

Predictive re-activation of the upcoming verb explains (anti-)locality effects in Hindi

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Abstract

A well-established empirical phenomenon in human sentence comprehension is the locality effect: reading time at a verb is slower when its argument (e.g., the subject) is placed linearly farther away than when it is kept closer to the verb. The locality effect has been robustly observed across languages and attributed to working memory constraints: due to limited working memory, it becomes difficult to maintain the accessibility of the argument nouns as the distance between the argument and the verb increases. However, working memory-based theories fail to explain the anti-locality effect. In verb-final languages like German and Hindi, increased distance between the arguments and the verb causes a speedup in reading times at the verb. Anti-locality effects have been attributed to predictive processing. However, it remains unclear how predictive processing produces the anti-locality effect and why the locality effect is not found in verb-final languages. We explore the Vasishth and Lewis (2006) proposal, the *VP-reactivation hypothesis*: intervening items between the subject and the verb reactivate the prediction of the upcoming verb phrase. As distance increases, the verb phrase becomes highly preactivated in memory, facilitating processing at the verb and, consequently, overriding the locality effect. We computationally implement this proposal within a cue-based retrieval framework and conduct two self-paced reading experiments on Hindi that manipulate whether the intervening material directly modifies the upcoming verb or not. The reading data support the key prediction of the *VP-reactivation model*: anti-locality effects are stronger when preverbal material directly modifies the upcoming verb.

Keywords: Working memory constraints; cue-based retrieval; predictive processing; anti-locality

Introduction

Comprehending a sentence requires us to identify, maintain, and integrate linguistically related words, e.g., the subject and the verb. In some sentences, linguistically related words may be separated in linear distance from each other. Due to the serial nature of input during sentence comprehension, the word that is first encountered must be stored temporarily in memory until its codependent word is encountered for successful integration.

In sentence comprehension (reading) tasks, it is observed that reading time at a word is slower when its preceding codependent is placed linearly farther away in the sentence compared to when it is kept closer (Gibson, 1998, 2000). This slowdown in reading times at a word due to increased dependency distance has been called the locality effect. The locality effect has been robustly observed in argument-verb dependencies across languages. For example, in sentences like (1a), the reading times at the verb *supervised* are observed to be slower because its co-dependent, the subject noun *nurse*,

is kept linearly apart in the sentence, in contrast to sentences like (1b) where the subject and the verb are kept close to each other.

1. (a) **The nurse** from the clinic **supervised** the patient.
- (b) **The nurse supervised** the patient.

Evidence for the locality effect comes from English (Grodner & Gibson, 2005; Bartek, Lewis, Vasishth, & Smith, 2011), Spanish (Nícenboim, Vasishth, Gattei, Sigman, & Kliegl, 2015), Danish (Balling & Kizach, 2017), and Russian (Levy, Fedorenko, & Gibson, 2013).

The locality effect has motivated theories that assume working-memory constraints play a central role in sentence comprehension (Gibson, 2000; Lewis, 1996; Lewis & Vasishth, 2005b). One of the well-established working memory-based models is the cue-based retrieval model of Lewis and Vasishth (2005a). The model assumes that linguistically related words are identified and linked together through a content-addressable search in memory. For example, in the sentence (1a), when the verb *supervised* is encountered, a search is triggered in memory for the target subject noun using retrieval cues such as *subject* and *animate*; the nouns that match these cues receive a certain amount of activation. A noun with the highest activation is retrieved to complete the subject-verb dependency. The retrieval cost is determined by the activation of the target noun to be retrieved from memory. The model can explain the locality effect: when the linear distance between the subject and the verb increases, the activation of the subject noun decays in memory over time, making it difficult to retrieve the subject noun when the verb is encountered. The cue-based retrieval model enjoys good empirical coverage as it can explain a range of sentence processing phenomena, including similarity-based interference, locality, and agreement attraction.

A major empirical challenge to the cue-based retrieval model and other working memory-based models is the absence of locality effect in verb-final languages such as German and Hindi. Reading studies from German, Hindi, and Japanese present strong counter-evidence for the predicted locality effect (Konieczny, 2000a; Vasishth & Lewis, 2006a; Husain, Vasishth, & Srinivasan, 2014b; Nakatani & Gibson, 2010). Contrary to predictions of working memory-based models, when the distance between a verb and its arguments is increased, a speedup is observed in reading times at the verb. This effect has been called the anti-locality effect.

The anti-locality effect has been attributed to robust top-down prediction of the upcoming verb phrase (VP) in verb-final languages (Konieczny, 2000b; Husain et al., 2014b). Possibly, extensive exposure to rich case-marking in these languages allows comprehenders to reliably predict the properties of the upcoming verb phrase.

It remains unclear how exactly top-down prediction influences dependency completion in real time and how it interacts with working memory constraints. This is because the prediction proposal has never been systematically implemented as a computational model. An attempt in this direction was made by Vasishth and Lewis (2006a). They propose a prediction reactivation mechanism within the cue-based retrieval framework of (Lewis & Vasishth, 2005a). They assume that the subject noun predicts a verb phrase (VP) based on prior grammatical knowledge. The predicted VP remains activated in memory for a while, but its activation decays over time. However, the intervening items between the subject and verb may reactivate the prediction of the VP. If the intervening items syntactically modify the upcoming verb, they will reactivate the VP prediction. We call it the *VP-reactivation hypothesis*.

The *VP-reactivation proposal* can explain the anti-locality effect: As the number of intervening items that modify the upcoming verb increases, the activation of the predicted VP increases, causing a facilitation in retrieving the VP when the verb is encountered. This facilitation may override the retrieval cost at the verb posited by increased subject-verb distance.

We implement the VP-reactivation proposal within the cue-based retrieval model of Lewis and Vasishth (2005b). We call it the *prediction reactivation model*. The model assumes that each pre-verbal noun syntactically modifies the upcoming verb reactivates the prediction of the upcoming verb phrase in memory, causing a facilitation in processing when the verb is encountered.

To test the predictions of the prediction reactivation model, we conduct two self-paced reading experiments on argument-verb dependencies in Hindi. In Experiment 1, we increase the linear distance between the argument and the verb by inserting adjuncts that syntactically modify the upcoming verb. While in Experiment 2, we increase the argument-verb distance by inserting adjectives and verbal modifiers that do not directly modify the verb but some other noun phrases. The prediction reactivation model will predict a stronger anti-locality effect for Experiment 1 and a weaker/no anti-locality effect for Experiment 2. The data from two experiments are consistent with the predictions of the prediction reactivation model. The results imply that dependency completion between arguments and the verb is driven by top-down predictive reactivations and bottom-up retrieval processes.

The paper is organized as follows. First, we present the assumptions of the prediction reactivation model. Then, we present our two experiments and spell out model predictions for each experiment. Finally, we discuss the findings and conclude.

Integrating working memory constraints and top-down prediction

A key prediction of working memory-based models, the locality effect, which is robustly observed in verb-medial languages, does not find any support in verb-final languages. This is a serious empirical challenge to existing models of sentence comprehension. Not only this, another key prediction of the cue-based retrieval models, similarity-based interference, which is again robustly observed in English, does not find convincing support in verb-final languages.

Empirical data from typologically different languages demand a new theory that can explain all key phenomena observed on sentence comprehension tasks across languages. Such a theory will need to reasonably integrate working memory mechanisms and top-down prediction in a single set of assumptions.

Lossy-context surprisal theory is one such attempt (Futrell, Gibson, & Levy, 2020). The theory builds on the classic surprisal theories (Hale, 2001; Levy, 2008), which maintain that processing difficulty is determined by the surprisal, i.e., the negative log conditional probability of a word given the context. The lossy-context surprisal theory makes the further assumption that the true context is probabilistically distorted to a non-veridical memory representation, and this memory representation is used to predict the upcoming word. This representation distortion assumption allows the theory to incorporate working memory limitation. The lossy-context surprisal model can potentially explain both locality and anti-locality effects. However, a recent implementation of the lossy-context surprisal model by Hennert et al. (2025) failed to account for locality and anti-locality effects observed in Russian (Levy et al., 2013), Hindi (Husain et al., 2014b) and Persian (Safavi et al., 2016).

In this paper, we explore another proposal that has remained speculative for quite some time but has not been systematically implemented and tested as a computational model. It is the prediction reactivation proposal by Vasishth and Lewis (2006b). We implement this proposal as a computational model and generate testable quantitative predictions.

The prediction reactivation model

The prediction reactivation model draws its assumptions from the cue-based retrieval model of Lewis and Vasishth (2005b) and the reactivation proposal by Vasishth and Lewis (2006b).

The model assumes that the activation of a pre-verbal noun i stored in memory decays with time, such that the activation of the item i at time t is given by:

$$A_{i,t} = A_{i,0}e^{-t} \quad (1)$$

where $A_{i,0}$ is the activation of the noun phrase at the time t_0 when it was first accessed for the current sentence from the declarative memory.

The model further assumes that when the verb is encountered, a cue-based retrieval process is triggered in memory to

search for its arguments. Each noun phrase that matches a retrieval cue receives a certain amount of activation. The total activation of a noun phrase i at time t can be given by

$$A_{i,t} = A_{i,0}e^{-t} + \sum_{j=1}^n W_j S_{ji} + \epsilon_n \quad (2)$$

where the $\sum_{j=1}^n W_j S_{ji}$ term means that the noun phrase i receives activation from all matching cues j depending on the associative strength S_{ji} between the cue j and the noun i . The term ϵ_i is activation noise, such that $\epsilon_i \sim \text{Normal}(0, \sigma)$.

Following the Vasishth and Lewis (2006b) proposal, the model assumes the argument noun predicts and builds a verb phrase (VP) based on prior grammatical knowledge.

Each intervening item between the argument and the verb may reactivate the prediction of the VP if it is a syntactic dependent of the verb. If an intervener is a syntactic dependent of the verb, we call it a verb-dependent intervener; otherwise, we call it a verb-independent intervener.

The activation of the predicted verb phrase k in memory increases due to reactivations from each intervening item that syntactically modifies the verb k :

$$A_{k,t} = ((B_k + W_1 S_{1,k})e^{-(t_2-t_1)} + W_2 S_{2,k})e^{-(t_3-t_2)} + \dots \quad (3)$$

where B_k is the baseline activation of the verb phrase k ; $W_1 S_{1,k}$ is the amount of activation spread from the intervening item 1 to the verb phrase k . Here, W_1 and W_2 are weightage for how strongly a particular intervener type reactivates the verbal prediction, we assume it to be equal for all intervener types; $(t_2 - t_1)$ is the time elapsed between the noun 1 and the noun 2 and $(t_3 - t_2)$ is the time elapsed between the noun 2 and the noun 3. The associative strength $S_{1,k}$ between an intervening item 1 and verb k implies how strongly the intervener can reactivate the VP k .

The associative strength between an intervening item and the verb is determined by their history of co-retrievals, which can be captured using head-dependent mutual information between the two. For simplified model simulations here, we assume that intervening items that syntactically modify the upcoming verb phrase has higher associative strength, say 0.6. While intervening items that do not syntactically modify the upcoming VP will have lower associative strength, say 0.3 or even lower. The items that do not syntactically modify the VP can be of two types. First, modifiers of an argument noun phrase. Such items can reactivate the VP indirectly because they retrieve/reactivate the argument noun, which would reactivate the VP indirectly; we assume a low association strength of approx. 0.3 for these items. Second, intervening items that do not modify the argument or the verb, for these items, we assume an associative strength of 0.

The reading time at the verb k in the n^{th} trial is determined by the time taken to retrieve the verb phrase k and the time taken to retrieve its argument noun i :

$$T_{k,t} = Fe^{-A_{k,t}} + Fe^{-A_{i,t}} \quad (4)$$

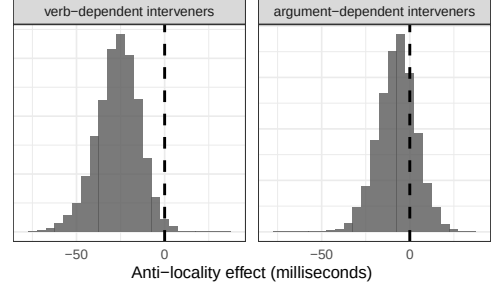


Figure 1: Prior predictions of the prediction reactivation model for two types of dependency distance manipulation: One where intervening items are syntactic dependents of the verb (left panel), and the other where interveners syntactically modify an argument noun, not the verb directly (right panel). The x-axis shows the predicted anti-locality effect in milliseconds.

where F is the latency factor parameter, which reflects the overall reading speed of the comprehender. The latency factor is the only free parameter in the model.

We choose the following prior on the latency factor F to avoid unreasonably fast and unreasonably slow reading times (see Yadav et al., 2023):

$$F \sim \text{Normal}_{lb=0.05}(0.45, 0.05) \quad (5)$$

We generate prior predictions of the prediction reactivation model locality effect for the construction where the distance is increased by verb-dependent interveners (syntactic dependents of the verb) as well as for the construction where the distance is increased by argument-dependent interveners (syntactic dependents of the argument noun). The associative strength between the intervener and the verb is assumed to be 0.6 and 0.3 respectively.

Figure 1 shows model predictions for the locality effect in verb-dependent intervener construction vs. argument-dependent intervener construction. The model predicts a strong anti-locality effect when verbal dependents increase the distance. Interestingly, when argument dependents increase the distance, the model predicts a weak, close-to-zero anti-locality effect.

Testing the prediction reactivation model

We test the key predictions of the prediction reactivation model, shown in Figure 1, using data from two self-paced reading (SPR) experiments on Hindi.

We conduct two SPR experiments in Hindi that directly test the model predictions for both the verb-dependent intervener design and the argument-dependent intervener design.

In Experiment 1, we use the constructions where interveners syntactically modify the verb. In Experiment 2, we use constructions where the interveners do not directly modify the verb but they syntactically modify an argument noun.

The prediction reactivation model predicts an anti-locality effect in Experiment 1, but a weak, close-to-zero effect in Experiment 2.

Experiments 1 and 2

To build a theory of locality and anti-locality effects, it is necessary to investigate under what conditions these effects arise across languages.

In previous studies on Hindi (Husain et al., 2014a; Vasisht & Lewis, 2006b), the distance between the verb and its arguments was increased by intervening material that directly (syntactically) modified the verb, which possibly causes strong reactivations of the upcoming verb phrase. It is unlikely to attest a locality effect in such constructions.

Can the locality effect be attested in Hindi (a verb-final language) if we increase the argument-verb distance using interveners that do not directly modify the upcoming verb phrase? We address this question using two SPR experiments on Hindi.

More specifically, we test a key prediction of our model: Intervening items that syntactically modify the upcoming verb will cause a stronger anti-locality effect compared to interveners that do not directly modify the verb.

Material In Experiment 1, we used the subject relative clause (RC) constructions; see sentences (2a-b). The distance between the relative pronoun (RelPro) subject and the RC verb in condition (2a) was increased by inserting adjuncts that directly modify the RC verb. Thus, Experiment 1 uses the verb-dependent intervener design.

2. Experiment 1: Verb-dependent interveners

- (a) A boy **who** yesterday school-LOC everyone-GEN front song **sing-PROG** was ...
- (b) A boy **who** song **sing-PROG** was ...

3. Experiment 2: Argument-dependent interveners

- (a) A boy **whom** yesterday school-LOC music teach.NFV PART a strict teacher-ERG office-LOC **call.perf** was
- (b) A boy **whom** a teacher-ERG office-LOC **call.perf** was

In Experiment 2, we used the object relative clause (RC) constructions; see sentences (3a-b). The distance between the relative pronoun (RelPro) object *whom* and the RC verb *call.perf* was manipulated. In condition (3a), the distance was increased by inserting the interveners that syntactically modify the subject noun *teacher*. The intervening items do not directly modify the verb; they modify an argument noun. Thus, Experiment 2 uses the argument-dependent intervener design.

Following Nicenboim et al. (2016), we also controlled for potential verb-position effects by adding control conditions that match the verb position in long vs./ short RC conditions.

Procedure Native Hindi speakers (N=62 for Experiment 1; N=53 for Experiment 2) were recruited for each Experiment.

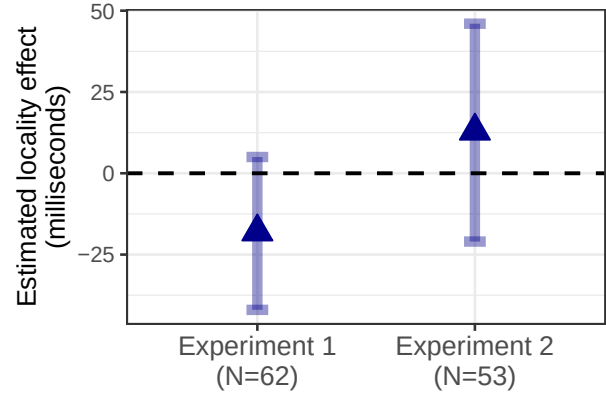


Figure 2: The 95% credible intervals of the estimated locality effects (milliseconds) in Experiment 1 and Experiment 2. The credible intervals are shown using the error bars.

ment. A centered self-paced reading paradigm was employed to record word-by-word reading times. The experiment was designed and presented using PCibex software (Zehr & Schwarz, 2021). The stimuli consisted of 24 critical items and 72 fillers.

Predictions In Figure 1, we have already showed predictions from the prediction reactivation for the kind of constructions used in Experiment 1 and Experiment 2. The left panel in Figure 1 shows the predicted anti-locality in Experiment 1, and the right panel shows the predicted effect in Experiment 2. A stronger anti-locality effect is predicted for Experiment 1, because here the intervening material directly modifies the upcoming verb, causing strong reactivations of the predicted VP and consequently, stronger processing facilitation at the verb. In Experiment 2, the interveners modify the subject noun phrase, not the verb. Thus, do not directly reactivate the VP. However, these interveners indirectly reactivate the VP using a pre-activated representation of the subject noun phrase. But these reactivations are not strong enough to produce an anti-locality effect, but they do cancel out the locality effect.

Results We analyzed the effect of RelPro-RCverb distance on reading times at the RC verb using Bayesian regression models. Using the *brms* package (Bürkner, 2017), we estimated the posterior distribution of the (anti-)locality effect in Experiment 1 and Experiment 2 separately.

Figure 2 shows the 95% credible intervals of the locality effect estimated from Experiment 1 and Experiment 2 data.

We find two key results. First, the anti-locality effect is relatively stronger in Experiment 1, where the intervening material syntactically modifies the RC verb. Second, there is a weak locality effect in Experiment 2, where the intervening material does not directly modify the RC verb.

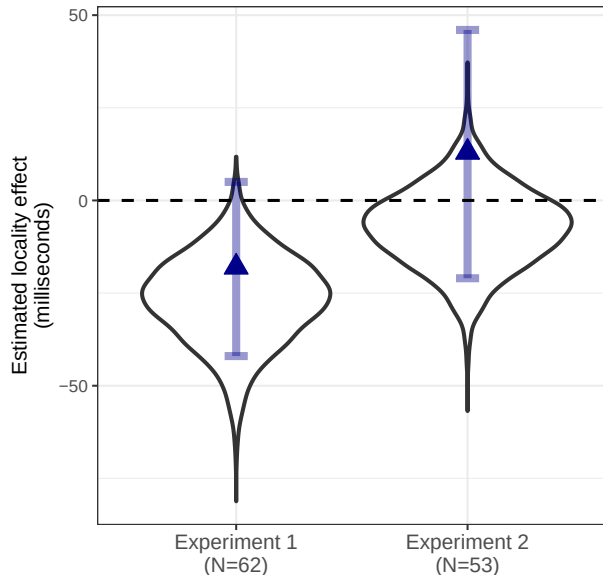


Figure 3: The prior predictions of the prediction reactivation model for the two experiments are shown as violin plots; the mean estimate and 95% credible intervals of the observed locality effect in each experiment are shown using blue triangles and error bars.

Model evaluation

We assess whether the prediction reactivation model can qualitatively account for the observed (anti-)locality effects in both Experiment 1 and Experiment 2.

Figure 3 compares the prior predictions of the prediction reactivation against the observed (anti-)locality effect in the two experiments. We find that the observed data from both experiments are consistent with model predictions.

Discussion

We computationally implemented the prediction reactivation proposal of Vasissth and Lewis (2006b) for Hindi, a verb-final, rich case-marking language. The model assumed the arguments and the verb in a sentence are identified, maintained, and linked together through top-down predictive reactivations and a bottom-up retrieval process. We demonstrate that the model can generate different extents of anti-locality effect given different kinds of intervening material that increases the dependency distance. The model can generate testable quantitative predictions for locality and anti-locality effects under different kinds of manipulations used to increase argument-verb dependency distance.

A key prediction of the model is that when the argument-verb distance is increased by interveners that directly syntactically modify the verb, the anti-locality effect will be stronger compared to when the interveners do not directly modify the verb.

We design two hard empirical test cases for the model us-

ing Hindi relative clause constructions, where the argument-verb distance is manipulated either by using adjuncts that syntactically modify the RC verb (Experiment 1) or by using interveners that do not directly modify the RC verb (Experiment 2).

We find that (1) A locality effect can be attested in Hindi (a verb-final language) when the intervening items do not directly modify the verb; (2) A stronger anti-locality effect arises when the intervening material directly modifies the verb; (3) the observed (anti-)locality effects in both experiments are consistent with the prediction reactivation model.

These findings have important theoretical implications for sentence comprehension. The integration of a top-down predictive activation component within a dynamic memory activation architecture can explain the cross-linguistic differences observed in sentence processing behavior.

How does our model differ from the lossy-context surprisal model of Futrell et al. (2020)? In the lossy-context surprisal model, as the distance between mutually informative words increases, locality effects arise due to progressive noise on the memory representation of the context. With a noisy context, the surprisal of the upcoming word may increase as the distance increases.

In the prediction reactivation model, due to prior grammatical knowledge, pre-verbal chunks spread some activation to reactivate a predicted VP in memory. Such multiple reactivated verb phrases are retrieved faster compared to when the predicted VP does not receive any reactivations. The model can, therefore, explain the locality effect when the verb chunk is not sufficiently pre-activated, and an anti-locality effect when the verb chunk has strong enough pre-activation to override the cost of retrieving its arguments.

A principled empirical test of the predictive reactivation mechanism would be in assessing whether the individuals who exhibit strong predictability of the upcoming verb phrase also show a stronger anti-locality effect. We can independently measure predictability strength for each individual, and conditioned on these predictability estimates, we can generate predictions from the model, for each individual, for the anti-locality effect. Using this approach, we can test whether the model can predict an individual’s anti-locality effect on a sentence comprehension task, given their independent measurement of prediction strength. We plan to take this up in future work.

The present work leads to important theoretical insights into the underlying sentence comprehension process: the arguments and the verbs are identified, maintained, and linked together via a predictive reactivation mechanism and a bottom-up cue-based retrieval process.

This is the first attempt to computationally implement top-down prediction in a working memory-based model and generate testable predictions for (anti-)locality in different types of constructions. Our work contributes to understanding how does locality or anti-locality effect arise in certain constructions in a language, which is crucial for building cross-

linguistically generalizable theories of sentence comprehension in humans.

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