Context-Sensitive Measurement of Word Distance
by Adaptive Scaling of a Semantic Space

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Abstract
The paper proposes a computationally feasible method for measuring context-sensitive semantic distance between words. The distance is computed by adaptive scaling of a semantic space. In the semantic space, each word in the vocabulary $V$ is represented by a multi-dimensional vector which is obtained from an English dictionary through a principal component analysis. Given a word set $C$ which specifies a context for measuring word distance, each dimension of the semantic space is scaled up or down according to the distribution of $C$ in the semantic space. In the space thus transformed, distance between words in $V$ becomes dependent on the context $C$.

An evaluation through a word prediction task shows that the proposed measurement successfully extracts the context of a text.

Keywords: context-sensitivity, lexical similarity, semantic network, thesaurus, word association.

1 Introduction
Semantic distance (or similarity) between words is one of the basic measurements used in many fields of natural language processing, information retrieval, etc. Word distance provides bottom-up information for text understanding and generation, since it indicates semantic relationships between words that form a coherent text structure (Grosz & Sidner 86; Mann & Thompson 87); word distance also provides basis for episode association (Schank 90), since it works as associative links between episodes.

A number of methods for measuring semantic distance between words have been proposed in the studies of psycholinguistics, computational linguistics, etc. One of the pioneering works in psycholinguistics is the “semantic differential” (Osgood 52), which analyzes meaning of words by means of psychological experiments on human subjects. Recent studies in computational linguistics proposed computationally feasible methods for measuring semantic word distance. For example, (Morris & Hirst 91) used Roget’s thesaurus as knowledge base for determining whether or not two words are semantically related; (Brown et al. 92) classified a vocabulary into semantic classes according to co-occurrence of words in large corpora; (Kozima & Furugori 93) computed similarity between words by means of spreading activation on a semantic network of an English dictionary.

The measurements in the former studies above are so-called context-free or static ones, since they measure word distance irrespective of contexts. However, word distance changes in different contexts. Even in free-association tasks, we often imagine a certain context for retrieving related words. In this paper, we will incorporate the context-sensitivity into semantic distance between words.

A context can be specified by a word set $C$ consisting of keywords of the context (for instance, $C = \{\text{car, bus}\}$ for the context “vehicle”). Now we can exemplify the context-sensitive word association as follows.

- $C = \{\text{car, bus}\}$
  $\rightarrow \text{taxi, railway, airplane, \ldots}$
- $C = \{\text{car, engine}\}
  \rightarrow \text{tire, seat, headlight, \ldots}$

Generally, if we change the context $C$, we will observe different distance for the same word pair. So, we in this paper will deal with the following problem.

Under the context specified by a given word set $C$, compute semantic distance $d(w, w'|C)$ between any two words $w, w'$ in our vocabulary $V$.

Our strategy for computing the context-sensitive word distance is “adaptive scaling of a
Each word in the vocabulary \( V \) is represented by a multi-dimensional semantic vector. The semantic vectors, called Q-vectors, are obtained through a principal component analysis on P-vectors. P-vectors are generated by spreading activation on the semantic network which is systematically constructed from an English dictionary. Section 3 describes adaptive scaling of the semantic space. For a given word set \( C \) that specifies a context, each dimension of the semantic space is scaled up or down according to the distribution of \( C \) in the semantic space. In the semantic space thus transformed, distance between Q-vectors becomes dependent on the given context. Section 4 shows some examples of the context-sensitive word distance computed by this method. Section 5 evaluates the proposed measurement through word prediction, i.e. predicting succeeding words by using preceding words in a text. Section 6 discusses some theoretical aspects of the proposed method, and Section 7 gives conclusion of this paper and puts this work in perspective.

2 Vector-Representation of Word Meaning

Each word in the vocabulary \( V \) is represented by a multi-dimensional Q-vector. In order to obtain Q-vectors, we first generate 2851-dimensional P-vectors by spreading activation on a semantic network of an English dictionary (Kozima & Furugori 93). Next, through a principal component analysis on P-vectors, we map each P-vector onto a Q-vector with a reduced number of dimensions. (See Figure 1.)

2.1 From an English Dictionary to P-Vectors

Every word \( w \) in the vocabulary \( V \) is mapped onto a P-vector \( P(w) \) by spreading activation on the semantic network. The network is systematically constructed from a subset of the English dictionary, LDOCE (Longman Dictionary of Contemporary English). The network has 2851 nodes corresponding to the words in LDV (Longman Defining Vocabulary, 2851 words). The network has 295914 links between the nodes — each node has a set of links corresponding to the words in its definition in LDOCE. Note that every headword in LDOCE is defined by using LDV only. The network becomes a closed cross-reference network of English words.

Each node of the network can hold activity, and it flows through the links. Hence, activating a node of the network for a certain period of time causes the activity to spread over the network and forms a pattern of activity distribution on it. Figure 2 shows the pattern generated by activating the node red; the graph plots the activity values of 10 dominant nodes at each step of time. We empirically found that the activated pattern reaches equilibrium approximately after 10 steps, whereas it will never reach the actual equilibrium.

The P-vector \( P(w) \) of a word \( w \) is the pattern of activity distribution generated by activating the node corresponding to \( w \). \( P(w) \) is a 2851-dimensional vector consisting of activity values of the nodes at \( T = 10 \) as an approximation of the equilibrium. \( P(w) \) indicates how strongly each node of the network is semantically related with \( w \).

We in this paper define the vocabulary \( V \) as LDV (2851 words) in order to make our argument and experiments simple. Although \( V \) is not a large vocabulary, it covers 83.07% of 1006815 words of the LOB corpus with the help of a morphological analysis. In addition, \( V \) can be extended to the set of all headwords in LDOCE (more than 56000 words). Obviously, an LDV word can be mapped indirectly onto a P-vector by spreading activation on the network; a non-LDV word can be mapped indirectly onto a P-vector by

![Figure 1: Mapping words onto Q-vectors](image)

![Figure 2: Spreading activation on the network](image)
activating a set of the words in its dictionary definition. (Recall that every headword in LDOCE is defined by using LDV only.)

The P-vector $P(w)$ represents the meaning of the word $w$ as its relationships with other words in the vocabulary $V$. Geometric distance between two P-vectors $P(w)$ and $P(w')$ indicates semantic distance between the words $w$ and $w'$. Figure 3 shows a part of the result of hierarchical clustering on P-vectors, using Euclidean distance between centers of clusters. The dendrogram reflects intuitive semantic similarity between words: for instance, rat/mouse, tiger/lion/cat, etc. However, the similarity thus observed is context-free and static, and the purpose of this paper is to make it context-sensitive and dynamic.

2.2 From P-Vectors to Q-Vectors

Through a principal component analysis, we map every P-vector into a Q-vector on which we will define context-sensitive distance later. The principal component analysis on P-vectors provides a series of 2851 principal components. The most significant $m$ principal components work as new orthogonal axes, that span $m$-dimensional vector space. By the $m$ principal components, every P-vector (with 2851 dimensions) is mapped onto a Q-vector (with $m$ dimensions). The value of $m$, which will be determined later, is much smaller than 2851. This means not only compression of the semantic information, but also elimination of the noise in P-vectors.

First, we compute the principal components $X_1, X_2, \ldots, X_{2851}$ — each of them is a 2851-dimensional vector — under the following conditions.

- For any $X_i$, its norm $|X_i|$ is 1.
- For any $X_i, X_j$ ($i \neq j$), their inner product $(X_i, X_j)$ is 0.
- The variance $v_i$ of P-vectors projected onto $X_i$ is not smaller than any $v_j$ ($j > i$).

In other words, $X_1$ is the first principal component which has the largest variance of P-vectors, and $X_2$ is the second principal component which has the second-largest variance of P-vectors, and so on. Consequently, the set of principal components $X_1, X_2, \ldots, X_{2851}$ provides a new orthonormal coordinate system for P-vectors.

Next, we pick up the first $m$ principal components $X_1, X_2, \ldots, X_m$. The principal components are in descending order of their significance, because the variance $v_i$ indicates the amount of information represented by $X_i$. The cumulative variances $\sum_{i=1}^{m} v_i$ in Figure 4 shows that even a few hundred axes can represent more than half of the total information of P-vectors. The amount of information represented by Q-vectors increases with $m$. However, for large $m$, each Q-vector would be isolated because of overfitting — a large number of parameters could not be estimated by a small number of data.

We estimate the optimal number of dimensions of Q-vectors at $m=281$ by minimizing the proportion of noise remained in Q-vectors. The amount of the noise is estimated by $\sum_{w \in F} |Q(w)|$, where $F (\subset V)$ is a set of 210 function words — determiners, articles, prepositions, pronouns, and conjunctions. We estimated the proportion of noise for all $m = 1, \ldots, 281$ and obtained the minimum for $m = 281$. Hereafter, we will use a 281-dimensional semantic space.

Lastly, we map each P-vector $P(w)$ onto a 281-dimensional Q-vector $Q(w)$. The $i$-th component of $Q(w)$ is the projected value of $P(w)$ on the principal component $X_i$; the origin of $X_i$ is set to the average of the projected values on it. We can ignore the direction of $X_i$, which determines the sign of projected values, since it has no effect on distance between Q-vectors.

3 Adaptive Scaling of the Semantic Space

Adaptive scaling of the semantic space of Q-vectors provides context-sensitive and dynamic distance between Q-vectors. Simple Euclidean distance between Q-vectors is not so different from that between P-vectors illustrated in Figure 3; both are context-free and static distance. The
adaptive scaling process transforms the semantic space so as to make it adapt to a given context $C$. In the semantic space thus transformed, simple Euclidean distance between $Q$-vectors becomes dependent on $C$. (See Figure 5.)

3.1 Semantic Subspaces

A subspace of the semantic space of $Q$-vectors works as a simple device for semantic word clustering. In a semantic subspace with the dimensions appropriately selected, the $Q$-vectors of semantically related words are expected to form a cluster. The reasons for this are as follows.

- Semantically related words have similar $P$-vectors, as illustrated in Figure 3.
- The dimensions of $Q$-vectors are extracted from the correlations between $P$-vectors by means of the principal component analysis.

As an example of word clustering in the semantic subspaces, let us consider the following 15 words.

1. after, 2. ago, 3. before, 4. bicycle, 5. bus, 6. car, 7. enjoy, 8. former, 9. glad, 10. good, 11. late, 12. pleasant, 13. railway, 14. satisfaction, 15. vehicle.

We scattered these words on the subspace $X_2 \times X_3$, namely the plane spanned by the second and third dimensions of $Q$-vectors. As shown in Figure 6, the words form three apparent clusters, namely “goodness”, “vehicle”, and “past”.

However, it is still difficult to select appropriate dimensions for making a semantic cluster for given words. In the example above, we used only two dimensions; most semantic clusters need more dimensions to be well-separated. Moreover, each of the 2851 dimensions is just selected or discarded; this ignores their strengths of contribution to forming clusters.

3.2 Adaptive Scaling

Adaptive scaling of the semantic space provides a weight for each dimension in order to form a desired semantic cluster; the weights are given by scaling factors of the dimensions. The method makes the semantic space adapt to a given context $C$ in the following way.

Each dimension of the semantic space is scaled up or down, so as to make the words in $C$ form a cluster in the semantic space.

In the semantic space thus transformed, the distance between $Q$-vectors will change with $C$. For example, as illustrated in Figure 7, when $C$ has oval-shaped (generally, hyper-elliptic) distribution in the pre-scaling space, each dimension is scaled up or down so that $C$ has a round-shaped (generally, hyper-spherical) distribution in the post-scaling space. This coordinate transformation changes the mutual distance among $Q$-vectors. Before scaling, the $Q$-vector $\bullet$ is closer to $C$ than the $Q$-vector $\circ$; after scaling, $\circ$ comes near to $C$, and $\bullet$ goes away.
The distance \(d(w, w'|C)\) between two words \(w, w'\) under the context \(C = \{w_1, \cdots, w_n\}\) is defined as follows.

\[
d(w, w'|C) = \sqrt{\sum_{i=1,m} (f_i \cdot q_i - f'_i \cdot q'_i)^2},
\]

where \(Q(w)\) and \(Q(w')\) are the \(m\)-dimensional Q-vectors of \(w\) and \(w'\), respectively:

\[
Q(w) = (q_1, \cdots, q_m), \quad Q(w') = (q'_1, \cdots, q'_m).
\]

The scaling factor \(f_i \in [0, 1]\) of the \(i\)-th dimension is defined as follows.

\[
f_i = \begin{cases} 
1 - r_i & (r_i \leq 1) \\
0 & (r_i > 1),
\end{cases}
\]

\[
r_i = SD_i(C)/SD_i(V),
\]

where \(SD_i(C)\) is the standard deviation of the \(i\)-th component values of \(w_1, \cdots, w_n\), and \(SD_i(V)\) is that of the words in the whole vocabulary \(V\).

The operation of the adaptive scaling described above is summarized as follows.

- If \(C\) forms a compact cluster on the \(i\)-th dimension \((r_i \approx 0)\), the dimension is scaled up \((f_i \approx 1)\) so as to be sensitive to small differences on the dimension.
- If \(C\) does not form an apparent cluster on \(i\)-th dimension \((r_i \gg 0)\), the dimension is scaled down \((f_i \approx 0)\) so as to ignore small differences on the dimension.

Now we can compute distance between Q-vectors to a given word set \(C\) which specifies the context for measuring the distance. In other words, we can tune the semantic space of Q-vectors to the context \(C\). This tune-up procedure is not computationally expensive, because once we have computed the set of Q-vectors and \(SD_i(V), \cdots, SD_m(V)\), then all we have to do is to compute the scaling factors \(f_1, \cdots, f_m\) for a given word set \(C\). Computing distance between Q-vectors in the semantic space transformed is no more expensive than computing simple Euclidean distance between Q-vectors.

4 Examples of Measuring the Word Distance

Let us see a few examples of the context-sensitive distance between words computed by adaptive scaling of the semantic space with 281 dimensions. Here we deal with the following problem.

Under the context specified by a given word set \(C\), compute the distance \(\bar{d}(w, C)\) between \(w\) and \(C\), for every word \(w\) in our vocabulary \(V\).

The distance \(\bar{d}(w, C)\) is defined as follows.

\[
\bar{d}(w, C) = \frac{1}{|C|} \sum_{w' \in C} d(w, w'|C),
\]

**Table 1:** \(C^+\) from \(C = \{\text{bus, car, railway}\}\)

| \(w \in C^+(15)\) | \(d(w, C)\) |
|----------------|----------|
| bus_1          | 0.100833 |
| scenery_1      | 0.112169 |
| tour_2         | 0.121133 |
|tour_1          | 0.128796 |
| abroad_1       | 0.155860 |
| tourist_1      | 0.159336 |
| passenger_1    | 0.162187 |
| make_2         | 0.169097 |
| make_3         | 0.170602 |
| everywhere_1   | 0.171251 |
| garage_1       | 0.171469 |
| set_2          | 0.172322 |
| machinery_1    | 0.173291 |
| something_1    | 0.174268 |
| timetable_1    | 0.174417 |

**Table 2:** \(C^+\) from \(C = \{\text{bus, scenery, tour}\}\)

The distance \(\bar{d}(w, C)\) is equal to the distance between \(w\) and the center of \(C\) in the semantic space transformed. In other words, \(d(w, C)\) indicates the distance of \(w\) from the context \(C\).

Now we can extract a word set \(C^+(k)\) which consists of the \(k\) closest words to the given context \(C\). This extraction is done by the following procedure.

1. Sort all words in our vocabulary \(V\) in the ascending order of \(\bar{d}(w, C)\).
2. Let \(C^+(k)\) be the word set which consists of the first \(k\) words in the sorted list.

Note that \(C^+(k)\) may not include all words in \(C\), even if \(k \geq |C|\).

Here we will see some examples of extracting \(C^+(k)\) from a given context \(C\). When the word set \(C = \{\text{bus, car, railway}\}\) is given, our context-sensitive word distance produces the cluster \(C^+(15)\) shown in the Table 1. We can see from the list that our word distance successfully associates related words like \textit{motor\ } and \textit{passenger\ } in the context of “vehicle’. On the
other hand, from $C = \{\text{bus, scenery, memory}\}$, the cluster $C^+(15)$ shown in Table 2 is obtained. We would see the context “bus tour” from the list. Note that the list is quite different from that of the former example, though both contexts contain the word bus.

When the word set $C = \{\text{read, paper, magazine}\}$, the cluster $C^+(12)$ shown in Table 3 is obtained. It is obvious that the extracted context is “education” or “study”. On the other hand, when $C = \{\text{read, machine, memory}\}$, the word set $C^+(12)$ shown in Table 4 is obtained. It seems that most of the words are related to “computer” or “mind”. These two clusters are quite different, in spite of that both contexts contain the word read.

| $w \in C^+(12)$ | $d(w, C)$ |
|-----------------|-------------|
| paper_1         | 0.109046    |
| read_1          | 0.109750    |
| magazine_1      | 0.109763    |
| newspaper_1     | 0.157823    |
| print_2         | 0.181900    |
| book_1          | 0.207245    |
| print_1         | 0.207537    |
| wall_1          | 0.220417    |
| something_1     | 0.228622    |
| article_1       | 0.232953    |
| specialist_1    | 0.240456    |
| that_1          | 0.243379    |

Table 3: $C^+$ from $C = \{\text{read, magazine, paper}\}$

| $w \in C^+(12)$ | $d(w, C)$ |
|-----------------|-------------|
| machine_1       | 0.111984    |
| memory_1        | 0.120595    |
| read_1          | 0.125057    |
| computer_1      | 0.146274    |
| remember_1      | 0.180258    |
| someone_1       | 0.200385    |
| have_2          | 0.203706    |
| that_1          | 0.203536    |
| instrument_1    | 0.205979    |
| feeling_2       | 0.212790    |
| that_2          | 0.214245    |
| what_2          | 0.214589    |

Table 4: $C^+$ from $C = \{\text{read, machine, memory}\}$

5 Evaluation through Word Prediction Task

We evaluate the context-sensitive word distance through predicting words in a text. When one is reading a text (for instance, a novel), he or she often predicts what is going to happen next by using what has happened already. Here we will deal with the following problem. (See Figure 8.)

For each sentence in a given text, predict the words in the sentence by using the preceding $n$ sentences.

This task is not so difficult for human adults because a target sentence and the preceding sentences tend to share their contexts; in other words a target sentence and the preceding sentences are in the same context. This means that predictability of the target sentence suggests how successfully we extract information about the context from preceding sentences.

Consider a text as a sequence $S_1, \cdots, S_N$, where $S_i$ is the $i$-th sentence of the text. For a given target sentence $S_i$, let $C_i$ be a set of the concatenation of the preceding $n$ sentences:

$$C_i = \{ S_{i-n}, \cdots, S_{i-1} \}. $$

Then, the prediction error $e_i$ of $S_i$ is computed as follows.

1. Sort all the words in our vocabulary $V'$ in the ascending order of $d(w, C_i)$.
2. Compute the average rank $r_i$ of $w_{ij} \in S_i$ in the sorted list.
3. Let the prediction error $e_i$ be the relative average rank $r_i/|V'|$.

Note that we here use the vocabulary $V'$ which consists of 2641 words — we removed 210 function words from the vocabulary $V$. Obviously, the prediction is successful when $e_i \approx 0$.

We used O.Henry’s short story “Springtime à la Carte” (Thornley 60) for the evaluation. The text consists of 110 sentences (1620 words). We computed the average value $\bar{e}$ of the prediction error $e_i$ for each target sentence $S_i$ ($i = n + 1, \cdots, 110$). For different numbers of preceding sentences ($n = 1, \cdots, 8$) the average prediction error $\bar{e}$ is computed as summarized in Table 5.

If prediction is random, the expected value of the average prediction error $\bar{e}$ is 0.5 (i.e. chance). Our method predicted the succeeding words better than random; the best result was observed for

\[\text{Note that words with different suffix numbers correspond to different headwords of the English dictionary LDOCE. For instance, motor_1 / noun, motor_2 / adjective.} \]

\[\text{Strictly, } C_i \text{ is not a set but a bag, since it allows duplication of the elements.}\]
Table 5: Average prediction error

| n  | \(\bar{e}\) |
|----|-----------|
| 1  | 0.324792  |
| 2  | 0.183826  |
| 3  | 0.162266  |
| 4  | 0.160213  |
| 5  | 0.163533  |
| 6  | 0.169595  |
| 7  | 0.174895  |
| 8  | 0.180140  |

Table 5: Average prediction error

\(n = 4\). Without adaptive scaling of the semantic space, simple Euclidean distance resulted in \(\bar{e} = 0.29050\) for \(n = 4\); our method is better than this except for \(n = 1\). When the succeeding words are predicted by using prior probability of word occurrence, we obtained \(\bar{e} = 0.22907\). The prior probability is estimated by the word frequency in West’s 5-million-word corpus (West 53). Again, our result is better than this except for \(n = 1\).

6 Discussion

6.1 Semantic Vectors

A monolingual dictionary describes denotational meaning of words by using the words defined in it; a dictionary is a self-contained and self-sufficient system of words. Hence, a dictionary contains the knowledge for natural language processing (Wilks et al. 89). We represented meaning of words by the semantic vectors generated by the semantic network of the English dictionary LDOCE. While the semantic network ignores the syntactic structures in dictionary definitions, each semantic vector contains at least a part of the meaning of the headword (Kozima & Furugori 93).

Co-occurrence statistics on corpora also provides the semantic information for natural language processing. For example, mutual information (Church & Hanks 90) and \(n\)-grams (Brown et al. 92) can extract semantic relationships between words. We can represent meaning of words by the co-occurrence vectors extracted from corpora. In spite of sparseness of corpora, each co-occurrence vector contains at least a part of the meaning of the word.

Semantic vectors from dictionaries and co-occurrence vectors from corpora would have different semantic information (Niwa & Nitta 94). The former displays paradigmatic relationships between words, and the latter syntagmatic relationships between words. We should take both of the complementary knowledge sources into the vector-representation of word meaning.

6.2 Word Prediction and Text Structure

In the word prediction task described in Section 5, we observed the best average prediction error \(\bar{e}\) for \(n = 4\), where \(n\) denotes the number of preceding sentences. It is likely that \(\bar{e}\) will decrease with increasing \(n\), since the more we read the preceding text, the better we predict the succeeding text. However, we observed the best result for \(n = 4\).

Most studies on text structure assume that a text can be segmented into units that form a text structure (Grosz & Sidner 86; Mann & Thompson 87). Scenes in a text are contiguous and non-overlapping units, each of which describes certain objects (characters and properties) in a situation (time, place, and backgrounds). This means that different scenes have different context.

The reason why \(n = 4\) gives the best prediction lies in the alternation of the scenes in the text. When both a target sentence \(S_i\) and the preceding sentences \(C_i\) are in one scene, prediction of \(S_i\) from \(C_i\) would be successful. Otherwise, the prediction would fail. In fact, we observed peaks and dips in the graph of the prediction error \(e_i\) plotted against the sentence position \(i\), as shown in Figure 9. In addition, (Kozima 93; Kozima & Furugori 94) reported that 21 scenes (5.24 sentences/scene on the average) were extracted from the same text (O. Henry’s short story) through a psychological experiment on human subjects.

6.3 Towards the Model of Memory and Attention

We here try to put our method in perspective towards a model of human memory and attention. The model should give an explanation to the following human abilities.

- To focus on the important part of information, and to ignore the rest of it.
- To change the direction of attention dynamically, and to follow the current state of the environment.

These abilities are required in many fields of artificial intelligence as well as contextual processing of natural language.

Let us consider the memory system illustrated in Figure 10, which is intended to recall the concepts and episodes related to the current state of environment. The system has a short-term mem-
ory (STM) that stores the concepts or episodes recently recalled; the STM provides a context for adaptive scaling. Hence, the system will recall the words or episodes related to the preceding experiences. With the STM of limited size (for example, 7 ± 2 chunks), the system will change the direction of attention dynamically.

7 Conclusion

We proposed a context-sensitive and dynamic measurement of word distance computed by adaptive scaling of the semantic space. In the semantic space, each word in the vocabulary is represented by an \( m \)-dimensional Q-vector. Q-vectors are obtained through a principal component analysis on P-vectors. P-vectors are generated by spreading activation on a semantic network which is constructed systematically from the English dictionary (LDOCE). The number of dimensions, \( m = 281 \), is determined by evaluating noise remained in Q-vectors.

Given a word set \( C \) which specifies a context, each dimension of the Q-vector space is scaled up or down according to the distribution of \( C \) in the semantic space. In the semantic space thus transformed, word distance becomes dependent on the context specified by \( C \). An evaluation through predicting words in a text shows that the proposed measurement captures well the context of the text.

The context-sensitive and dynamic word distance proposed here can be applied in many fields of natural language processing, information retrieval, etc. For example, the proposed measurement can be used for word sense disambiguation, in that the extracted context makes preference for ambiguous word senses. Also prediction of succeeding words will reduce the computational cost in speech recognition tasks. In future research, we regard the adaptive scaling method as a model of human memory and attention that enables us to follow a current context, to put restriction on memory search, and to predict what is going to happen next.

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