production system proper (Bell et al., 2009), and those that evoke “audience design”, a language-specific application of theory of mind (Arnold et al., 2009; Arnold, Kahn, & Pancani, 2012; Watson et al., 2008, 2010). Our proposal is that the assignment of prosodic prominence is the primary driver of the patterns.

In assessing the degree to which our account is compatible with those put forward to explain duration-based patterns, it is useful to compare the results on forward vs. backward predictability/informativity. Forward informativity indicates how predictable, on average, a word is from its preceding context. A word with high forward informativity is typically predictable from what comes before it. This type of predictability is useful in speech perception, on the common assumption that listeners actively narrow the field of competitors based on preceding context (Marslen-Wilson & Welsh, 1978; McClelland & Elman, 1986; Norris, 1994). Listeners also make backward inferences, using information that comes
later in time to resolve earlier uncertainty (e.g., Toscano & McMurray 2010), and there is evidence that both backward and forward predictability are relevant to Chinese word formation processes (Shaw et al., 2014). However, backward inference in perception is generally slower and less efficient than forward inference (Nooteboom, 1981). Varying word forms according to listener needs (audience design) would entail phonetic variation conditioned by forward predictability. Backward informativity is consistent with production-based accounts of probabilistic reduction. The speaker typically plans chunks of speech consisting of multiple words. Consider a sequence of words, AB, in the production plan. If A is predictable from B, then A can be retrieved from the lexicon more easily. The speaker has access to both A and B in speech planning while the listener receives information more linearly, having to wait to hear A before getting information about B (modulo any effects of anticipatory coarticulation). For this reason, backward informativity has been more closely linked to production-based accounts.

An example of a production-based account is that lexical items that are harder to retrieve are also produced more slowly (Bell et al., 2009). Coupling the time course of lexical access with the speed of word production is possibly crucial to fluent speech. Hesitations or pauses would result if lexical access lags behind speech rate; lexical access outpacing speech rate could lead to pathological coarticulation or anticipatory substitution errors, both of which are well-documented speech anomalies (Cutler, 1982; Dell, 1986; Frisch & Wright, 2002; Fromkin, 1984; Goldstein, Pouplier, Chen, Saltzman, & Byrd, 2007; McMillan & Corley, 2010). Considering that a larger sequence of words is available for production planning, it is reasonable to assume that backward predictability may aid lexical access in speech production. In the only other study to date reporting effects of informativity on word duration, it was backward informativity that showed reliable effects across corpora (Seyfarth, 2014).

In our study, forward informativity was stronger than backward informativity in two ways. First, forward informativity had a significant positive effect on all three phonetic dimensions under study (duration, pitch, intensity); backward informativity only had a significant positive effect on duration. Second, the size of the coefficients relative to the standard error was greater for forward informativity than for backward informativity. Additionally, we had one informativity result that went in the opposite direction—the effect of backward informativity on pitch. We note that Watson et al., (2010), which investigated effects of predictability on pitch, duration, intensity, also found significant effects on duration and intensity but not pitch.

We speculate that assignment of prosodic prominence (at least in Chinese) operates primarily on forward predictability. This is the direction that is maximally useful to listener perception, per the audience design account. Since we also observe positive effects of backward informativity, but only for duration, it is possible that prosodic prominence is only part of the story. Production-based factors may have also left their imprint on our spontaneous speech data.

A number of factors are known to influence both lexical access and word duration, including word frequency, phonological neighborhood density (Gahl & Strand, 2016; Gahl, Yao, & Johnson, 2012) and metrical predictability (Breen, 2018; Shaw, 2013). The dual effects of such factors on both lexical access and speech rate are consistent with the proposal that speech rate is yoked to lexical access or “production ease”. Whether or not there is a causal relation between lexical access and word duration or whether these factors operate on lexical access and word production independently is an area that requires future research. Work on one of these factors, phonological neighborhood density, has found that its influence on speech rate (word duration) is independent of its influence on lexical access, which challenges some versions of the production ease account (Buz & Jaeger, 2016). This still leaves open the possibility that backward predictability facilitates lexical access in spontaneous speech
production and that this has a knock-on effect on word duration, which may be independent of prosodic prominence. Other studies as well have concluded that a complete account of word prominence variation likely involves multiple cognitive factors (e.g., Lam & Watson 2010; Fitzroy & Breen 2019).

In summary, our results bear directly on recent debates about the cognitive mechanism(s) responsible for the observation that word length/duration correlates with contextual predictability; see Jaeger and Buz (2017) for an overview. One perspective is that speakers actively balance contextual predictability with signal redundancy (e.g., Jaeger, 2015; Wedel, Nelson, & Sharp, 2018) possibly driven by audience design (Watson, Arnold, & Tanenhaus, 2008, 2010). Fewer resources in production are expended when communication is not at risk (predictable contexts); additional production resources are drawn upon in challenging communication environments (unpredictable contexts, noisy environments, etc.). A key characteristic of audience design accounts is that speakers adjust pronunciation based on an internal model of listener perception (Rosa, Finch, Bergeson, & Arnold, 2015). The internal model informs speakers of how words are likely to be understood given the context. Speakers use this knowledge to modulate the phonetic signal to facilitate listener recognition of the intended message.

One important aspect of our result is that effects of predictability were found not just on word duration but also on other dimensions of prosodic prominence that are not directly mediated by word duration. We have argued that this supports a prosodic account. Speakers vary prosodic prominence according to the local (forward) predictability of words. A second important aspect of the result is that a word-based variable, informativity, predicted variation in duration, pitch, and intensity above and beyond the effects of local predictability. We have argued on the basis of this result that prosodic influences on words affect long-term memory, reflected in speech production. We view this account in terms of prosodic prominence as consistent with audience design. Future research may show that the assignment of prosodic prominence is very much tied to the speakers rendering of their interlocutors mental state. In this case, the assignment of prosodic prominence may provide a mechanism through which audience design operates. The strongest version of this hypothesis makes the prediction that the resources available to audience design considerations are constrained by the resources of prosody in language-specific ways. If so, deeper evaluation of these cognitive mechanisms must be pursued in the context of the linguistic systems in which they operate. Finally, our account in terms of prosody does not preclude the operation of certain production-based factors on word duration, which may be required to explain backward predictability/informativity effects on duration.

5 Conclusion

Phonetic correlates of prosodic prominence in Mandarin Chinese, pitch, intensity, and duration, were shown to vary with the average predictability of a word in context, i.e., the word’s informativity. The sensitivity of phonetic dimensions associated with prosody to predictability underscores a relation identified in past work—less predictable words tend to attract prosodic prominence. More importantly, the influence of a word’s informativity on the phonetic dimensions of prosody indicates that the level of prominence with which a word is typically produced may influence its lexical representation. That is, the long-term representation of a lexical item takes on the phonetic characteristics of the prosodic context in which it typically occurs. This result builds on a substantial body of work establishing phonetic cues to prosodic structure in Mandarin Chinese, a language with lexical tone. More broadly, the findings suggest that the phonetics of a prosodic system can contribute as well to an understanding of phonetic variation in the lexicon.
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