# Low resource scalar implicature in te reo Māori

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## Abstract

In this paper, we attempt to design and test a learning system taking inspiration from a commonly used methodology for language teaching known as "the Silent Way" and operationalised by the Indigenous Māori community in New Zealand as "Te Ataarangi". We describe a dialogue agent system, and use the methodology to motivate a scalar-implicature game based on cuisenaire rods. We compose a dataset for solving this game, and implement a data-augmentation strategy, and a rule-based system using part of speech labels to cope with the low-resource nature of the problem.

## 1 Introduction

The Silent Way (Gattegno, 2010) is a language teaching methodology which emphasises the subordination of teaching to learning. Lessons are conducted entirely in the target language, with a minimal vocabulary established in the early stages which incorporates simple utterances, instructions as well as hand-gestures. Cuisenaire rods are used to establish a world-state, which becomes a point for discussion where utterances can be hypothesised by the student and tested. When done in groups, lessons are overseen by a teacher but students take turns demonstrating their understanding to each other, and are able to correct and learn together.

In New Zealand, as well as in other countries, the Silent Way has been adopted by the Māori people as a dominant teaching methodology, especially for second-language learners of the Māori language (te reo Māori). The methodology was specifically adapted to te reo Māori (Mataira, 1980; Ka'Ai, 2008) by Dame Kāterina Te Heikōkō Mataira and Ngoingoi Pewhairangi where it is referred to as "Te Ataarangi". In the classroom, students in Te Ataarangi are encouraged to master grammar by experiencing the language primarily through speaking and listening, and doing practical exercises with other students. The classroom operates according to the following rules:

- Speaking in English is not allowed.
- Belittling other students is not allowed.
- Students are not allowed to prompt other students.
- Students can only reply when a question is posed directly to them.
- Students must practice empathy with their peers.

The experiments in this paper have been designed with the aim of replicating the Te Ataarangi method of teaching using computational techniques. One long-term goal of doing this could be to design computational language agents that are capable of teaching the language to new students using the method. In this paper, we aimed to investigate the feasibility of training an agent to deliver a Te Ataarangi lesson by carefully formulating the problem, defining the requirements of the agent and then testing out the components one by one. At the end, we would like to demonstrate that our computational model works *because* it follows the principles of the original method.

Following this line of thinking, we observe that a typical Te Ataarangi lesson generally takes the form of a scalar-implicature game, wherein the teacher uses cuisenaire rods and hand gestures to specify a world state, or a *context* ($c$) for discussion. They then give an *utterance* ($u$) corresponding to that context, and over time the job of the student is to identify the relevant grammatical rules and vocabulary so that they can generalise the given utterance to other contexts. The student can then demonstrate their knowledge by carefully constructing their own contexts, and proving they have the correct utterance to the teacher.

The lesson bears a resemblance to a Socratic dialogue and incorporates aspects of pragmatics. Since the teacher must think about what the student knows or does not know about the language, and construct examples in order to falsify incorrect assumptions, or to add missing context that may also be leading the student astray. We therefore propose to model the lesson with a pair of Rational Speech Actors according to the Rational Speech Act (Frank and Goodman, 2012; Goodman and Frank, 2016) framework. We define two Rational Speech Actors, one each for the teacher and the student. Both agents implement a literal listener, a pragmatic speaker and a pragmatic listener. The literal listener is a model that defines a mapping from contexts ($c$) to utterances ($u$). The teacher agent is pre-trained, such that it has prior knowledge of the rules of the language. The student agent then learns through a dialogue with the teacher agent. The dialogue is set up in the following way:

- The teacher selects an (context, utterance) pair and provides it to the student by way of demonstration.
- The student then selects an (context, utterance) pair and conjectures an utterance for that state for the teacher to evaluate.
- The student receives feedback from the teacher, either by way of correction, or the conversation may move on indicating that the selection was correct. The feedback is provided as an additional (context, utterance) pair.
- This loop continues until the teacher is satisfied that the student has acquired the required knowledge.

The contexts under consideration are defined as an arrangement of cuisenaire rods. Each rod has a colour and a length, and they are sampled at random and arranged into a row. From the sample, a selection is made and the utterance is constructed to accurately identify the selected rods among their neighbours. In English, utterances therefore look like “The red rod”, “The blue rod on the left”, or “All of the rods” if all of the rods in the context are selected.

Throughout this work, we operate under the assumption that we are working with an under-resourced language. So we place an emphasis on methods that could reasonably be applied by a language community in the absence of large training datasets containing millions of tokens. Te reo Māori is used as the language for all experiments, although it would be easy to run these experiments in any language, and would require the hand labelling of no more than 1,000 examples. As a speaker of the Māori language, I was able to prepare the dataset for these experiments alone, in only a few hours.

We begin the project by training a recurrent neural network to solve this scalar implicature problem, using a small training dataset. Initially, it was proposed to use a small dataset for parsimony reasons, as the task as designed resembles a very early beginner Māori language lesson, requiring minimal prior knowledge of the language. This problem proved to be more difficult than initially anticipated, and so various strategies, such as data augmentation were attempted in order to pre-train a competent teacher agent for this task.

## 2 Related Work

### 2.1 Scalar implicature

Scalar implicature (Grice, 1975) is a fundamental problem class for any language learning system. As such, learning a new language involves solving implicature tasks of a range of types, in increasing complexity. While not sufficient on its own, mastering scalar implicature will teach a student about grammar, vocab and syntax that are common in everyday life. It is clear that in order for a conversational agent to be an effective teacher, it first must have a mastery of the target task.

The task of learning natural language quantifiers from abstracted world states was investigated in (Sorodoc et al., 2016), where the authors trained and tested whether neural networks were able to learn natural language quantifiers such as *no*, *some* and *all*. In their task, the model was trained on images containing 1-16 circles of up to 15 different colours. They generated all possible colourings in their dataset. They compared an RNN with a quantised memory network (qMN) and found that the latter outperformed the RNN with a model accuracy of 88.8% on familiar examples vs 65.7% for the RNN.

In (Zheng et al., 2021) the authors prepare a dataset of sample dialogues, where implicature is present, and models are then trained in order to resolve the implicature to an explicit form by answering targeted questions constructed based on the sample dialogue. This bears some resemblance to the language instruction problem, in the sense that the question-answer pairs are given after a dialogue in order to check understanding. The formulation of the $n$-round dialogue as a sequence of QA-pairs $\{(Q_1, A_1), (Q_2, A_2), \cdots, (Q_n, A_n)\}$, where $Q_i$ is the question raised by the first agent, and $A_i$ is the response provided by the second agent, which may contain an implicature. The dataset contains 15,000 dialogues, where 6,000 were used for training, 4,000 for development and 5,000 for testing. This is considerably more than the dataset we are currently using, and also the dialogues are quite rich and varied, as compared to ours which focus on a very specific task.

### 2.2 Dialogue agents

Dialogue agents are often envisioned as a method for teaching new information. However, to convey information well it is necessary for a model to know when the information has been acquired by the target or not. This is a necessary part of teaching to any kind of curriculum. So the purpose of our use of dialogue agents in this paper is to track the progress of the student and make recommendations about what they need to learn next.

Previous work has trained rational pragmatic models for correctly generating and following natural language instructions for complex tasks (Fried et al., 2017). Indeed, sequential language games (Khani et al., 2018) have been explored using training data acquired via Amazon Mechanical-Turk. Personality modelling (Yang et al., 2020) is related to our goal task because it is necessary for the teacher to have an implicit model of the student's progress in order to make sensible world state recommendations. Other work has focused on making agents that communicate with humans in natural language (Lazaridou et al., 2020).

### 2.3 Under-resourced language modelling

Low resource language work in pragmatics often uses the term "low-resource" to refer to "not having a lot of data" as opposed to data from or relating to under-resourced language communities. In this way, there are a lot of low-resource works that have little resemblance to work on language revitalisation. Some work has focused on implementing pragmatic reasoning under computational constraints (Van Arkel et al., 2020), which the authors referred to "frugal pragmatism". This gap in the literature may reflect the fact that many under-resourced languages have yet to acquire models which are powerful enough to demonstrate strong pragmatic capabilities.

In some ways, many of the well known pragmatics problems are readily expressed in English as well as in other languages, and so to keep the work accessible to the largely English speaking research community, it makes sense that pragmatics work in other languages is still quite rare. Perhaps relatedly, a large proportion of the under-resourced language language modelling work focuses on translation compared to solving task specific goals like question-answering. Generally speaking, the goal appears to be to translate out of the under-resourced language into a high resource language like English, and then to do any question-answering or other complex tasks in the high resource language, before translating it back.

## 3 Method

### 3.1 World state generation

The world states under consideration in this task are referred to as "contexts". Each context comprises a sequence of randomly chosen cuisenaire rods, each of which has a given colour (chosen from a set of 8) and length (ranging from 1-10). A context can have up to 13 rods, and from the context a random subset is selected.

The goal of the task is to write an utterance which correctly identifies the selected rods from among the rest in the context. This problem was constructed to be similar to a typical first language lesson according to the Te Ataarangi method.

Sampling uniformly from a large world state space would result in a large proportion of states with high entropy. This would be undesirable, since the goal is to teach the language so we chose to start from simpler world states and gradually increase the complexity. For that reason, we used the following procedure to generate arrangements of cuisenaire rods:

- An entropy budget is chosen, calculated as the sum of the entropy for colour and height.
- A rod is selected with random height and colour, and the entropy for the new configuration is computed.
- If this entropy exceeds the threshold, the process ends; otherwise, another rod is added.

### 3.2 Labelling world states

During labelling, the entropy budget begins set to 0.5, and then every 66 examples the budget was increased by 0.5 to a cap of 8.0 resulting in a sample size of 990. For certain easy cases, such as when all rods are selected, a pre-computed utterance such as "ngā rākau katoa" ("all of the rods") or "te rākau" ("the rod") would automatically be entered on behalf of the user. This happened in approximately 30% of the examples in the dataset.

### 3.3 Conversational Agents

In this work, we aim to implement a pair of conversational agents. A teacher $A_{teacher}$, and a student $A_{student}$. The agents comprise of two models, the first maps contexts to utterances. In the case of the teacher, this model is pre-trained to be correct, while the student begins with a randomly initialised model.

The second model is designed to suggest world states for demonstration. For the teacher, this functions as a curriculum that takes in the history of (context, utterance) pairs from the student, and suggests world states that will help the student arrive at correct conclusions. In the case of the student, the world states are chosen to demonstrate that it has acquired the ability to produce correct utterances for the kinds of world states that the teacher has demonstrated so far, as well as to make conjectures that will demonstrate that the patterns it has learned generalise in the right way.

### 3.4 The dataset

In order to learn this task, we prepared a dataset of (context, utterance) pairs. The dataset consists of 1,017 such pairs, where each world state is represented as a list of rod objects each with colour, height and an additional true/false value indicating whether it has been selected or not. The world states were rendered as images, and then labelled with the utterance.

| te reo Māori | English translation |
|---|---|
| Ngā rākau katoa | All of the rod |
| Te rākau | The rod (singular) |
| Te rākau iti | The small rod |
| Te rākau whero | The red rod |
| Te rākau whero me te rākau iti rawa | The red rod and the smallest one |

Table 1: Example utterances from the dataset

The utterances for all of the (context, utterance) pairs are written using only 29 unique tokens.

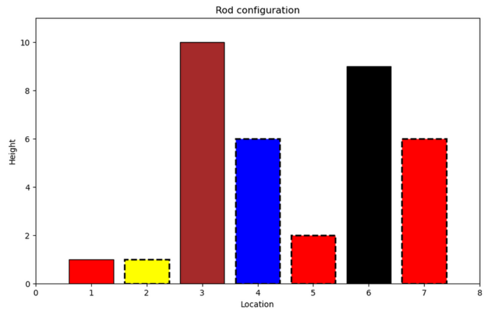


Figure 1: An example arrangement of rods. The utterance for this configuration is: "te rākau kōwhai me te rākau kikorangi me ngā rākau whero katoa hāunga te rākau iti rawa"/"The yellow rod, and the blue rod, and all of the red rods except for the smallest one". Note that the selection is given by dotted-lines.

### 3.5 Tokenisation

Each context was converted to a sequence of tokens so that the labelling problem could be approached as a translation task. The complete list of context tokens are given in table 2. The tokens are then arranged in the order `[SOS]`, then whether the current rod is selected (`[SELECTED]`/`[NOT_SELECTED]`) then its colour (e.g. `[COLOUR_RED]`), followed by its height (e.g. `[HEIGHT_3]`). Subsequent rods are then appended to this sequence according to the same rule (selection, colour, height), and the last state token is followed by the `[SEP]` token.

The utterances were tokenised simply as regular words, and the complete token list is included in the appendix.

### 3.6 Data augmentation

With such a small dataset, it would be challenging to learn a mapping even with a simple model. For this reason, we used data augmentation to increase the size of the dataset one thousand-fold. This was done by exploiting the following properties of the simple world-model.

- If you permute the colours in the context and the utterance in the same way, the resulting pair is still valid.
- Unless the utterance mentions something location-specific (such as 'left'/'right') then the order of the rods can be permuted.

| Token | Description |
|---|---|
| [PAD] | Padding token used to fill empty spaces in data sequences to ensure uniform length. |
| [SOS] | Start of sequence token, used to signal the beginning of a new data sequence. |
| [SELECTED] | Token indicating that an item or feature is selected or active in the context. |
| [NOT_SELECTED] | Token indicating that an item or feature is not selected or inactive in the context. |
| [COLOURS] | Tokens representing various colors (red, blue, green, yellow, black, white, brown, pink). |
| [HEIGHTS] | Tokens representing various height levels (1 to 10). |
| [SEP] | Separator token. |

Table 2: Context state tokens with descriptions

- If 'left'/'right' are mentioned, then if you reverse the order of the rods then you can flip 'left'/'right' in the utterance.
- In the utterances, the height of each rod was used only as an ordinal variable. Therefore any re-scaling of the rod heights which preserves order is consistent with the original utterance.

There are some limitations to this approach. In particular, permuting the rods randomly in this manner could result in an arrangement where some other utterance would more naturally occur to a human. For example, if the selected rods are all put on one side of the arrangement, then it may not be necessary to individually name specify each rod.

For the sake of keeping the problem simple, while growing the dataset enough that a model would be able to learn the pattern we went ahead with this approach.

### 3.7 one-gram model

To try and help the model learn with less human-labelled data we also used the labelled data to construct a one-gram model, which was used to constrain the output of the model by penalising the model for predicting any (previous, next) token pair that is not in the training data.

Since it is possible the coverage of all of the important token-pairs in the training set was not complete, each token in the dataset was assigned a part of speech class. Then the next-token restriction was applied based on token classes rather than individual tokens. This way words that have equivalent functions are treated equally by the one-gram model, and in case the training data did not cover a particular case (e.g. "te rākau iti whero kei te taha mauī"/"the small red stick on the left") we can still ensure that the model is aware that it's a valid utterance in principle. This does not prevent many other kinds of errors, such as infinite repetition using conjunction.

In order to penalise the model, the logits for any next-tokens that are not valid according to the one-gram model were set to a large negative value. The class labels assigned to each token, as well as the next-token classes map are provided in the appendix.

### 3.8 Models

The goal task was framed as translation, where the input sequence was the tokenised representation of the context, and the target sequence to be predicted is the utterance corresponding to that state. Therefore we approached this problem using sequence-to-sequence models.

We tried three model architectures, transformer, vanilla RNN and LSTM. Parameter sweeps were conducted to find hyperparameters for each.

## 4 Experiments & Results

After data augmentation, we had 778,001 training samples 124,763 samples in the dev set and 101,314 samples were used for testing. These examples were used to train a range of transformer, RNN and LSTM models.

We were unable to obtain a model that was competent at the target task with the problem formulation we described.

## 5 Discussion and Conclusion

The labelling task was designed to represent the kind of task that might be expected of a beginner language learner, and the dataset was constructed to have many ($\sim$50+) times the amount of data that would ordinarily be needed by a human to learn this sort of task. Because of this, it was surprising that a model was not able to effectively learn the goal task, even with the significant data augmentation and heavy guidance provided by the 1-gram model.

It is possible the problem was still too complex for a simple model to solve, and we could have tried removing some variables such as length, or reducing the size of some of the categories. This might have been one way to verify that the task was solvable in principle.

Another thing that might have helped is to train the model for far longer. The longer training runs we ran took around six hours to run to completion and over 1,000 epochs. While the loss for some runs was below 0.000001, we still found the model had not learned how to produce a plausible looking sequence.

The overall aim of the project was to design and test a learning system that functioned in a similar way to the Te Ataarangi method. Some progress was made towards this goal in terms of formulating the problem, but having a competent model at the target task is necessary for that model to act as a teacher and test out the theory further.

At the same time, the task we designed has some potential as a simple world model that can use used to test low-resource languages. It can be simplified further, or extended in new ways, similar to a grid-world. In the classroom the rods are used in many other ways in practice. It seems possible that we got close to training a competent model, and if we had achieved that it would have been interesting to investigate the other parts of the problem further.

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# A Appendix

In the appendix we have included the complete table of token classes with translation [3], as well as the table showing which token class is allowed to follow after a given class according to the 1-gram model [4].

| Māori | English | Token Class |
|---|---|---|
| mā | white | colour |
| kōwhai | yellow | colour |
| kikorangi | blue | colour |
| kākāriki | green | colour |
| pango | black | colour |
| māwhero | pink | colour |
| whero | red | colour |
| parauri | brown | colour |
| te | the (singular) | det |
| ngā | the (plural) | det |
| me | and | conjunction |
| rākau | rod | noun |
| iti | small | size |
| nui | large | size |
| hāunga | except | except |
| kei | at | locative |
| taha | side | position |
| mauī | left | side |
| matau | right | side |
| rua | two | number |
| toru | three | number |
| katoa | all | all |
| tawhiti rawa | furthest | furthest |
| rawa | most | most |
| ki | to | to |
| i | in | in |
| e | - | e |
| waenganui | between | preposition |
| mai | from | particle |
| tuarua | second | ordinal |

Table 3: Translation and Token Classes of Māori Words

| Token class | Allowed next token classes |
|---|---|
| [SEP] | det |
| all | except |
| colour | [EOS], all, conjunction, e, furthest, in, locative, ordinal, size, to |
| conjunction | det |
| det | noun, position |
| e | number |
| except | det |
| furthest | to |
| in | det, preposition |
| locative | det, preposition |
| most | [EOS], conjunction, e |
| noun | [EOS], all, colour, e, except, furthest, size |
| number | [EOS], conjunction, furthest, locative |
| ordinal | particle |
| particle | in |
| position | colour, side |
| preposition | [EOS], conjunction |
| side | [EOS], conjunction |
| size | [EOS], conjunction, e, locative, most |
| to | det |

Table 4: Token classes and the token classes that are allowed to follow them according to the 1-gram model