Signs & Sounds: Phonaesthematic Association of Japanese Mimetics Using Artificial Neural Networks

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Uttering a word is like striking a note on the keyboard of imagination.

—Wittgenstein

Abstract

The Japanese mimetic lexicon displays a number of phonaesthematic regularities associating phonological features with semantic characteristics. Artificial Neural Networks can be used to good effect in mapping phonological patterns onto semantic features. This paper demonstrates a proof-of-concept by training an ANN to associate phonological features with meaning to a large degree of success. Cluster analysis reveals that activation patterns for tokens matching the same phonaesthematic pattern group together. Larger corpora and more sophisticated techniques are required for further research.

Mimetics

Saussure famously argued that that the linguistic sign is completely arbitrary in nature. According to orthodox linguistic theory, a word's phonological representation bears no relationship to its semantic referent. The existence of mimetics poses a problem for this analysis. Mimetic words are either sound-symbolic or in some other way a mimesis of a physical or psychological phenomenon. The mimetic domain does indeed display a correspondence between sign and signified. Specifically, in Japanese, associations exist between the phonological features of mimetics and the semantic properties of the phenomena they represent.

These representations are in a sense no less arbitrary than those made in other parts of the lexicon. Phonological symbolism simply displays a finer granularity of arbitrary representation than that of the non-mimetic lexicon. However, there may be limitations on the space of possible mimetic representations. Consider what might be called "the Tinkerbell phenomenon." Tinkerbell, a pint-sized fairy who appears to us as an ethereal glimmer, speaks with the high-pitched ringing of a tiny bell. The ubiquitous sound-effect for the glinting of light is a sharp, high sound. Could Tinkerbell plausibly be associated with a deep, rumbling boom? Even in a radically different social and linguistic context, this seems impossible. Although the sounds in the play are not linguistic representations proper, this question should give us pause before we so easily assume that linguistic signs are entirely arbitrary.

The Japanese Mimetic Lexicon

The Japanese lexicon is stratified into four distinct sub-lexica: Yamato (native) words, Sino-Japanese words and compounds, non-Chinese loans, and mimetics. The Japanese mimetic lexicon is extremely rich in comparison with that of English; not limited to sound-symbolism, it contains thousands of words describing a wide variety of phenomena. Speakers classify these into four types: *giseigo* (sounds of living things), *giongo* (sounds of the inanimate world, *gitaigo* (mimesis of physical states or events), and *gijougo* (mimesis of psychological states or events) (see Table 1). Korean has a similarly rich lexicon. (Shibatani 1990)

Japanese has a rich lexicon of mimetics that represent visual, psychological, and a variety of abstract phenomena. Among these are *pika-pika* ("shining") and *nobi-nobi* ("feel at ease"). Japanese mimetics typically fill an adverbial role, as found in sentences like *ame*

giseigo	*wan-wan* *kero-kero* *nya-nya*	dog's bark frog's croak cat's meow	sounds of living things
giongo	*gujya-gujya* *kara-kara* *baki-baki*	slushy, sloppy dry rustling snapping, breaking	sounds of the inanimate world
gitaigo	*pika-pika* *neba-neba* *kunya-kunya*	shining sticky, greasy soft and cuddly	mimesis of physical states or events
gijougo	*mura-mura* *sobo-sobo* *wasa-wasa*	irresistible temptation dispirited nervous, restless	mimesis of psychological states or events

Table 1: Tokens from the mimetic lexicon by type

ga zaa-zaa futteiru ("The rain is falling *zaa-zaa*" or "The rain is falling hard"). They can also be adjectival or even verb-like when used with a light verb such as the copula (*da*) or "do" (*suru*). Thus, the phrase *kyoro-kyoro suru* means "to look about helplessly."

Mimetics are often (but not always) at least partially reduplicative in their structure. The prototypical mimetic is one like *petya-petya* ("talk like birds chirping"), which has a fully reduplicated CVCV-CVCV structure. Another, related token is *petya-kutya*, "to talk (in an annoying way) as a crowd talks." Ivanova (2002) observes that the first, fully-reduplicated word neutrally describes a phenomenon, while the second, partially-reduplicated version applies a subjective judgement to the activity described. In addition to fully- and partially-reduplicated forms, a third class of non-reduplicative mimetics exist. These make use of fixed endings with a set semantic association onto which only a single mora is prefixed. They include words like *ha*Q-*kiri* "clearly" and *ku*Q-*kiri* "distinctly."[1]

Regularities in the mimetic lexicon are best understood in terms of mora. Mora are

[1]This paper uses a modified version of Kunrei romanization for Japanese; Q denotes a geminate, and N a moraic nasal.

sub-morphological units of uniform length in Japanese. They often, but not always, correspond to syllables. A mora can be (1) a CV string in which the vowel is not long, (2) a CyV string where '*y*' denotes palatalization (eg. *kyo* in *to.kyo.u* [Tokyo]); (3) a single vowel which may stand alone or lengthen another vowel, (4) a nasal (in restricted distribution), and (5) a geminate (also restricted). The mimetic *petya-petya*, for example, is divided into four mora: *pe.tya.pe.tya*. All of the mimetics discussed in this paper are of this typical four-mora type.

Japanese mimetics are used to describe everything from a person's manner of walking to the distribution of checks in a restaurant. They are a vital, daily part of spoken Japanese and are necessary for basic understanding of the language. In addition to lexical knowledge, Japanese speakers have access to a regular system of mimetic construction, and mimetics have at least a limited productivity. In other words, the distribution of phonemes in the mimetic lexicon is not random. Certain phonological features are associated with semantic "features" of mimetics. Perhaps most prominently, voicing is associated with what might be called "intensity;" pouring rain is described with *zaa-zaa*, while a soft shower is described by a devoiced version of the same mimetic: *saa-saa*; *baki-baki* describes the breaking larger objects than does *paki-paki*. Other associations exist; velars, for instance, correspond with quick, decisive movement or action. No comprehensive account exists, however, of all associations between phonological features in mimetics and the features of their semantic interpretation.

Approaches to Classification

One approach to discovering these associations might be to interview native speakers and test their intuitions. This, however, is problematic in several ways. First, native speakers are not particularly attuned to the relation between phonology and semantics in mimetics. Their production takes place largely outside of consciousness. Second, such a methodology lacks a rigorously quantitative approach that might shed light on the relative strengths of semantic associations and how conflicts between them are resolved. Finally, interviewing native speakers is time-consuming and difficult. A great deal of research would be required to uncover a complete account of Japanese mimetics.

Another possible method for discovering phono-semantic associations is a brute-force human analysis of the lexicon. This approach could certainly be sufficiently quantitative, but the flood of raw numeric data might make recognizing relevant patterns extremely difficult. Such an analysis could mean countless hours wasted for little gain in predictive capability.

The problems involved with the methods above motivates a third approach: analysis by Artificial Neural Network (ANN). ANNs are computer-simulated networks designed to discover, with minimal intervention, salient patterns in noisy data. They are modeled on the neural structure of the human brain, and they excel in extracting relevant associations from data which is often inconsistent, difficult to visualize, and overwhelming. ANNs are employed effectively in such tasks as face-recognition, artificial speech production, and interpretation of robot vision. ANNs are well-suited to the task of discovering the phono-semantic associations in the Japanese mimetic lexicon.

The lexicon in question is simultaneously vast and intricate, and it has proven resistant to previous attempts at systematic classification. Hamano (1998) attempted to directly associate phonemes in specific word-positions with semantic features. Although some associations can be made, they are not robust and many counterexamples are attested. Ivanova (2002) suggests a more nuanced approach, which takes the phonaesthematic pattern as its basic unit of analysis. The word phonaesthematic describes "the presence of a sequence of phonemes shared by words with some perceived common element in meaning," eg. *glimmer*, *glisten*, *glint*, and *glamour*. By examining sub-morphological phonaesthematic sequences instead of individual phonemes, a more robust analysis of the Japanese mimetic lexicon can be developed.

The phonaesthematic nature of the regularities in the lexicon does not present a problem for ANN analysis. Although the direct inputs to the network will consist exclusively of an ordered set of phonemes identified by their features, the internal layer of the network provides a medium in which to build associations between specific sequences of phonemes or even abstract relationships such as complete or partial reduplication. An ANN should theoretically be capable of identifying any relevant pattern in the data provided.

Ivanova identifies a staggering number of robust and well-attested phonaesthematic regularities in the lexicon. These, with some additions and modifications, appear in Appendix A. ANN analysis could provide an interesting point of comparison to Ivanova's manual survey. It also might be more able to uncover a hierarchy of associations and shed light on their interaction.

Crucially, Ivanova points out that tokens fitting multiple phonaesthematic patterns often display semantic characteristics of both. This points to a difficulty in the classification of mimetic tokens that ANNs are particularly suited to address. Each token is, in effect, placed on one or more dimensions of meaning. If each semantic feature with a phonaesthematic association is imagined in this way, any given token can be plotted in an n-dimensional space, where n is the number of semantic characteristics. This n-dimensional space would model the entire range of phonoaesthematic possibility. Tokens with similar meanings would cluster close to each other, while opposites would be distant from on another.

This method, however, presents a problem. What if two phonaesthematic associations are in conflict? For instance, initial *mo* carries the meaning of "murky," (Ivanova 2002) while the ending Q-*kiri* indicates clarity. Could a word like *mo*Q-*kiri* exist in Japanese? Speakers confirm that it could not (Terasaki, Okamoto 2006). The two semantic associations are in conflict. Perhaps they are not, however, so directly opposed that they could be collapsed into a single semantic dimension. This means that there is a region in the spatial model which is effectively off-limits. In a perfect model, every point in the theoretical space should correspond to a possible (but not necessarily attested) token in the mimetic lexicon. What does this mean for our analysis? It may not be possible to predict the outcome of all phonaesthematic conflicts and develop a set of semantic features which will allow a perfect modeling of the lexicon's phonaesthematic space, or, alternatively, a set of ideal meta-features might be required to obtain such a result.

Artificial Neural Networks

The ANN developed in this investigation takes as its inputs the phonological features of a given mimetic from the lexicon. After training, it should be capable of associating those phonological features with a given set of "semantic features" such as intensity and others. Determining the relevant set of semantic features is the primary challenge of this approach. If features with no phonological association are selected, no pattern can be discovered in the data. Thus, this method necessitates an approach informed by the intuition of native speakers and an analysis of the lexicon.

Training an ANN requires a large corpus of representative data tagged with the correct associations between a given input and the "correct" output. In the case of Japanese mimetics, this consists of a list of as many mimetics as possible, their phonological features, and the semantic features with which those phonological features are to be associated. The phonological features make up the data for the input layer of the neural network. The activations of the input layer are then multiplied by the network weights of the ANN and passed to the "hidden" layer. The hidden layer again multiplies its input by network weights as it passes its activations to the output layer. The nodes of this layer correspond to the semantic features of a given mimetic.

Over time, the ANN adjusts the network weights between its layers to better reflect the associations between phonological and semantic features. It does this using an algorithm

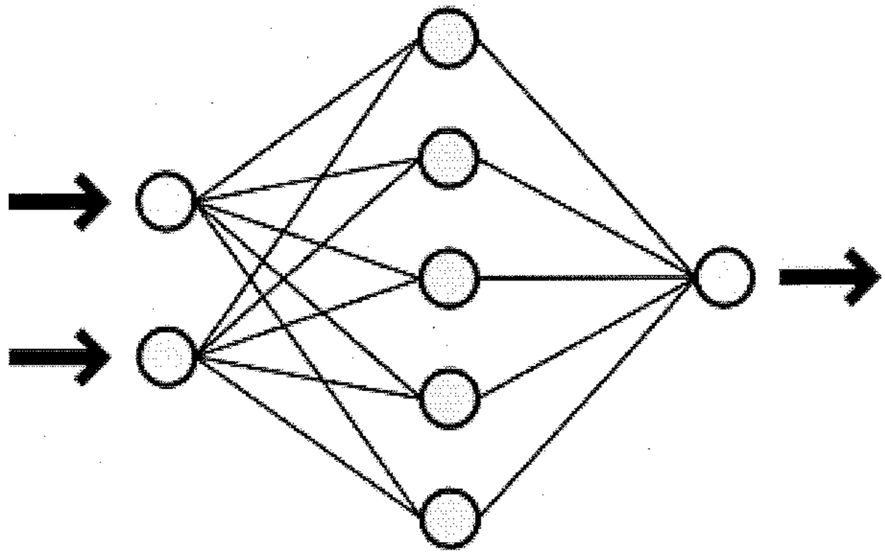

Figure 1: Simplified view of an Artificial Neural Network (Wikipedia.org, Creative Commons Attribution license)

called "Back-Propagation," or BACKPROP. BACKPROP performs a stochastic gradient descent to minimize error in the network. (Meeden 2005)

Cluster Analysis

One problem with the ANN approach is that, while a network is capable of finding associations in the raw data, it often provides little insight into the structure of the system being investigated. Although the network may predict semantic associations for a given set of phonological features, it may reveal little about the underlying rules governing such associations. In order to discover these, an analysis of the network weights must be performed.

The network weights are the components of the ANN that store the associations between inputs and outputs. Each node in the network receives an input value between zero and one. It then multiplies that value by a network weight and passes it to each node in the next layer. Each node has a network weight associated with every node in the next layer of the ANN. When it passes a value to another node, it multiplies that value by a weight that is used exclusively for that other node. The process of adjusting these weights in response to training data is what gives ANNs their associative power.

To test the performance of an ANN at a given task, two data sets are required. The first is the training set, tagged with both the inputs (phonological features) and the correct outputs (semantic features). The ANN adjusts its network weights in response to the associations found in the training data set. Then, to evaluate the performance of the network, a corpus novel tokens in the same class is presented. The network predicts the outputs associated with the inputs. If its accuracy does not exceed that of a random guess, it is unlikely that any pattern of association exists between inputs and outputs. If the ANN analysis of Japanese mimetics were successful, the network, given a novel token, would predict the same semantic associations as a native speaker would upon hearing the mimetic for the first time.

Even if the network can accurately predict outputs from inputs, its methods of association remain opaque. In order to extract information from the ANN, it is necessary to interpret the network weights. Superficially they are nothing more than a series of meaningless numerical values. To discover their significance, a cluster analysis can be performed. Cluster analysis models the network weights in an n-dimensional space, where n is the total number of network weights. This space corresponds to the n-dimensional space of phonoaesthematic association discussed above. A set of inputs is fed into the network, possibly even the entire corpus. The activations of each node (the input multiplied by the network weight) are then plotted into this n-dimensional model. The distance between each set of activations is determined, and the associated inputs are grouped by their proximity to one another. The two closest inputs are grouped together under the input which was closest to both of them, and so on. The entire set of inputs can be grouped in this way into hierarchical clusters, revealing the underlying system of categorization that drives the association of input and output. Thus, we might expect that voiced mimetics would cluster apart from unvoiced mimetics, and that below this major association in the hier-

#	*Mimetic*	*Gloss*	[VOICED.VELAR.FRICATIVE] x 4 mora	INTENSE
1	pi.ka.pi.ka	"shining"	[0.0.0][0.1.0][0.0.0][0.1.0]	0
2	sa.a.sa.a	"soft rain sound"	[0.0.1][1.0.0][0.0.1][1.0.0]	0
3	za.a.za.a	"hard rain sound"	[1.0.1][1.0.0][1.0.1][1.0.0]	1
4	ku.tya.gu.tya	"speak worthlessly"	[0.1.0][0.0.0][1.1.0.][0.0.0]	0

Table 2: Trial one test corpus

archy, other clusters (around, say, velar-decisiveness) would form. Cluster analysis is a convenient way to discover which patterns are prominent and which are relatively weak.

Semantic Features

As mentioned above, determining the best set of semantic features to associate with phonological features is the primary challenge of ANN classification of the mimetic lexicon. INTENSE is certainly one of these. Other relevant characteristics found in the literature include tautness, hardness, viscosity, weakness, friction, protrusion, largeness, even emotionality, normativity and self-confidence. The only way to find the most effective feature set is through trial and error.

Trial One: Feature Extraction

Trial One demonstrates the process through which ANNs extract relevant features from noisy data. A small four-token test corpus was used to demonstrate the network's basic ability to associate phonologically +VOICED mimetics with the +INTENSE semantic feature.

In order to maintain a constant number of phonological inputs to the neural network, phonological assignments were made to each of the four mora in these typical four-mora mimetics. Mora were marked +VELAR if their initial consonant was a velar, and +FRICATIVE if their initial consonant was a fricative. Because all vowels are voiced, a mora was required to be entirely +VOICED (including the initial consonant) in order to be marked

1	pi.ka.pi.ka	0.208295724222
2	sa.a.sa.a	0.159071080922
3	za.a.za.a	0.420666643129
4	ku.tya.gu.tya	0.17328400539
5	pi.ka.pi.ka	0.140041028372
6	sa.a.sa.a	0.107125475597
7	za.a.za.a	0.496530943773
8	ku.tya.gu.tya	0.127372183711
9	pi.ka.pi.ka	0.105973608446
10	sa.a.sa.a	0.0836767780189
11	za.a.za.a	0.538912477283
12	ku.tya.gu.tya	0.104159019003
13	pi.ka.pi.ka	0.0884180378068
14	sa.a.sa.a	0.0716269472153
15	za.a.za.a	0.563691291134
16	ku.tya.gu.tya	0.091032369665

Table 3: Error reports for first sixteen cycles in Trial One

+VOICED. It should be made clear that the ANN is agnostic to the theoretical correctness of the feature assignment; as long as a relation is preserved between input and target output, it will discover it.

Table 2 gives the four-token test-corpus, selected phonological features associated with each mora in each mimetic, and the intensity value associated with each mimetic. They are numbered in the sequence in which were presented to the network. Table 3 gives the error reports of the network over the first sixteen cycles, through four presentations of each mimetic. The error rate is reported as the average difference between the target output values (in this case there is only one output value: zero or one, for -INTENSE and +INTENSE respectively) and the values produced in the network's output layer. As expected, error rates for the +INTENSE token *zaa-zaa* are much higher than those for the other three tokens in the first several hundred cycles; the error rate for *saa-saa* is also higher than the two remaining tokens between cycles 100 and 1,000. The graph in Figure 2 shows a point-by-point error plot in which the error trajectories for *zaa-zaa*, *saa-saa*, and the other two (indistinguishable) tokens are clearly differentiated.

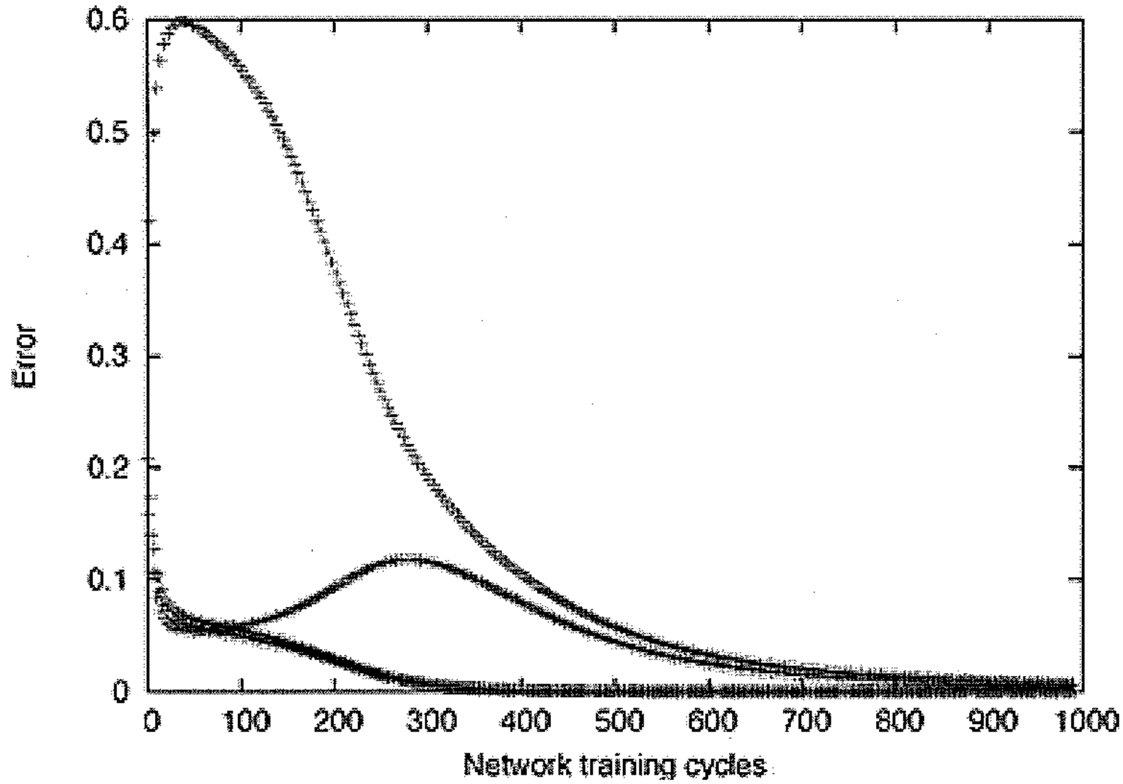

Figure 2: Intensity prediction error for four-token training corpus in Trial One

Figure 3 shows a closer view of error rates for eight passes through the training corpus from cycles 201 to 232. At this stage, the network has begun to misidentify +FRICATIVE as a predictor for +INTENSE. The peaks in the graph represent the high error reports for *zaa-zaa*, the +INTENSE token. The two low reports in each pass through the corpus are from *pika-pika* and *gu.tya.gu.tya*, the -FRICATIVE tokens. The reports immediately to the left of each peak are for *saa-saa*; the +FRICATIVE feature it shares with *zaa zaa* is temporarily confusing the network.

The error rates converge over 1,000 training cycles as the network discovers that +VOICED is the relevant feature for predicting +INTENSE. The elevated error for *saa saa* is due to the fact that it shares a feature—+FRICATIVE—with *zaa-zaa*. The network temporarily misidentifies +FRICATIVE in addition to +VOICED as a relevant feature for the prediction of INTENSE. By cycle 1,000, however, the network has correctly identified +VOICED as the

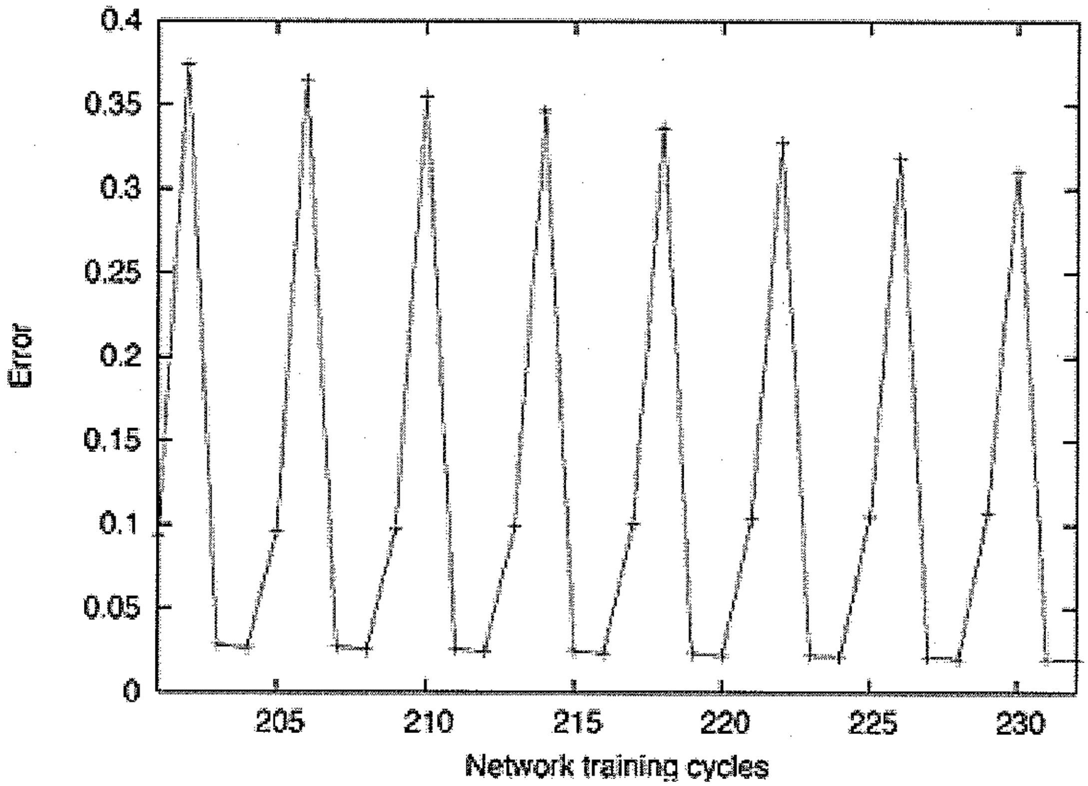

Figure 3: Distinct error trajectories for tokens in Trial One training corpus

#	*Mimetic*	*Gloss*	INTENSE	*Error*
1	ti.bi.ti.bi	'little by little'	0	0.00159028974308
2	ka.ra.ka.ra	'dry rustling'	0	0.00154425726513
3	ga.ra.ga.ra	'clattering'	1	0.012309590643
4	su.be.su.be	'slick'	0	0.00490661539401

Table 4: Trial one evaluation corpus

only relevant feature and error for all tokens approaches zero.

At this point, the network has learned the correct associations for the corpus data. However, as any parent knows, just because a child can recite the text of her favorite book as the pages are turned does not mean that she can read. Table 4 demonstrates that the network has in fact learned a general method for distinguishing +INTENSE tokens—error was minimal on a novel evaluation corpus.

Another way of assessing the network's "understanding" of patterns in the corpus is through cluster analysis of its hidden activations. Figure 4 gives a cluster hierarchy of the training and evaluation corpora in Trial One. Clusters for both the training corpus and the evaluation corpus show the +INTENSE token (*zaa-zaa* and *gara-gara* respectively) farthest in Euclidean distance from the other tokens. In other words, distinct clusters of hidden activation patterns correspond to +INTENSE and -INTENSE.

Trial Two

Trial One demonstrates the ANNs basic capability and workings, but does not enhance our understanding of the mimetic lexicon. Trial Two will build on the methodology in Trial One to analyze a larger corpus for more complex phonaesthematic associations. As a step toward classifying a corpus representative of the entire mimetic lexicon, Trial Two demonstrates the network's ability to extract multiple patterns from a data set.

Ivanova (2002) provides a list of observed phonaesthemes and give several examples of each. The phonaesthemes were analyzed and reworked with collaboration with

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Training Corpus

minimum distance = 0.000383     ( to.ki.do.ki ) ( pi.ka.pi.ka )
minimum distance = 0.760665     ( pi.ka.pi.ka to.ki.do.ki )     ( sa.a.sa.a )
minimum distance = 1.710566     ( sa.a.sa.a pi.ka.pi.ka to.ki.do.ki )    ( za.a.za.a )
Resulting Tree =
_|----------------------------------------> za.a.za.a
 |_________________________________________|-------------------> sa.a.sa.a
                                           |___________________|-> pi.ka.pi.ka
                                                               |-> to.ki.do.ki

Evaluation Corpus

minimum distance = 0.090262     ( ka.ra.ka.ra ) ( ti.bi.ti.bi )
minimum distance = 0.228090     ( su.be.su.be ) ( ti.bi.ti.bi ka.ra.ka.ra )
minimum distance = 1.236330     ( ti.bi.ti.bi ka.ra.ka.ra su.be.su.be ) ( ga.ra.ga.ra )
Resulting Tree =
 |----------------------------------------------> ga.ra.ga.ra
-|                                                _________|----> ti.bi.ti.bi
 |-----------------------------------------------|         |----> ka.ra.ka.ra
                                                 |---------> su.be.su.be
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Figure 4: Cluster analysis of hidden activations in Trial One

Terasaki and further tokens were uncovered. Appendix A shows the final phonaesthematic clusters and their associated feature IDs the trial. The Trial Two corpus will consist of these 150 tokens. The network's performance on the corpus will be evaluated using Ivanova's and Terasaki's analyses as a reference.

Table gives a complete listing of the phonological and semantic features presented to the network. The 14 phonological features are sufficient to distinguish any two possible tokens from one another. The semantic features listed, however, nowhere near exhaust the number of possible (or even probable) feature set available to native speakers.

Certain stumbling blocks were encountered in the preparation of the corpus. First, mimetics are often similar in structure to words derived from reduplication in other parts of the lexicon. *toki-doki* (occasional) and *betsu-betsu* (separately) seem similar to mimetics but are in fact derived from reduplication of the non-mimetic words *toki* (time) and *betu* (separate) respectively. Some of these tokens exist on a continuum with mimetics, as

Phonological features	*Semantic features*
VELAR	MURKY
PALATAL	EXEN
NASAL	STICKY
CORONAL	NOSTRSS
LABIAL	UNSTEAD
FRICATIVE	FREE
VOICED	DEFIC
MORAIC_N	NOSPACE
GEMINATE	NOVIT
V_HIGH	IDLE
V_LOW	BADSFT
V_BACK	SHAKING
V_LABIAL	RSTLSS
V_TENSE	LIQSWAY
	DISORD
	NOCONF
	COWARD
	IMPERT
	BRISK
	MEANDER
	SFTUNR
	PRESS
	TIMID
	EXPROP
	ANXIETY
	SUDDEN
	GENTLE
	SUCCESS
	CLEAR
	EXGOOD
	SUFF
	MANY
	PLENTY
	HEAVY
	RELAX
	UNATTR
	FIDGET

Table 5: Phonological and semantic features in Trial Two

Token	*Meaning*	*Lexical Association*	*Classification*
toki-doki	occasional	*toki* ("time")	non-mimetic
tibi-tibi	little by little	*tiisai* ("small")	mimetic
doki-doki	heavy pounding (of the heart)	[none]	mimetic

Table 6: Mimetics and Lexical Reduplication

laid out in Table 6. In some cases of conflict the non-mimetic lexeme may contradict the phonaesthematic association. The token *mote-mote*, for instance, fits the pattern for both "murkiness" and "exceeding the proper amount," but its lexical association withholding "possess" (*motsu*) gives it the interpretation of "sexually attractive."

Another difficulty in dealing with the corpus is the slippery nature of the semantic content of the phonaesthemes themselves. For instance, Ivanova (2002) identifies the pattern in Table 7 as a phonaestheme corresponding to "slow action / idleness." Consultation with Terasaki (personal communication, 2006), however, revealed that tokens that Ivanova classified as exceptions to the phonaesthematic pattern are in fact part of the same phonaestheme. A more accurate characterization of the semantic association in question might be "in round drops, rolling." The token *goro-goro* means lolling about, as in rolling around on a futon or kicking around the house; *oro-oro* means to be mentally off-balance, with thoughts rolling about in the head at random. The tokens that Ivanova (2002) classified as exceptions—*boro-boro* etc.—are in fact closer to the core, non-metaphorical meaning associated with the phonaestheme than the ones classified as representative. As the "slow action / idleness" phonaestheme demonstrates, the semantic associations of many mimetics are difficult to pin down with other language.

Despite these difficulties, the ANN in Trial Two successfully classified most of the tokens in the corpus with minimal error. Figure 5 shows the short term error reports, and Figure ?? shows them over the full trial. There are some outliers whose error levels drop only slightly over time, but given enough training, the network would simply "memorize" these tokens and classify them correctly.

Pattern	*Meaning*	*Tokens*	*Anomalous tokens*
(C) + *oro* + (C) + *oro*	slow action, idleness	*doro-doro* (pulpy, mushy, thick) *oro-oro* (thrown off balance) *goro-goro* (lie about idly)	*boro-boro* (in big drops; worn-out), *horo-horo* (in small drops), *poro-poro* (in drops)

Table 7: Ivanova's problematic classification

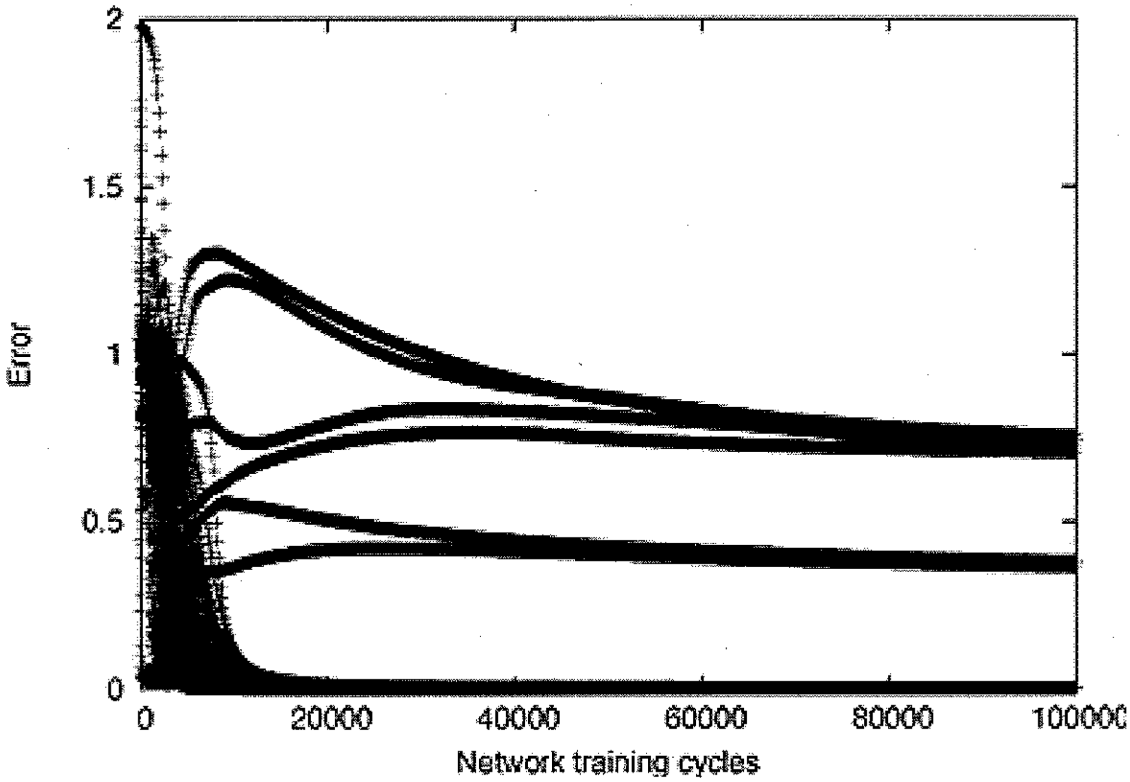

Figure 5: First 100,000 cycles in Trial Two training corpus error

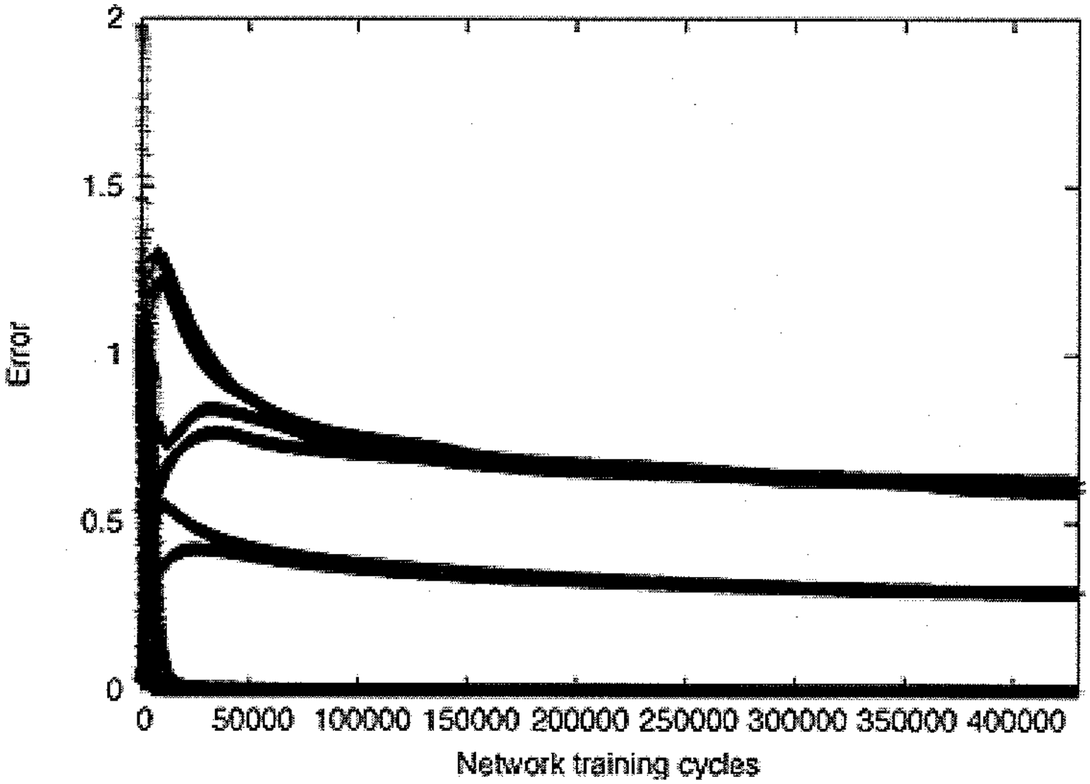

Figure 6: Complete Trial Two error reports

Table 8 shows error reports for specific novel tokens in the evaluation corpus. As anticipated, patterns represented with a large number of tokens in the corpus, such as *gotya-gotya* etc. for the NOCONF phonaestheme, were identified with a lower rate of error. Patterns with only one or two tokens in the training corpus, like BETYA-BETYA for the RSTLSS phonaestheme, were not identified at all due to the fact that the presence of only one token did not give the ANN an opportunity to distinguish the relevant pattern from the characteristics of its tokens. Cluster analysis, shown in Appendix D reveals that some mimetics have been clustered by phonaestheme, but no robust pattern has emerged. A larger corpus might produce better results.

Programs and Conclusions

This paper demonstrates a successful proof-of-concept for phonaesthematic association of Japanese mimetics using Artificial Neural Networks. For future work, a corpus of perhaps one hundred times the size might be required. With such a corpus, it would be possible to specify "naïve" semantic features such as wetness, speed, hardness etc. and have the network search for patterns to associate with them. These features might work to break down the semantic associations into smaller, more common elements that would render the space of phonaesthemes in higher resolution.

The work also might benefit from more sophisticated computational methods. One way to speed up the learning of problematic tokens would be to use a Genetic Algorithm (GA). One problem often confronted in the training of neural networks is the phenomenon of the local minimum. If the error function of the network were mapped in a multi-dimensional space, we can imagine how, in its attempt to descend along the error gradient, the network might settle into a configuration that has a lower level of error than the surrounding area, but which does not represent the best possible solution. This is part of the reason why the ANN in Trial Two was unable to classify all of the tokens correctly.

mo.so.mo.so	0.998694319028
mu.ka.mu.ka	1.36113869166
ne.ba.ne.ba	1.01487529777
no.ko.no.ko	1.87014146777
yo.bo.yo.bo	1.99242816593
yu.Q.ku.ri	1.04669909089
ba.sa.ba.sa	2.49753137008e-05
gi.ti.gi.ti	1.12817480377
to.bo.to.bo	0.00214731167517
o.ro.o.ro	4.84269103649e-06
gu.jya.gu.jya	0.00299313717304
yu.ra.yu.ra	1.74301395223
hyo.ro.hyo.ro	0.0906405269696
de.bu.de.bu	0.00220005934501
go.tya.go.tya	1.4080120943e-05
su.go.su.go	1.30561197121
i.ji.i.ji	1.0004849271
nu.ke.nu.ke	0.981309841762
me.ki.me.ki	0.673205094683
u.ne.u.ne	9.58668169567e-05
fu.nya.fu.nya	7.1996645154e-06
do.si.do.si	0.364352304025
ga.si.ga.si	6.91751350252e-06
hi.so.hi.so	1.34500042008
bo.te.bo.te	0.000394612296337
mu.zu.mu.zu	0.699978662153
ga.Q.ta.ri	0.00198909687591
fu.N.wa.ri	0.000603075600391
ba.Q.ti.ri	0.000829279222434
ha.Q.ki.ri	0.853517334462
go.Q.po.ri	0.323952721098
ta.Q.pu.ri	0.00458525164778
ba.Q.sa.ri	1.70046316943
do.Q.si.ri	0.100842889473
go.Q.te.ri	0.000599389182655
o.Q.to.ri	0.00361815702284
be.tya.be.tya	1.97831760239
ji.ta.ba.ta	1.77028268892

Figure 7: Error reports on Trial Two evaluation corpus

In the worst cases, the network is like a marble sitting in a basin on top of a mountain. Some method is required to test configurations that are relatively distant from the best solution currently within reach.

In order to do this without sacrificing hard-won training on random reconfiguration, a Genetic Algorithm (GA) could be employed. A population of neural networks is instantiated, trained, and made to compete for survival. In each generation, a certain amount of random mutation is introduced. Low-performing networks are eliminated. New networks are produced through crossover, which is the "breeding" of successful networks to produce new networks that contain characteristics from both of them. In this way, the problem of local minima can be mitigated without giving up the ANNs ability to learn through experience.

Another technique of ANN analysis might also prove useful. It is possible to reverse the direction of the network's throughput (move activation from the output layer through to the input layer) and derive "paradigmatic" representations of the types the network is classifying. The ANN could be given a set of semantic features and made to produce the mimetic token that best represents them. In this way, new phonaesthemes could be more easily uncovered.

Overall, ANNs seem to be a promising tool for classifying mimetics and may prove even more useful than they have already in theoretical linguistics generally. They cannot compare, however, to the learning capacity of the human brain. A speaker can learn a new mimetic and integrate it into her phonaesthematic system after only hearing it once. What child requires 3000 exposures in order to become competent with a new vocabulary item? Even so, ANNs and related tools seem to open up a rich new vein of inquiry.

The above investigation shows that there is a real relationship between semantic characteristics and phonological representations in the Japanese mimetic lexicon. The function of their relation, however, is far from a bijection. Phonaesthematic associations do not constitute a one-to-one correspondence between sign and signified. Tools like Artificial Neural Networks, however, are the best lights we have in the murky world of natural language.

Appendix A: Ivanova/Terasaki Phonaesthemes

Feature ID	*Pattern (1st & 3rd)*	*Meaning*	*Tokens*	*Anomalous tokens*
MURKY	*mo* + CV + *mo* + CV or *mo* + *x*	murkiness	*mogo-mogo* (mumble), *moso-moso* (mumble), *mo*Q*-sari* (sluggish), *moya-moya* (hazy,murky), *moku-moku* (send up great volumes of smoke)	*mori-mori* (eat hea have a thick wa muscles)
EXEN	*mu* + CV + *mu* + CV or *mu* + *x*	excessive energy, suppression	*muka-muka* (retch, go mad), *muku-muku* (growing), *muN-muN* (stuffy, sultry), *mura-mura* (irresistible temptation)	*muki-muki* (thick mu
STICKY	*ne* + CV + *ne* + CV or *ne* + *x*	stickiness, tenacity	*neba-neba* (sticky, greasy), *nechi-nechi* (sticky, persistent), neQ-tori (clammy, viscous)	
NOSTRS	*no* + CV + *no* + CV or *no* + *x*	slow action, lack of stress, anxiety, or uneasiness	*nobi-nobi* (feel at ease, be relaxed/relieved), *noko-noko* (nonchalantly), *noro-noro* (drag oneself, walk slowly)	
UNSTEAD	*yo* + CV + *yo* + CV	unsteady, unreliable	*yobo-yobo* (feeble, shaky), *yoro-yoro* (unstable, weak), *yochi-yochi* (toddle), *yota-yota* (totter)	
FREE	*yu* + CV + *yu* + CV or *yu* + *x*	free of pressure, relaxing	*yu-*Q*kuri* (slowly, at one's leisure), *yu-rari* (slowly), *yusa-yusa* (sway, to and fro), *yu*Q*-tari* (slow), *yuu-yuu* (chill / relaxed)	
Feature ID	*Pattern (vowel-mora)*	*Meaning*	*Tokens*	*Anomylous tokens*
DEFIC	C + *asa* + C + asa	disappointing appearance due to some deficiency	*basa-basa* (crumbly, friable, disheveled), *pasa-pasa* (dry), *kasa-kasa* (dry, rough), wasa-wasa (nervous, restless)	

NOSPACE	*g/k* + V + *ti* + *g/k* + V	lack of fluidity and space	*giti-giti* (very tight), *bati-bati* (heavy, brittle), *pati-pati* (brittle), *kati-kati* (frozen hard, dried up completely), *koti-koti* (tense, stiff, frozen hard)	*moti-moti* mushy
NOVIT	C + *obo* + C + *obo*	lack of vitality and energy	*syobo-syobo* (dispirited, despondent, bleary-eyed)	*tobo-tobo* (trudge wea *yobo-yobo* (feeble, sh unsteady)
IDLE	(C) + *oro* + (C) + *oro*	slow action, idleness	*doro-doro* (pulpy, mushy, thick) *oro-oro* (thrown off balance) *goro-goro* (lie about idly), *boro-boro* (in big drops; worn-out), *horo-horo* (in small drops), *poro-poro* (in drops)	
BADSFT	(C) + *ujya* + (C) + *ujya*	unpleasant softness	*gujya-gujya* (slushy, sloppy), *ujya-ujya* (wriggle)	
SHAKING	(C) + *ura* + (C) + *ura*	shaking, swaying	*kura-kura* (dizzy, reeling, spinning), *yura-yura* (quake, sway), *mura-mura* (unsteady), *gura-gura* (toppling), *bura-bura* (swaying, hanging out)	*sura-sura* smoothly, out a hitch
RSTLSS	(C) + *yoro* + (C) + *yoro*	restless, unstable	*nyoro-nyoro* (long and squirming), *gyoro-gyoro* (water dribbling) *tyoro-tyoro* (trickle, flicker), *hyro-hyoro* (totter, toddle, stagger), *kyoro-kyoro* (look around restlessly, nervously)	

Feature ID	*Pattern (2nd & 4th)*	*Meaning*	*Tokens*	*Anomylous tokens*
LIQSWAY	CV + *bu* + CV + *bu*	a great amount of liquid or flesh swaying	*debu-debu* (fat and flabby), *gabu-gabu* (guzzle/chug, slosh), *zabu-zabu* (splash)	
DISORD	(C)V + *tya* + (C)V + *tya*	disorder, disappointing experience	*itya.itya* (behave flirtatiously), *bitya-bitya* (spurting, *gotya-gotya* (worthless speech), {*gotya-gotya* (messy, jumbled-up), *kutya-kutya* (crumpled)	

NOCONF	CV + *go* + CV + *go*	lack of confidence	*mago-mago* (at a loss, disorganized), *mogo-mogo* (mumble), *sugo-sugo* (disheartened, downcast)	
COWARD	(C)V + *ji* + (C)V + *ji*	cowardice, bewilderment, lack of enthusiasm/initiative	*iji-iji* (hesitantly, timidly), *moji-moji* (bashful, fidget), *taji-taji* (quail)	*maji-maji* (to stare [to tently)
IMPERT	CV + *ke* + CV + *ke*	impertinent	*nuke-nuke* (impudently, brazenly) *zuke-zuke* (bluntly, without reserve), *tuke-tuke* (rudely)	
BRISK	(C)V + *ki* + (C)V + *ki*	brisk, dynamic action	*doki-doki* ([heart] beat fast, throb), *paki-paki* (breaking), *bati-bati* (heavy breaking), *poki-poki* (breaking), *baki-baki* (heavy breaking), *meki-meki* (remarkably, rapidly), *syaki-syaki* (briskly, concisely), *melting, weakening*	
MEANDER	(C)V + *ne* + (C)V + *ne*	meandering, winding	*kune-kune* (sway, meander), *une-une* (winding, tortuous)	
SFTUNR	CV + *nya* + CV + *nya*	soft, unreliable, unstable	*funya-funya* (limply, flabby), *kunya-kunya* (soft and cuddly) *munya-munya* (mumble), *gunya-gunya* (melting, weakened)	
PRESS	CV + *si* + CV + *si*	pressure	*dosi-dosi* (hand over fist, without hesitation), *gosi-gosi* (scrub), *basi-basi* (whack), *gasi-gasi* (fierce scrubbing), *gisi-gisi* (squeeze, be packed), *hisi-hisi* (press, feel keenly)	
TIMID	CV + *so* + CV + *so*	timid, retiring	*boso-boso* (in a subdued voice), *hiso-hiso* (in whispers), *koso-koso* (secretly, stealthily), *moso-moso* (slow movement), *boso-boso* (under one's breath), *goso-goso* (rummage)	

EXPROP	CV + *te* + CV + *te*	exceed the proper amount	*bote-bote* (fat, obese), *gote-gote* (gaudy, heavy), *kote-kote* (thickly, lavishly), *bate-bate* (exhausted)	*mote-mote* (sexually tractive)
ANXIETY	(C)V + *zu* + (C)V + *zu*	anxiety, impatience	*guzu-guzu* (grumble), *muzu-muzu* (burning with desire), *uzu-uzu* (impatient, itching)	
Feature ID	*Pattern (2nd, 3rd & 4th)*	*Meaning*	*Tokens*	*Anomylous tokens*
SUDDEN	C + Q-*tari*	sudden/abrupt action	*ga*Q-*tari* (destroy suddenly), *ba*Q-*tari* (run into, stop suddenly), *pa*Q-*tari* (suddenly, abruptly)	
GENTLE	CV + *N-wari*	gentleness	*fuN-wari* (fluffy), *jiN-wari* (well up slowly),*yaN-wari* (gentle, mild)	
SUCCESS	CV + Q-*tiri*	successful, positively evaluated, compact	*ba*Q-*tiri* (perfect), *mi*Q-*tiri* (full, soft), *ga-tiri* (full, hard), *ga*Q-*tiri* (solid, steady, tight), *ki*Q-*tiri* (exact, perfect, tight)	
CLEAR	CV + Q-*kiri*	clear-cut, exactly	*ha*Q-*kiri* (clearly, without any misunderstanding), *ku*Q-*kiri* (clearly, distinctly), *nyo*Q-*kiri* (stuck out), *tyo*Q-*kiri* (exactly)	
EXGOOD	CV + Q-*pori*	exceed the proper amount (with positive connotation)	*ga*Q-*pori* (make a pile of money), *go*Q-*pori* (in a large quantity), *si-pori* (wet through, tender, passionate), *su*Q-*pori*	
SUFF	CV + Q-*puri*	sufficient amount	*do*Q-*puri* (to the full, be up to one's neck in), *ga*Q-*puri* (drink up a large amount of liquid), *ta*Q-*puri* (plenty, full of)	
MANY	CV + Q-*sari*	many	*ba*Q-*sari* (make a drastic cut), *gu*Q-*pori* (stab / plunge in completely), *do*Q-*sari* (heaps/loads of), *fu*Q-*sari* (abundant hair)	

PLENTY	CV + Q-*siri*	plenty, packed	*do*Q-*siri* (massive), *gi*Q-*siri* (closely, tightly), *bi*Q-*siri* (filled completely), *zu*Q-*siri* (heavy)	
HEAVY	CV + Q-*teri*	heavy, fat	*go*Q-*teri* (thick, stodgy), *ko*Q-*teri* (filling, rich), *po*Q-*teri* (plump, chubby)	
RELAX	(C)V + Q-*tori*	relaxing	*o*Q-*tori* (composed, gentle [personality]), *si*Q-*tori* (quiet, calm), *u*Q-*tori* (enchanted)	*yo*Q-*tori* (chill, relaxe

Feature ID	*Pattern (partial redup)*	*Meaning*	*Tokens*	*Anomylous tokens*
UNATR	C1V1 + *tya* + C2V2 + *tya*	disorder, unattractiveness	*betya-kutya* (gab), *metya-kutya* (unreasonable, incoherent), *petya-kutya* (chatter)	
FIDGET	(C1)V1 + *ta* + C2V2 + *ta*	restlessness, fidgety	*ata-futa* (hastily), *dota-bata* (make a fuss), *jita-bata* (flail)	

Appendix B: Combined Trial Two Corpus

mo.go.mo.go	mumble
mo.Q.sa.ri	sluggish
mo.so.mo.so	slow movement
mo.ya.mo.ya	hazy, murky
mo.ku.mo.ku	send up lots of smoke
mo.ri.mo.ri	have thick muscles [e]
mu.ka.mu.ka	retch
mu.N.mu.N	stuffy, sultry
mu.ra.mu.ra	irresistible temptation
mu.ku.mu.ku	growing
mu.ki.mu.ki	have thick muscles
ne.ba.ne.ba	sticky, greasy
ne.ti.ne.ti	sticky, persistent
ne.Q.to.ri	clammy, viscous
no.bi.no.bi	feel at ease
no.ko.no.ko	nonchalantly
no.ro.no.ro	drag oneself
yo.bo.yo.bo	feeble, shaky
yo.ti.yo.ti	toddle
yo.ta.yo.ta	toddler
yo.ro.yo.ro	unstable, weak
yu.Q.ku.ri	slowly, at leisure
yu.Q.ra.ri	slowly
yu.sa.yu.sa	sway to and fro
yu.Q.ta.ri	slowly
yu.u.yu.u	chill (not temperature)
ba.sa.ba.sa	crumbly, disheveled
ka.sa.ka.sa	dry, rough
wa.sa.wa.sa	nervous, restless
pa.sa.pa.sa	dry
gi.ti.gi.ti	very tight
ka.ti.ka.ti	frozen hard, dried up
ko.ti.ko.ti	tense, stiff, frozen
ba.ti.ba.ti	brittle (large)
pa.ti.pa.ti	brittle
so.bo.so.bo	dispirited
to.bo.to.bo	trudge wearily
yo.bo.yo.bo	feeble, shaky, unsteady
do.ro.do.ro	pulpy, mushy
o.ro.o.ro	thrown off balance
go.ro.go.ro	lie about idly
bo.ro.bo.ro	in big drops
ho.ro.ho.ro	in small drops
po.ro.po.ro	in drops
gu.jya.gu.jya	slushy, sloppy
u.jya.u.jya	wriggle
ku.ra.ku.ra	dizzy, reeling
u.ra.u.ra	gentle
yu.ra.yu.ra	quake, sway
su.ra.su.ra	smoothly, without a hitch

mu.ra.mu.ra	swaying
gu.ra.gu.ra	toppling
bu.ra.bu.ra	swaying, idling
tyo.ro.tyo.ro	trickle, flicker
hyo.ro.hyo.ro	totter, toddle, stagger
kyo.ro.kyo.ro	look around restlessly, nervously
nyo.ro.nyo.ro	long and squirming
gyo.ro.gyo.ro	dribbling
de.bu.de.bu	fat and flabby
ga.bu.ga.bu	guzzle, chug, slosh
za.bu.za.bu	splash
i.tya.i.tya	flirt
go.tya.go.tya	messy, jumbled
ku.tya.ku.tya	crumpled
bi.tya.bi.tya	spurting
go.tya.go.tya	speak worthlessly
ma.go.ma.go	at a loss, disorganized
su.go.su.go	disheartened, downcast
i.ji.i.ji	hesitantly, timidly
mo.ji.mo.ji	bashful, fidget
ta.ji.ta.ji	quail
nu.ke.nu.ke	impudently, brazenly
zu.ke.zu.ke	bluntly, without reserve
tsu.ke.tsu.ke	rudely
do.ki.do.ki	beat fast, throb
me.ki.me.ki	remarkably, rapidly
sya.ki.sya.ki	biskly, concisely
pa.ki.pa.ki	breaking
ba.ki.ba.ki	heavy breaking
po.ki.po.ki	breaking
ku.ne.ku.ne	sway, meander
u.ne.u.ne	winding, tortuous
fu.nya.fu.nya	limply, flabby
ku.nya.ku.nya	soft and cuddly
mu.nya.mu.nya	mumble
gu.nya.gu.nya	soft, weakened
do.si.do.si	hand over fist, without hesitation
gi.si.gi.si	squeeze, be packed
hi.si.hi.si	press, feel keenly
go.si.go.si	scrub
ba.si.ba.si	whack
ga.si.ga.si	fierce scrubbing
bo.so.bo.so	in a subdued voice
hi.so.hi.so	in whispers
ko.so.ko.so	secretly, stealthily
mo.so.mo.so	slow movement
go.so.go.so	rummage
bo.te.bo.te	fat, obese
go.te.go.te	gaudy, heavy
ko.te.ko.te	thickly, lavishly
ba.te.ba.te	exhausted
mo.te.mo.te	sexy [e]
gu.zu.gu.zu	grumble

mu.zu.mu.zu	burning with desire
u.zu.u.zu	impatient, itching
ga.Q.ta.ri	destroy suddenly
ba.Q.ta.ri	run into, stop suddenly
pa.Q.ta.ri	suddenly, abruptly
fu.N.wa.ri	fluffy
ji.N.wa.ri	well up slowly
ya.N.wa.ri	gently, mild
ba.Q.ti.ri	perfect
ga.Q.ti.ri	solid, steady, tight
ki.Q.ti.ri	exactly, perfect, tight
ha.Q.ki.ri	clearly, without misunderstanding
ku.Q.ki.ri	clearly, distinctly
nyo.Q.ki.ri	stuck out
tyo.Q.ki.ri	exactly
ga.Q.po.ri	make a pile of money
go.Q.po.ri	in a large quantity
si.Q.po.ri	wet though, tender and passionate
do.Q.pu.ri	to the full, be up to one's neck
ga.Q.pu.ri	drink up a lot of liquid
ta.Q.pu.ri	plenty, full of
su.Q.pu.ri	fits perfectly
ba.Q.sa.ri	make a drastic cut
do.Q.sa.ri	heaps / loads of
fu.Q.sa.ri	abundant hair
gu.Q.sa.ri	heaps, loads of
do.Q.si.ri	massive
gi.Q.si.ri	closely, tightly
zu.Q.si.ri	heavy
go.Q.te.ri	thick, stodgy
ko.Q.te.ri	filling, rich
po.Q.te.ri	plump, chubby
o.Q.to.ri	composed, gentle
si.Q.to.ri	quiet, calm
u.Q.to.ri	enchanted
yo.Q.to.ri	laid back
ne.Q.to.ri	clammy, viscous
be.Q.to.ri	sticky, tight [e]
ji.Q.to.ri	damp, moist [e]
be.tya.ku.tya	gab
me.tya.me.tya	unreasonable, incoherent
pe.tya.pe.tya	chatter
a.ta.fu.ta	hastily
do.ta.do.ta	make a fuss
ji.ta.ba.ta	flail

Appendix C: Original Code

This research is greatly indebted to Lisa Meeden and Doug Blank of Swarthmore and Bryn Mawr colleges and their colleagues for their work on the Python Robotics. The complete source is available at http://www.pyrobotics.org. See Blank, D.S., Kumar D., Meeden, L. (2005).

```
VOWELS = "aiueo"
VELARS = "kg"
NASALS = "mn"
FRICATIVES = "szSZT"
PALATALS = "y"
CORONALS = "stzdnyr"
LABIALS = "mbwp"

V_HIGH = "iu"
V_LOW = "a"
V_BACK = "aou"
V_LABIAL = "ou"
V_TENSE = "iuoe"

MORAIC_N = "N"
GEMINATE = "Q"


VOICED = "zbgr" + VOWELS + NASALS + MORAIC_N

def firstPosFeature(string, fset):
    if fset.find(string[0]) == -1:
        return 0
    else:
        return 1

def secondPosFeature(string, fset):
    if fset.find(string[len(string)-1]) == -1:
        return 0
    else:
        return 1

def floatingFeature(string, fset):
    for c in fset:
        if string.find(c) != -1:
            return 1
    return 0

def moraFeatures(string):

    features = []
```

```
    """
    FEATURE ORDER:

    velar palatal nasal coronal labial fricative
    voiced moraic_nasal geminate vowel_high vowel_low
    vowel_back vowel_labial vowel_tense (14)
    """

    features = features + [firstPosFeature(string, VELARS)]
    features = features + [floatingFeature(string, PALATALS)]
    features = features + [firstPosFeature(string, NASALS)]
    features = features + [firstPosFeature(string, CORONALS)]
    features = features + [firstPosFeature(string, LABIALS)]
    features = features + [floatingFeature(string, FRICATIVES)]
    features = features + [firstPosFeature(string, VOICED)]
    features = features + [firstPosFeature(string, MORAIC_N)]
    features = features + [firstPosFeature(string, GEMINATE)]
    features = features + [secondPosFeature(string, V_HIGH)]
    features = features + [secondPosFeature(string, V_LOW)]
    features = features + [secondPosFeature(string, V_BACK)]
    features = features + [secondPosFeature(string, V_LABIAL)]
    features = features + [secondPosFeature(string, V_TENSE)]

    """
    #voicing
    if VOICED.find(string[0]) == -1:
        features = features + [0]
    else:
        features = features + [1]
    #velar
    if VELARS.find(string[0]) == -1:
        features = features + [0]
    else:
        features = features + [1]
    #fricative
    if FRICATIVES.find(string[0]) == -1:
        features = features + [0]
    else:
        features = features + [1]
    """

    return features

def featurize(string):
    moraList = string.split('.')
    features = []

    for mora in moraList:
        # print mora
        # print moraFeatures(mora)
        features = features + moraFeatures(mora)
```

```
    return features

def phonaesthize(n, fname, j, dValue, oFile):
    # retrieve string

    tdata_h = open(fname)
    tdata = tdata_h.readlines()

    """
    # debug printing
    print "read from file:"
    print tdata
    """

    k = 0

    #if we're dumping activations ...
    if dValue == 1:
        activationsFile = open("a_dump.dat", "w")
        namesFile = open("a_names.dat", "w")

    if oFile != "":
        oHandle = open(oFile, "w")

    # master loop
    eList = []

    while k < j:
        k = k + 1
        for line in tdata:
            pFeatures = line.split('\t')[0]
            sList = line.split()

            sFeatures = []
            #hack atoi for sFeatures
            i = 1
            while i < len(sList):
                sFeatures = sFeatures + [string.atoi(sList[i])]
                i = i + 1

            current = featurize(pFeatures)
            results = sFeatures


            #copy to layers
            n.getLayer('input').copyActivations(current)
            n.getLayer('output').copyTargets(results)

            #if we're dumping activations
            if dValue == 1:
                aList = n.getLayer('hidden').getActivationsList()
                for v in aList:
                    activationsFile.write(str(v))
```

```
                activationsFile.write("\n")
                namesFile.write(pFeatures)
                namesFile.write("\n")

            #step network
            (error, correct, count) = n.step()

            #record error
            print error
            eList = eList + [error]

            #if we're outputting to a file
            if oFile != "":
                oHandle.write(str(error))
                oHandle.write("\n")

        if k == j - 1:
            aError = 0
            for v in eList:
                aError = aError + v
                aError = aError / len(eList)
            print "FINAL AVERAGE ERROR:"
            print aError

    if dValue == 1:
        activationsFile.close()
        namesFile.close()

if __name__ == '__main__':

    """
    USAGE:
    python gitaigo.py trainingfile cycles header
    [-s nfile] [-l nfile] [-e efile] [-d] [-o outfile]

    """

    if sys.argv[3] == '1':
        print "\n...GITAIGO.v1.2...................."
        print "...Luke.Smith.2006................."
        print "...Swarthmore College Linguistics...\n"

    # If we're loading from a file ...

    try:
        fsIndex = sys.argv.index("-l") + 1
        n = loadNetworkFromFile(sys.argv[fsIndex])
        print "loaded network from file:"
        print sys.argv[fsIndex]
    except(ValueError):
        n = Network()
        n.addThreeLayers(56,60,37)
        n.setEpsilon(0.25)
```

```
    n.setMomentum(0.1)
    n.setBatch(0)
    n.setReportRate(100)
    n.setLayerVerification(0) # turn off automatic error checking

# check for activations dump
try:
    if sys.argv.index("-d") > 0:
        dValue = 1
except(ValueError):
    dValue = 0

# check for output dump"
oFile = ""
try:
    if sys.argv.index("-o") > 0:
        oValue = 1
        oFile = sys.argv[sys.argv.index("-o") + 1]
except(ValueError):
    oValue = 0


phonaesthize(n, sys.argv[1], string.atoi(sys.argv[2]), dValue, oFile)

# if we're saving to a file ...
try:
    fsIndex = sys.argv.index("-s") + 1
    n.saveNetworkToFile(sys.argv[fsIndex])
except(ValueError):
    n = Network()
```

Appendix D: Trial Two Cluster Analysis

```
minimum distance = 0.000000     ( mu.ra.mu.ra )       ( yu.Q.ta.ri )
minimum distance = 0.000000     ( ku.tya.ku.tya )       ( yu.Q.ta.ri mu.ra.mu.ra )
minimum distance = 0.000009     ( do.ta.do.ta )       ( bi.tya.bi.tya )
minimum distance = 0.000012     ( gu.ra.gu.ra )       ( mu.ku.mu.ku )
minimum distance = 0.000014     ( zu.Q.si.ri )       ( gi.si.gi.si )
minimum distance = 0.000017     ( ka.ti.ka.ti )       ( pa.sa.pa.sa )
minimum distance = 0.000019     ( ko.Q.te.ri )       ( ku.ra.ku.ra )
minimum distance = 0.000021     ( ku.Q.ki.ri )       ( ki.Q.ti.ri )
minimum distance = 0.000033     ( gi.si.gi.si zu.Q.si.ri )       ( mu.ku.mu.ku gu.ra.gu.ra )
minimum distance = 0.000055     ( mu.nya.mu.nya )       ( tsu.ke.tsu.ke )
minimum distance = 0.000057     ( tyo.Q.ki.ri )       ( gu.nya.gu.nya )
minimum distance = 0.000057     ( be.Q.to.ri )       ( yo.ti.yo.ti )
minimum distance = 0.000061     ( bi.tya.bi.tya do.ta.do.ta )       ( mu.ku.mu.ku gu.ra.gu.ra gi.si.gi.si :
minimum distance = 0.000064     ( ba.ki.ba.ki )       ( so.bo.so.bo )
minimum distance = 0.000074     ( ku.ra.ku.ra ko.Q.te.ri )       ( su.ra.su.ra )
minimum distance = 0.000082     ( yo.ro.yo.ro )       ( mo.go.mo.go )
minimum distance = 0.000089     ( yu.u.yu.u )       ( yu.sa.yu.sa )
minimum distance = 0.000112     ( mo.te.mo.te )       ( pa.ti.pa.ti )
minimum distance = 0.000116     ( tyo.ro.tyo.ro )       ( ka.sa.ka.sa )
minimum distance = 0.000120     ( ya.N.wa.ri )       ( ku.ne.ku.ne )
minimum distance = 0.000146     ( mu.ku.mu.ku gu.ra.gu.ra gi.si.gi.si zu.Q.si.ri bi.tya.bi.tya do.ta.do.ta )
minimum distance = 0.000149     ( su.ra.su.ra ku.ra.ku.ra ko.Q.te.ri )       ( yu.Q.ta.ri mu.ra.mu.ra ku.t]
minimum distance = 0.000212     ( pa.ti.pa.ti mo.te.mo.te )       ( po.ki.po.ki )
minimum distance = 0.000231     ( bu.ra.bu.ra mu.ku.mu.ku gu.ra.gu.ra gi.si.gi.si zu.Q.si.ri bi.tya.bi.tya (
minimum distance = 0.000248     ( yu.Q.ta.ri mu.ra.mu.ra ku.tya.ku.tya su.ra.su.ra ku.ra.ku.ra ko.Q.te.ri )
minimum distance = 0.000255     ( yo.bo.yo.bo )       ( mu.ki.mu.ki )
minimum distance = 0.000276     ( mo.ji.mo.ji )       ( u.jya.u.jya )
minimum distance = 0.000294     ( ga.Q.po.ri )       ( gyo.ro.gyo.ro )
minimum distance = 0.000308     ( tsu.ke.tsu.ke mu.nya.mu.nya )       ( go.tya.go.tya )
minimum distance = 0.000382     ( pe.tya.pe.tya )       ( ma.go.ma.go )
minimum distance = 0.000409     ( fu.Q.sa.ri )       ( u.zu.u.zu )
minimum distance = 0.000430     ( po.ki.po.ki pa.ti.pa.ti mo.te.mo.te )       ( so.bo.so.bo ba.ki.ba.ki )
minimum distance = 0.000465     ( go.tya.go.tya tsu.ke.tsu.ke mu.nya.mu.nya )       ( u.ra.u.ra )
minimum distance = 0.000475     ( ne.Q.to.ri )       ( nyo.Q.ki.ri )
minimum distance = 0.000505     ( si.Q.po.ri )       ( ji.N.wa.ri )
minimum distance = 0.000526     ( gu.nya.gu.nya tyo.Q.ki.ri bu.ra.bu.ra mu.ku.mu.ku gu.ra.gu.ra gi.si.gi.si
minimum distance = 0.000556     ( ka.sa.ka.sa tyo.ro.tyo.ro )       ( ne.Q.to.ri )
minimum distance = 0.000606     ( so.bo.so.bo ba.ki.ba.ki po.ki.po.ki pa.ti.pa.ti mo.te.mo.te )       ( bo.
minimum distance = 0.000710     ( ki.Q.ti.ri ku.Q.ki.ri )       ( u.ra.u.ra go.tya.go.tya tsu.ke.tsu.ke mu.
minimum distance = 0.000734     ( gyo.ro.gyo.ro ga.Q.po.ri )       ( no.bi.no.bi )
minimum distance = 0.000794     ( sya.ki.sya.ki )       ( yu.Q.ra.ri )
minimum distance = 0.000864     ( gi.Q.si.ri )       ( kyo.ro.kyo.ro )
minimum distance = 0.000907     ( ku.ne.ku.ne ya.N.wa.ri )       ( ko.ti.ko.ti )
minimum distance = 0.000959     ( su.Q.pu.ri )       ( mo.ya.mo.ya )
minimum distance = 0.001050     ( yo.ti.yo.ti be.Q.to.ri )       ( ne.Q.to.ri ka.sa.ka.sa tyo.ro.tyo.ro )
minimum distance = 0.001120     ( ga.Q.ti.ri )       ( za.bu.za.bu )
minimum distance = 0.001220     ( ta.ji.ta.ji )       ( mo.Q.sa.ri )
minimum distance = 0.001222     ( yu.Q.ra.ri sya.ki.sya.ki )       ( mu.ki.mu.ki yo.bo.yo.bo )
minimum distance = 0.001303     ( ko.ti.ko.ti ku.ne.ku.ne ya.N.wa.ri )       ( u.jya.u.jya mo.ji.mo.ji )
minimum distance = 0.001425     ( mo.go.mo.go yo.ro.yo.ro yu.Q.ta.ri mu.ra.mu.ra ku.tya.ku.tya su.ra.su.ra ]
minimum distance = 0.001539     ( ba.te.ba.te )       ( mu.N.mu.N )
minimum distance = 0.001552     ( ne.Q.to.ri ka.sa.ka.sa tyo.ro.tyo.ro yo.ti.yo.ti be.Q.to.ri )       ( do.
minimum distance = 0.001677     ( go.si.go.si )       ( hi.si.hi.si )
minimum distance = 0.001772     ( ga.Q.pu.ri )       ( ba.Q.ta.ri )
minimum distance = 0.002093     ( no.bi.no.bi gyo.ro.gyo.ro ga.Q.po.ri )       ( no.ro.no.ro )
minimum distance = 0.002527     ( po.Q.te.ri )       ( mu.ra.mu.ra )
minimum distance = 0.002778     ( do.ki.do.ki ne.Q.to.ri ka.sa.ka.sa tyo.ro.tyo.ro yo.ti.yo.ti be.Q.to.ri )
minimum distance = 0.002845     ( ji.N.wa.ri si.Q.po.ri )       ( mo.Q.sa.ri ta.ji.ta.ji )
minimum distance = 0.002980     ( kyo.ro.kyo.ro gi.Q.si.ri )       ( mu.ki.mu.ki yo.bo.yo.bo yu.Q.ra.ri sy
minimum distance = 0.003189     ( u.zu.u.zu fu.Q.sa.ri )       ( yu.sa.yu.sa yu.u.yu.u )
minimum distance = 0.003206     ( po.ro.po.ro )       ( bo.ro.bo.ro )
minimum distance = 0.003401     ( u.jya.u.jya mo.ji.mo.ji ko.ti.ko.ti ku.ne.ku.ne ya.N.wa.ri )       ( bo.
minimum distance = 0.003418     ( pa.Q.ta.ri )       ( ba.si.ba.si )
```

```
minimum distance = 0.003654        ( ko.te.ko.te )        ( mo.so.mo.so )
minimum distance = 0.003872        ( ma.go.ma.go pe.tya.pe.tya )        ( mo.ku.mo.ku )
minimum distance = 0.004173        ( za.bu.za.bu ga.Q.ti.ri )        ( ho.ro.ho.ro )
minimum distance = 0.004222        ( u.Q.to.ri )        ( hi.si.hi.si go.si.go.si )
minimum distance = 0.004790        ( yo.Q.to.ri )        ( ba.Q.ta.ri ga.Q.pu.ri )
minimum distance = 0.005105        ( gu.zu.gu.zu )        ( mo.ri.mo.ri )
minimum distance = 0.005478        ( ko.so.ko.so )        ( nyo.ro.nyo.ro )
minimum distance = 0.005564        ( u.ra.u.ra go.tya.go.tya tsu.ke.tsu.ke mu.nya.mu.nya ki.Q.ti.ri ku.Q.ki.ri
minimum distance = 0.005745        ( mu.ra.mu.ra po.Q.te.ri )        ( do.Q.sa.ri )
minimum distance = 0.005890        ( mu.ki.mu.ki yo.bo.yo.bo yu.Q.ra.ri sya.ki.sya.ki kyo.ro.kyo.ro gi.Q.si.ri
minimum distance = 0.006480        ( mu.N.mu.N ba.te.ba.te )        ( ba.ti.ba.ti )
minimum distance = 0.007183        ( ho.ro.ho.ro za.bu.za.bu ga.Q.ti.ri )        ( bo.so.bo.so so.bo.so.bo ba.l
minimum distance = 0.009678        ( mo.so.mo.so ko.te.ko.te )        ( bo.ro.bo.ro po.ro.po.ro )
minimum distance = 0.009957        ( me.tya.me.tya )        ( ne.ti.ne.ti )
minimum distance = 0.010037        ( hi.si.hi.si go.si.go.si u.Q.to.ri )        ( do.Q.sa.ri mu.ra.mu.ra po.Q.t
minimum distance = 0.010299        ( a.ta.fu.ta )        ( si.Q.to.ri )
minimum distance = 0.011167        ( nyo.Q.ki.ri ne.Q.to.ri )        ( ba.Q.ta.ri ga.Q.pu.ri yo.Q.to.ri )
minimum distance = 0.011349        ( do.Q.pu.ri )        ( pa.sa.pa.sa ka.ti.ka.ti )
minimum distance = 0.012010        ( no.ro.no.ro no.bi.no.bi gyo.ro.gyo.ro ga.Q.po.ri do.ki.do.ki ne.Q.to.ri ka
minimum distance = 0.012103        ( yo.ta.yo.ta mu.ki.mu.ki yo.bo.yo.bo yu.Q.ra.ri sya.ki.sya.ki kyo.ro.kyo.ro
minimum distance = 0.012453        ( mo.ri.mo.ri gu.zu.gu.zu )        ( ga.bu.ga.bu )
minimum distance = 0.013591        ( go.te.go.te )        ( zu.ke.zu.ke )
minimum distance = 0.015558        ( pa.sa.pa.sa ka.ti.ka.ti do.Q.pu.ri )        ( ba.si.ba.si pa.Q.ta.ri )
minimum distance = 0.016346        ( ba.ti.ba.ti mu.N.mu.N ba.te.ba.te )        ( nyo.ro.nyo.ro ko.so.ko.so )
minimum distance = 0.021130        ( ga.bu.ga.bu mo.ri.mo.ri gu.zu.gu.zu )        ( bo.ro.bo.ro po.ro.po.ro mo.
minimum distance = 0.021733        ( yu.sa.yu.sa yu.u.yu.u u.zu.u.zu fu.Q.sa.ri )        ( go.ro.go.ro )
minimum distance = 0.022283        ( si.Q.to.ri a.ta.fu.ta )        ( ne.ti.ne.ti me.tya.me.tya )
minimum distance = 0.023636        ( gu.Q.sa.ri )        ( wa.sa.wa.sa )
minimum distance = 0.025616        ( mo.Q.sa.ri ta.ji.ta.ji ji.N.wa.ri si.Q.po.ri )        ( nyo.ro.nyo.ro ko.s
minimum distance = 0.027316        ( ba.si.ba.si pa.Q.ta.ri pa.sa.pa.sa ka.ti.ka.ti do.Q.pu.ri )        ( pa.k
minimum distance = 0.027425        ( ba.Q.ta.ri ga.Q.pu.ri yo.Q.to.ri nyo.Q.ki.ri ne.Q.to.ri )        ( do.Q.sa
minimum distance = 0.030766        ( zu.ke.zu.ke go.te.go.te )        ( go.so.go.so )
minimum distance = 0.041142        ( ne.ti.ne.ti me.tya.me.tya si.Q.to.ri a.ta.fu.ta )        ( mo.ya.mo    su.
minimum distance = 0.045747        ( do.Q.sa.ri mu.ra.mu.ra po.Q.te.ri hi.si.hi.si go.si.go.si u.Q.to.ri   .Q.t
minimum distance = 0.052773        ( nyo.ro.nyo.ro ko.so.ko.so ba.ti.ba.ti mu.N.mu.N ba.te.ba.te mo.Q.sa.   ta.
minimum distance = 0.058806        ( pa.ki.pa.ki ba.si.ba.si pa.Q.ta.ri pa.sa.pa.sa ka.ti.ka.ti do.Q.pu.
minimum distance = 0.060869        ( mo.ku.mo.ku ma.go.ma.go pe.tya.pe.tya no.ro.no.ro no.bi.no.bi gyo.ro.gyo.
minimum distance = 0.071151        ( ji.Q.to.ri )        ( ku.nya.ku.nya )
minimum distance = 0.075812        ( mo.ya.mo.ya su.Q.pu.ri ne.ti.ne.ti me.tya.me.tya si.Q.to.ri a.ta.fu.ta )
minimum distance = 0.100507        ( wa.sa.wa.sa gu.Q.sa.ri mo.ya.mo.ya su.Q.pu.ri ne.ti.ne.ti me.tya.me.tya s
minimum distance = 0.102745        ( bo.ro.bo.ro po.ro.po.ro mo.so.mo.so ko.te.ko.te ga.bu.ga.bu mo.ri.mo.ri gu
minimum distance = 0.131916        ( go.so.go.so zu.ke.zu.ke go.te.go.te bo.ro.bo.ro po.ro.po.ro mo.so.mo.so ko
minimum distance = 0.135562        ( ku.nya.ku.nya ji.Q.to.ri )        ( i.tya.i.tya )
minimum distance = 0.171335        ( go.ro.go.ro yu.sa.yu.sa yu.u.yu.u u.zu.u.zu fu.Q.sa.ri do.Q.sa.ri mu.ra.mu
minimum distance = 0.412362        ( do.ro.do.ro yo.ta.yo.ta mu.ki.mu.ki yo.bo.yo.bo yu.Q.ra.ri sya.ki.sya.ki k
minimum distance = 0.841598        ( i.tya.i.tya ku.nya.ku.nya ji.Q.to.ri do.ro.do.ro yo.ta.yo.ta mu.ki.mu.ki y
Resulting Tree =
                   |-> bo.so.bo.so
                 |-|  _|-> so.bo.so.bo
                 | |-| |-> ba.ki.ba.ki
                 |   |_|-> po.ki.po.ki
               |-|     |_|-> pa.ti.pa.ti
               | |       |-> mo.te.mo.te
               | |   _|-> u.jya.u.jya
               | |-| |-> mo.ji.mo.ji
            |--|   |_|-> ko.ti.ko.ti
            |  |     |_|-> ku.ne.ku.ne
            |  |       |-> ya.N.wa.ri
            |  |_|-> ho.ro.ho.ro
            |    |_|-> za.bu.za.bu
        |---|      |-> ga.Q.ti.ri
        |   |     _|-> nyo.ro.nyo.ro
        |   |  |-| |-> ko.so.ko.so
        |   |  | |_|-> ba.ti.ba.ti
        |   |  |   |_|-> mu.N.mu.N
        |   |--|     |-> ba.te.ba.te
        |      |  _|-> mo.Q.sa.ri
```

```
 |-------------------|      |-| |-> ta.ji.ta.ji
 |                   |        |_|-> ji.N.wa.ri
 |                   |          |-> si.Q.po.ri
 |                   |    ___|-> go.so.go.so
 |                   |   |   |_|-> zu.ke.zu.ke
 |                   |   |     |-> go.te.go.te
 |                   |   |         _|-> bo.ro.bo.ro
 |                   |---|      |-| |-> po.ro.po.ro
 |                       |      | |_|-> mo.so.mo.so
 |                       |   |--|   |-> ko.te.ko.te
 |                       |   |  |_|-> ga.bu.ga.bu
 |                       |---|    |_|-> mo.ri.mo.ri
 |                            |      |-> gu.zu.gu.zu
 |                            |  |-> pa.ki.pa.ki
 |                            |--|  _|-> ba.si.ba.si
-|                               |-| |-> pa.Q.ta.ri
 |                                 |  _|-> pa.sa.pa.sa
 |                                 |-| |-> ka.ti.ka.ti
 |                                   |-> do.Q.pu.ri
 |                    _________|---> i.tya.i.tya
 |                   |         |___|--> ku.nya.ku.nya
 |                   |             |--> ji.Q.to.ri
 |                   |                  |-> do.ro.do.ro
 |                   |               |---| |-> yo.ta.yo.ta
 |                   |               |   | |    _|-> mu.ki.mu.ki
 |                   |               |   |-|  |-| |-> yo.bo.yo.bo
 |                   |               |     | | |_|-> yu.Q.ra.ri
 |                   |         |----|     |-|   |-> sya.ki.sya.ki
 |                   |         |    |       |_|-> kyo.ro.kyo.ro
 |-------------------|         |    |         |-> gi.Q.si.ri
                     |         |    |    __|-> wa.sa.wa.sa
                     |         |    |   |  |-> gu.Q.sa.ri
                     |         |    |---|   _|-> mo.ya.mo.ya
                     |         |        |  | |-> su.Q.pu.ri
                     |         |        |--|  _|-> ne.ti.ne.ti
                     |         |           |-| |-> me.tya.me.tya
                     |         |             |_|-> si.Q.to.ri
                     |         |               |-> a.ta.fu.ta
                     |         |          |-> go.ro.go.ro
                     |         |       |-|  _|-> yu.sa.yu.sa
                     |---------|       | |-| |-> yu.u.yu.u
                               |       |   |_|-> u.zu.u.zu
                               |       |     |-> fu.Q.sa.ri
                               |    |--|    _|-> do.Q.sa.ri
                               |    |  |   | |_|-> mu.ra.mu.ra
                               |    |  | |-|   |-> po.Q.te.ri
                               |    |  | | |  _|-> hi.si.hi.si
                               |    |  | | |-| |-> go.si.go.si
                               |    |  |-|   |-> u.Q.to.ri
                               |    |    |    _|-> ba.Q.ta.ri
                               |    |    | |-| |-> ga.Q.pu.ri
                               |    |    |-| |-> yo.Q.to.ri
                               |----|      |_|-> nyo.Q.ki.ri
                                    |        |-> ne.Q.to.ri
                                    |   _|-> mo.ku.mo.ku
                                    |  | |_|-> ma.go.ma.go
                                    |  |   |-> pe.tya.pe.tya
                                    |  |    _|-> no.ro.no.ro
                                    |  |   | |_|-> no.bi.no.bi
                                    |  |   |   |_|-> gyo.ro.gyo.ro
                                    |  | |-|     |-> ga.Q.po.ri
                                    |--| | | |-> do.ki.do.ki
                                       | | |-|  _|-> ne.Q.to.ri
                                       | |   | | |_|-> ka.sa.ka.sa
                                       | |   |-|   |-> tyo.ro.tyo.ro
                                       | |     |_|-> yo.ti.yo.ti
                                       | |       |-> be.Q.to.ri
```

```
|-|    _|-> u.ra.u.ra
  |   | |_|-> go.tya.go.tya
  | |-|   |_|-> tsu.ke.tsu.ke
  | | |     |-> mu.nya.mu.nya
  | | |_|-> ki.Q.ti.ri
  | |   |-> ku.Q.ki.ri
  | |    _|-> mo.go.mo.go
  |-|   | |-> yo.ro.yo.ro
    | |-|    _|-> yu.Q.ta.ri
    | | | |-| |-> mu.ra.mu.ra
    | | |-| |-> ku.tya.ku.tya
    | |   |_|-> su.ra.su.ra
    |-|     |_|-> ku.ra.ku.ra
      |       |-> ko.Q.te.ri
      |  _|-> gu.nya.gu.nya
      | | |-> tyo.Q.ki.ri
      |-| |-> bu.ra.bu.ra
        | |    _|-> mu.ku.mu.ku
        |-| |-| |-> gu.ra.gu.ra
          | | |_|-> gi.si.gi.si
          |-|   |-> zu.Q.si.ri
            |_|-> bi.tya.bi.tya
              |-> do.ta.do.ta
```

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