A

Kiki or Bouba?

A.1 Full set of images

This appendix presents the full set of images with visual shapes that were used in the experiments. Besides the original image pair from Köhler (1929, 1947) which was shown in Figure 4.1, we used four image pairs from Maurer et al. (2006), displayed in Figure A.1, four from Westbury (2005), displayed in Figure A.2, and 8 additional pairs we newly generated using a method inspired by the one described by Nielsen and Rendall (2013), displayed in Figure A.3. For each image pair, the Curved version is displayed on the left and the Jagged version on the right.

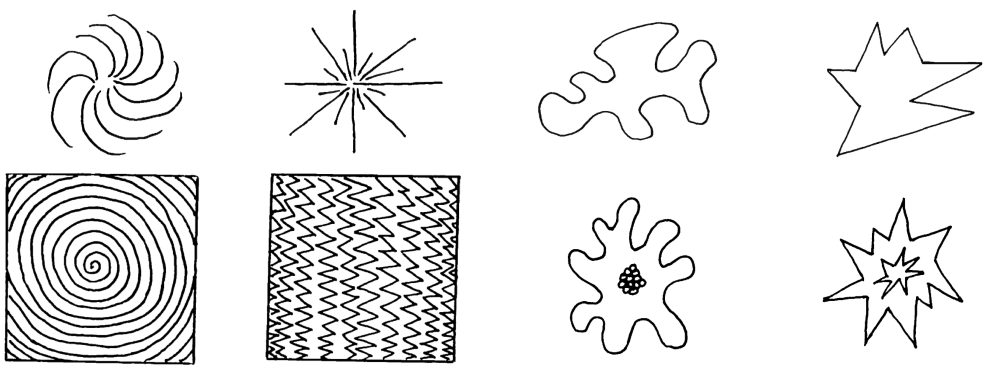


Figure A.1: Images from (Maurer et al., 2006)

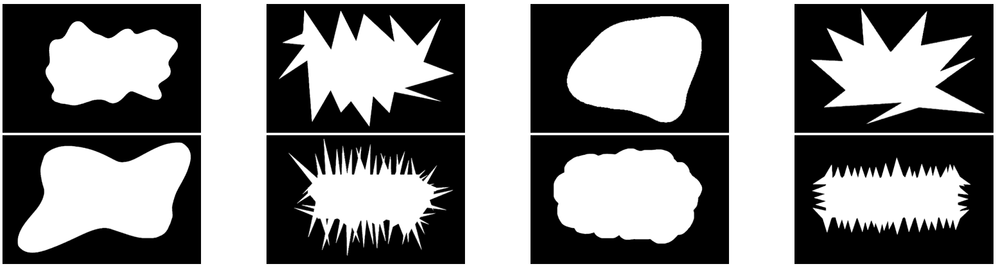


Figure A.2: Images from (Westbury, 2005)

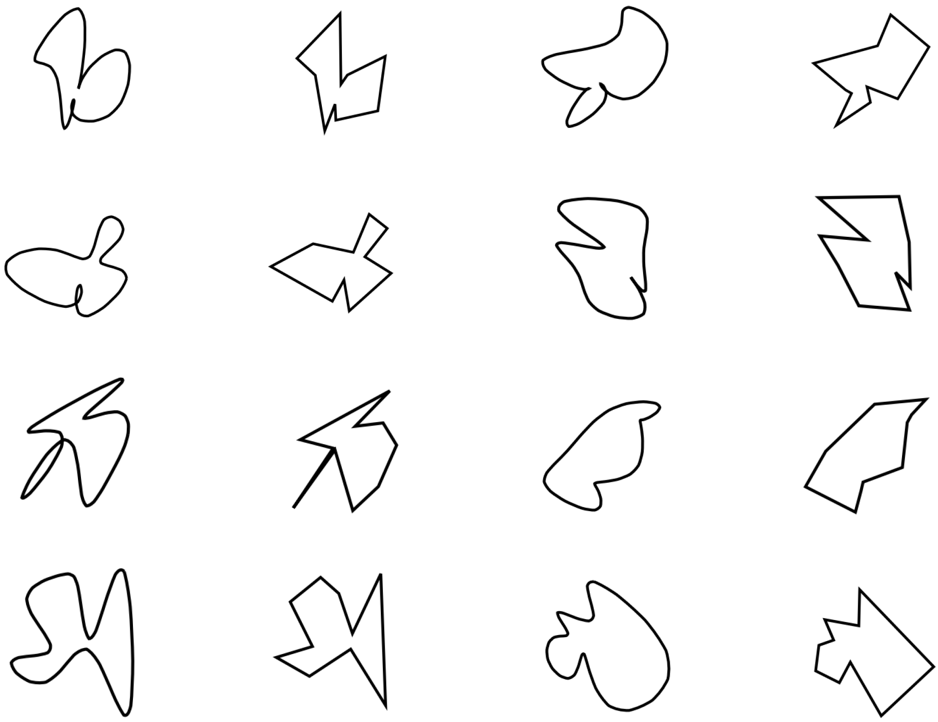


Figure A.3: Newly generated images

A.2 GPT-4o prompting

Image-label matching is not directly possible for GPT-4o since the probabilities of the input tokens cannot be accessed. We therefore prompt (Prompt A.2.1) this model, with the temperature being 0.0, to generate a syllable or pseudoword given an image and use the log probabilities of the generated tokens to calculate the probability for a label conditioned on an image. Just like in

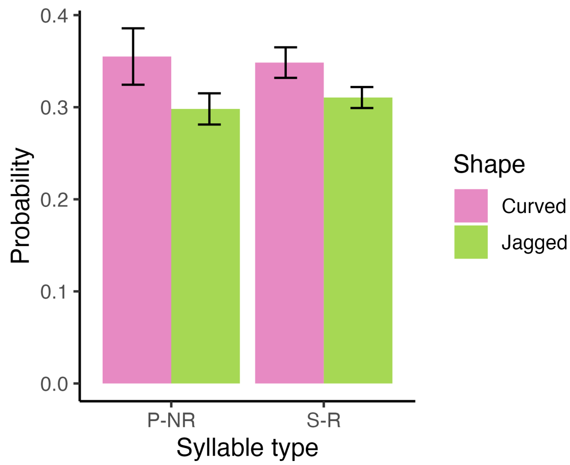


Figure A.4: Probability scores for GPT-4o when forced to generate a pseudoword for each image twice, once by combining two Jagged-associated syllables, and once with only the Curved-associated syllables as options.

the sentence setup used in the other models, our interest lies not primarily in the variability that may arise from using different prompts but rather focuses on the influence of the image on the predictions by using a simple and effective prompt that is identical for each image. Doing so allows us to use the resulting probabilities as a gauge for the models' preference of a label for a given image.

```
You are given an image for which you need to assign a label. Use {one
/two} of the following labels: {possible_labels}. Only respond with
the label.
```

Prompt A.2.1: The exact prompt used to obtain GPT-4o probabilities. $possible\_labels$ corresponds to the syllables of interest.

A.3 GPT-4o pseudoword probabilities

In Section 4.4.4 we describe the results of an experiment in which we asked GPT-4o to generate a pseudoword for each image twice, once when given only the set of Jagged-associated syllable options, and once with only the Curved-associated syllables as options. Figure A.4 shows the probabilities associated with these generated pseudowords. As concluded in the main text, no evidence for a preference to match P-NR syllables with Jagged shapes and S-R syllables with Curved shapes was found.

B

The Curious Case of Representational Alignment

B.1 Channel capacity

To test to what degree communicative success, *TopSim*, and representational alignment are confounded with the communication channel capacity, we ran simulations altering the vocabulary size ($V = \{3, 5, 10, 20, 40, 50, 100\}$) and message length ($L = \{2, 3, 5, 10, 50, 100\}$) resulting in 42 parameter settings per loss type. The parameters and seeds used to run the experiments in the main paper are displayed in Table B.1.

Overall, performance is relatively independent of the chosen configuration, but vocabulary size influences success more than message length (Figure B.1). The hyperparameters that resulted in the best validation accuracy (i.e., generalisation; Chaabouni et al., 2022) for the standard ce setup were $V = 40$ and $L = 2$. These parameters are used to produce the results

Parameter	**Value**
Batch size	32
Optimiser	Adam
Learning Rate (S & L)	0.01 & 0.001
Vocabulary size (V)	40
Message length (L)	2
Hidden size (S & L)	768 & 768
Embedding size	50
Listener cosine temperature	0.1
Seeds	16,22,41,56,67,77,14,78,99,23,82,40,51,37,62

Table B.1: Best-performing parameters resulting from the parameter sweep.

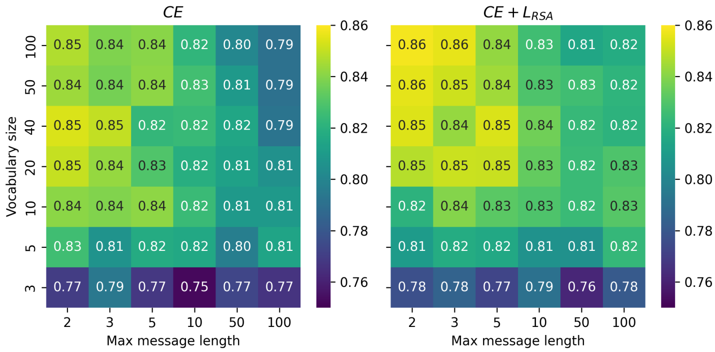


Figure B.1: The validation accuracy as a dependent factor of the vocabulary size and maximum message length. Values are averages across 15 seeds.

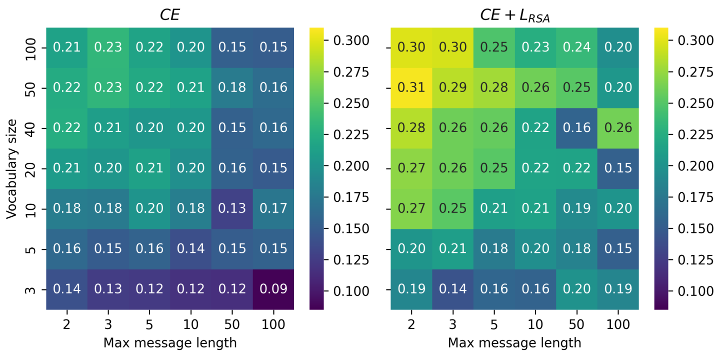


Figure B.2: *TopSim* as a dependent factor of the vocabulary size and maximum message length. Values are averages across 15 seeds.

in the main paper. Contra expectations, the vocabulary size also influenced *TopSim* more than message length. It, especially in the case of $ce + L_{RSA}$, is higher when messages are shorter but have access to a larger vocabulary (Figure B.2).

Figure B.3 shows that, regardless of the vocabulary capacity, inter-agent alignment (RSA_{sl}) increases while image-agent alignment (RSA_{si} and RSA_{li}) decreases with the ce loss. Interestingly, RSA_{sl} is agnostic to capacity but a larger vocabulary size, not message length, reduces the degree of drifting away from the input. We hypothesise this to result from lower pressure to compress rich continuous embeddings into smaller discrete vocabulary embeddings.

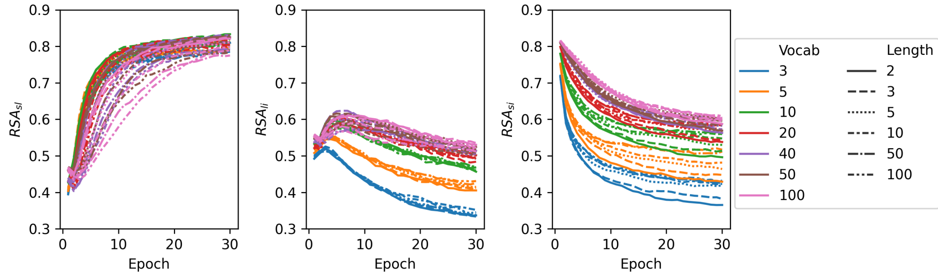


Figure B.3: Representational alignment metrics averaged over 15 simulations with the standard *ce* loss. Regardless of channel capacity, representational alignment always occurs while losing relation to the input.

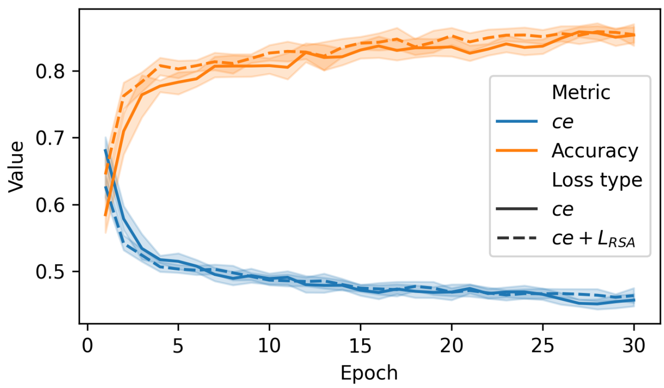


Figure B.4: Learning curves (accuracy) and cross-entropy loss (*ce*) for both loss settings. There is virtually no effect of the auxiliary term L_{RSA} on the cross entropy loss or communicative success.

B.2 Interaction between the alignment term and cross-entropy

To ensure that there is no impact of the alignment penalty on the pressure for communicative success, we ablated the L_{RSA} term of our proposed loss function and found that both, communicative success and *ce* are not affected by the alignment penalty (Figure B.4). Corroborating that only the *ce* term provides pressure for successful communication (Section 5.5.4).

B

B.3 Pre-trained vision modules

Although it is in principle possible to train the vision module of the agents from scratch (Dessi et al., 2021), in our work, agents' perception stems from a pre-trained vision-language model. Although there is reason to believe that DinoV2 embeddings capture high-level, conceptual image features useful for discriminating image pairs (Oquab et al., 2024), we assessed the degree to which the alignment problem occurs for different pre-trained models despite encoding the same objects. We ran additional simulations using image features obtained from ResNet (He et al., 2016) and CLIP (Radford et al., 2021) for 6 different parameter settings with the ce loss function. Here we used the parameters that resulted in the best, worst, mean, and quantile validation performance from the parameter sweep in Section B.1 (see Table B.2), and a sensible setup with $V = 10$ and $L = 5$.

Figure B.5 shows clearly that inter-agent alignment *increases* while agent-image alignment *decreases* for all models. In addition to the similar results reported by Bouchacourt and Baroni (2018) for VGG ConvNet embeddings, both 4096 and 1000 layers, our results confirm that the problem is agnostic to the input embeddings. Interestingly, agent representations drift most for CLIP embeddings. Nevertheless, the agents still develop a successful communication strategy, indicating that out-of-the-box CLIP embeddings are the least useful for agents in finding a (non-grounded) solution. No such differences are seen when the agents are trained with the additional alignment penalty term, inter-agent and image-agent alignment remain high for all models.

Message length (L)	Vocababulary Size (V)	Vision
2	40	
3	10	DinoV2
5	5	CLIP
5	10	ResNet
10	3	
50	100	

Table B.2: The parameters for running additional simulations with CLIP and ResNet to assess the robustness of our results. Each combination was run for 15 different seeds. Note: results for the DinoV2 simulations are from the sweep.

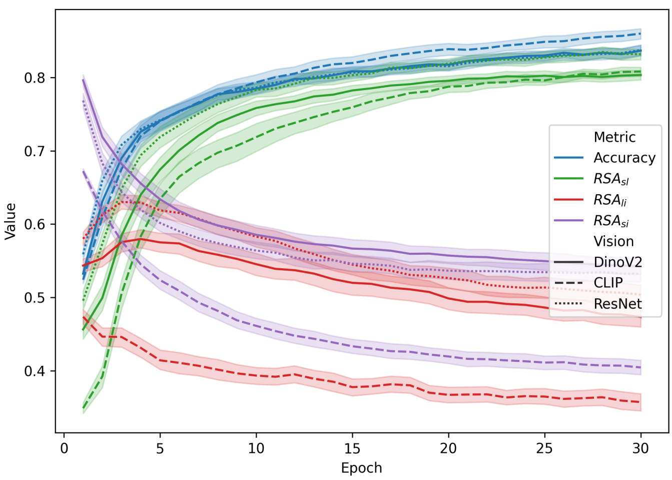


Figure B.5: Learning curves (accuracy) and *RSA* metrics for different vision models averaged over 6 parameter settings with 15 seeds each. The representational alignment problem always occurs. Line style corresponds to the vision module used to obtain image embeddings and colour indicates the metric. Areas indicate the 95% confidence intervals.

C
Searching for Structure

C.1 Additional results iterated learning

Figure C.1 shows how communicative success evolved across generations of language learners and users. There is no clear increase in communicative success. Figure C.2 shows that the average structure as measured by *TopSim* increases somewhat across generations, although not significantly. Interestingly, some generations display decreasing *TopSim*, indicating a loss of structure. This is reminiscent of findings in human iterated learning experiments, showing that processes of interaction and transmission sometimes generate fully systematic, compositional languages, but can also result in systems that lack structure entirely (Verhoef et al., 2022). In the case of *Ngram* diversity, we observe a decrease in the unique Ngrams produced, which indicates the languages re-use parts of signals more in later generations (Figure C.3).

C.2 Prompts

Our agents act based on prompts and system instructions. These are designed to be maximally close to the classical experimental setup and formatted similar to Galke et al. (2024). Prompt completion is used for labelling stimuli during the labelling and communication block. For the guessing task, we prefill the prompt with each possible word or distractor and pick the option with the highest probability. See the full prompts for labelling and guessing in Prompt C.2.1. Speaking during communication involved plain prompt completion (Prompt C.2.2). Discrimination during communication was done by prefilling the distractors attributes (Prompt C.2.3).

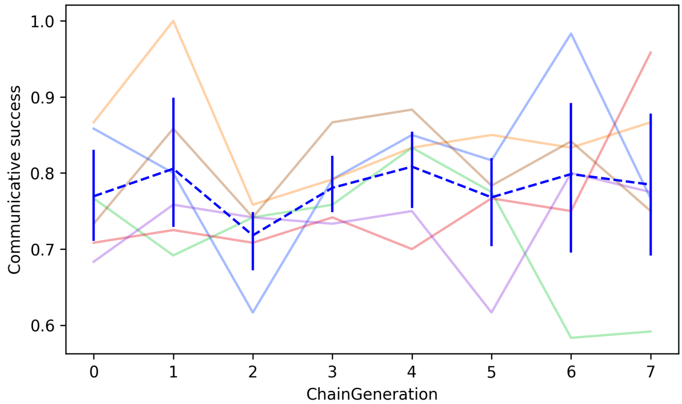


Figure C.1: The average communicative success across rounds for each generation. Each line represents a chain, and the dashed blue line indicates the average, with bars denoting the 95% confidence interval. See Table 6.2 for the descriptives of *PercCom*.

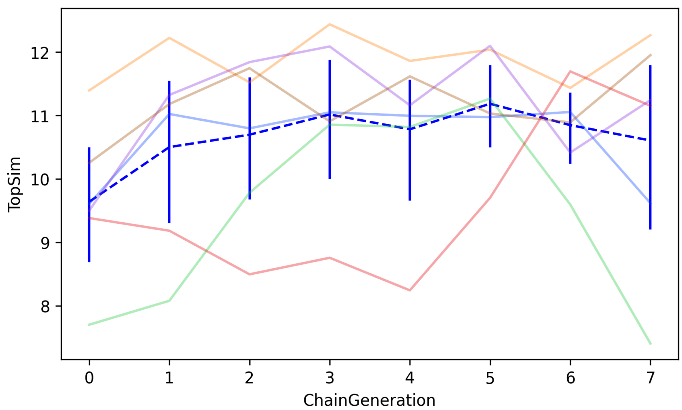


Figure C.2: The evolution of *TopSim* on the words produced in the testing block. Each line represents a chain, and the dashed blue line indicates the average, with bars denoting the 95% confidence interval. See Table 6.2 for the descriptives of *TopSim*.

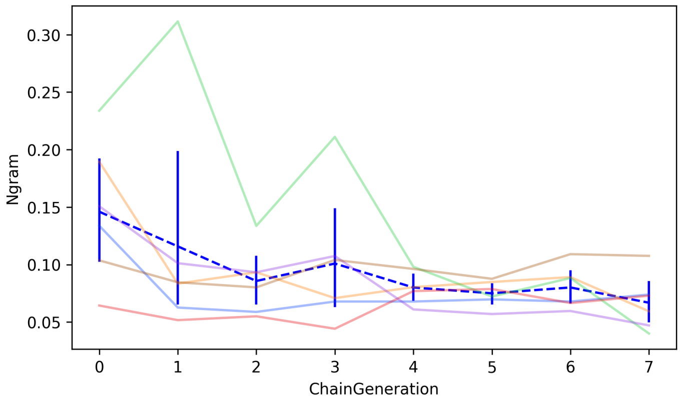


Figure C.3: The evolution of *Ngram* on the words produced in the testing block. Each line represents a chain, and the dashed blue line indicates the average, with bars denoting the 95% confidence interval. See Table 6.2 for the descriptives of *Ngram*.

```
<|begin_of_text|><|start_header_id|>system<|end_header_id|> You are a
 language learner who has to learn an artificial language with words
and their corresponding features. Your task is to complete the
vocabulary by generating a word that describes the last item. Only
respond with the word.<|eot_id|><|start_header_id|>user<|
end_header_id|>

{’shape’:2,’colour’:’orange’,’amount’:1,’word’:’giniwite’}
{’shape’:3,’colour’:’green’,’amount’:1,’word’:’ginisu’}
{’shape’:1,’colour’:’orange’,’amount’:2,’word’:’pinisugi’}
{’shape’:3,’colour’:’green’,’amount’:3,’word’:’sutepi’}
{’shape’:2,’colour’:’orange’,’amount’:2,’word’:’winisu’}
{’shape’:3,’colour’:’orange’,’amount’:1,’word’:’niwi’}
{’shape’:1,’colour’:’blue’,’amount’:2,’word’:’sutuwite’}
{’shape’:1,’colour’:’blue’,’amount’:3,’word’:’tupitene’}
{’shape’:3,’colour’:’blue’,’amount’:1,’word’:’wipinepi’}
{’shape’:2,’colour’:’orange’,’amount’:3,’word’:’gigi’}
{’shape’:1,’colour’:’green’,’amount’:2,’word’:’nite’}
{’shape’:3,’colour’:’blue’,’amount’:3,’word’:’wite’}
{’shape’:1,’colour’:’green’,’amount’:3,’word’:’sune’}
{’shape’:2,’colour’:’blue’,’amount’:2,’word’:’ninene’}
{’shape’:2,’colour’:’green’,’amount’:1,’word’:’tusetetu’}
{’shape’:1,’colour’:’green’,’amount’:3,’word’:’<|eot_id|><|
start_header_id|>assistant<|end_header_id|>
[COMPLETION OR PREFFILED]
```

Prompt C.2.1: Completion Prompt used for labelling and guessing.

```
<|begin_of_text|><|start_header_id|>system<|end_header_id|> You are a
 language learner who has to learn an artificial language with words
and their corresponding features. Your task is to generate a word
such that your communication partner can guess the correct meaning of
 the word. Communicative success is important. Only respond with the
word.<|eot_id|><|start_header_id|>user<|end_header_id|>

{’shape’:1,’colour’:’green’,’amount’:3,’word’:’sutupitite’,’
communicativeSuccess’:1}
{’shape’:2,’colour’:’orange’,’amount’:2,’word’:’ginupepi’,’
communicativeSuccess’:1}
{’shape’:1,’colour’:’orange’,’amount’:2,’word’:’sutupepi’,’
communicativeSuccess’:1}
{’shape’:1,’colour’:’green’,’amount’:2,’word’:’sutupepi’,’
communicativeSuccess’:0}
{’shape’:2,’colour’:’orange’,’amount’:1,’word’:’ginisu’,’
communicativeSuccess’:1}
{’shape’:2,’colour’:’orange’,’amount’:3,’word’:’ginupitite’,
’communicativeSuccess’:1}
{’shape’:3,’colour’:’green’,’amount’:1,’word’:’wipisu’,’
communicativeSuccess’:0}
{’shape’:2,’colour’:’green’,’amount’:1,’word’:’ginisu’,’
communicativeSuccess’:1}
{’shape’:1,’colour’:’blue’,’amount’:2,’word’:’sunupepi’,’
communicativeSuccess’:1}
{’shape’:3,’colour’:’green’,’amount’:3,’word’:’wipipitite’,’
communicativeSuccess’:1}
{’shape’:3,’colour’:’orange’,’amount’:1,’word’:’wipisu’,’
communicativeSuccess’:0}
{’shape’:1,’colour’:’blue’,’amount’:3,’word’:’sunupitite’,’
communicativeSuccess’:1}
{’shape’:3,’colour’:’blue’,’amount’:3,’word’:’wipipitite’,’
communicativeSuccess’:1}
{’shape’:3,’colour’:’blue’,’amount’:1,’word’:’wipisu’,’
communicativeSuccess’:1}
{’shape’:2,’colour’:’blue’,’amount’:2,’word’:’<|eot_id|><|
start_header_id|>assistant<|end_header_id|>
[COMPLETION]
```

Prompt C.2.2: Speaking Prompt during communication.

```
<|begin_of_text|><|start_header_id|>system<|end_header_id|> You are a
 language learner who has to learn an artificial language with words
and their corresponding features. Your task is to complete the
vocabulary by interpreting the intended meaning of the word generated
 by your communication partner. Communicative success is important.
Only respond with the complete last item.<|eot_id|><|start_header_id
|>user<|end_header_id|>

{’word’:’wipipitite’,’shape’:3,’colour’:’blue’,’amount’:3,’
communicativeSuccess’:1}
{’word’:’wipisu’,’shape’:3,’colour’:’orange’,’amount’:1,’
communicativeSuccess’:0}
{’word’:’wipisu’,’shape’:3,’colour’:’green’,’amount’:1,’
communicativeSuccess’:0}
{’word’:’sutupepi’,’shape’:1,’colour’:’orange’,’amount’:2,’
communicativeSuccess’:1}
{’word’:’ginupepi’,’shape’:2,’colour’:’orange’,’amount’:2,’
communicativeSuccess’:1}
{’word’:’sutupitite’,’shape’:1,’colour’:’green’,’amount’:3,’
communicativeSuccess’:1}
{’word’:’wipipitite’,’shape’:3,’colour’:’green’,’amount’:3,’
communicativeSuccess’:1}
{’word’:’wipisu’,’shape’:3,’colour’:’blue’,’amount’:1,’
communicativeSuccess’:1}
{’word’:’ginisu’,’shape’:2,’colour’:’green’,’amount’:1,’
communicativeSuccess’:1}
{’word’:’ginisu’,’shape’:2,’colour’:’orange’,’amount’:1,’
communicativeSuccess’:1}
{’word’:’sunupepi’,’shape’:1,’colour’:’blue’,’amount’:2,’
communicativeSuccess’:1}
{’word’:’sutupepi’,’shape’:1,’colour’:’green’,’amount’:2,’
communicativeSuccess’:0}
{’word’:’sunupitite’,’shape’:1,’colour’:’blue’,’amount’:3,’
communicativeSuccess’:1}
{’word’:’ginupitite’,’shape’:2,’colour’:’orange’,’amount’:3,
’communicativeSuccess’:1}
{’word’:’ginupepi’,’shape’:’<|eot_id|><|start_header_id|>assistant<|
end_header_id|>
[PREFILLED WITH DISTRACTOR ATTRIBUTES]
```

Prompt C.2.3: Guessing Prompt during communication.

D
Shaping Shared Languages

D.1 Prompts

The agents in our experiment act based on prompts and system instructions which are identical to those used in Chapter 6. These were designed to be maximally close to the classical experimental setup and formatted similar to Galke et al. (2024). During the labelling and guessing block, we use the completion Prompt D.1.1. In the labelling block, we simply ask the model to provide a completion. In the case of the guessing block, we prefill the word and pick the signal with the highest probability. See the full prompts for labelling and guessing (Prompt D.1.1), speaking (Prompt D.1.2), and discrimination (Prompt D.1.3) below.

As explained in the main body of our paper, we update the agent-specific vocabulary after each label prediction. This allows the vocabularies of signal-meaning mappings to evolve during the simulation. This entails that the prompts are also slightly different after each interaction or prediction. Moreover, given the observed bias for primacy and recency Liu et al. (2024) in LLMs, we shuffle the vocabulary before creating prompts to account for unwanted ordering effects.

D

```
<|begin_of_text|><|start_header_id|>system<|end_header_id|> You are a
 language learner who has to learn an artificial language with words
and their corresponding features. Your task is to complete the
vocabulary by generating a word that describes the last item. Only
respond with the word.<|eot_id|><|start_header_id|>user<|
end_header_id|>

{'shape':3,'colour':'green','amount':1,'word':'tego'}
{'shape':1,'colour':'green','amount':3,'word':'wananima'}
{'shape':2,'colour':'blue','amount':3,'word':'wumawaka'}
{'shape':2,'colour':'green','amount':3,'word':'mafa'}
{'shape':3,'colour':'orange','amount':2,'word':'wawa'}
{'shape':1,'colour':'orange','amount':1,'word':'gofa'}
{'shape':1,'colour':'blue','amount':1,'word':'maka'}
{'shape':3,'colour':'blue','amount':1,'word':'kama'}
{'shape':3,'colour':'blue','amount':3,'word':'mawa'}
{'shape':2,'colour':'orange','amount':2,'word':'nawa'}
{'shape':2,'colour':'blue','amount':1,'word':'kaka'}
{'shape':3,'colour':'green','amount':2,'word':'matefama'}
{'shape':1,'colour':'orange','amount':3,'word':'kagonigo'}
{'shape':2,'colour':'green','amount':2,'word':'nimaniwu'}
{'shape':1,'colour':'orange','amount':2,'word':'wago'}
{'shape':1,'colour':'orange','amount':2,'word':'<|eot_id|><|
start_header_id|>assistant<|end_header_id|>
[COMPLETION OR PREFFILED]
```

Prompt D.1.1: An example completion prompt used for labelling and guessing.

```
<|begin_of_text|><|start_header_id|>system<|end_header_id|> You are a
 language learner who has to learn an artificial language with words
and their corresponding features. Your task is to generate a word
such that your communication partner can guess the correct meaning of
 the word. Communicative success is important. Only respond with the
word.<|eot_id|><|start_header_id|>user<|end_header_id|>

{’shape’:1,’colour’:’green’,’amount’:3,’word’:’gofamama’,’
communicativeSuccess’:1}
{’shape’:2,’colour’:’orange’,’amount’:2,’word’:’kakafa’,’
communicativeSuccess’:1}
{’shape’:1,’colour’:’orange’,’amount’:2,’word’:’gofama’,’
communicativeSuccess’:1}
{’shape’:2,’colour’:’blue’,’amount’:1,’word’:’kaka’,’
communicativeSuccess’:1}
{’shape’:2,’colour’:’green’,’amount’:2,’word’:’kakafa’,’
communicativeSuccess’:1}
{’shape’:3,’colour’:’green’,’amount’:2,’word’:’tegoma’,’
communicativeSuccess’:1}
{’shape’:1,’colour’:’orange’,’amount’:1,’word’:’go’,’
communicativeSuccess’:1}
{’shape’:3,’colour’:’green’,’amount’:1,’word’:’tega’,’
communicativeSuccess’:1}
{’shape’:2,’colour’:’blue’,’amount’:3,’word’:’kakamama’,’
communicativeSuccess’:1}
{’shape’:3,’colour’:’blue’,’amount’:1,’word’:’tego’,’
communicativeSuccess’:1}
{’shape’:1,’colour’:’orange’,’amount’:3,’word’:’gofamama’,’
communicativeSuccess’:1}
{’shape’:2,’colour’:’green’,’amount’:3,’word’:’kakamama’,’
communicativeSuccess’:1}
{’shape’:3,’colour’:’orange’,’amount’:2,’word’:’tegoma’,’
communicativeSuccess’:0}
{’shape’:3,’colour’:’blue’,’amount’:3,’word’:’tegomama’,’
communicativeSuccess’:1}
{’shape’:1,’colour’:’blue’,’amount’:1,’word’:’<|eot_id|><|
start_header_id|>assistant<|end_header_id|>
[COMPLETION]
```

Prompt D.1.2: An example speaking prompt during communication. In this particular case, the speaker produced the label *’goa’* which was correctly interpreted by the human listener.

```
<|begin_of_text|><|start_header_id|>system<|end_header_id|> You are a
 language learner who has to learn an artificial language with words
and their corresponding features. Your task is to complete the
vocabulary by interpreting the intended meaning of the word generated
 by your communication partner. Communicative success is important.
Only respond with the complete last item.<|eot_id|><|start_header_id
|>user<|end_header_id|>

{'word':'kakafa','shape':2,'colour':'orange','amount':2,'
communicativeSuccess':1}
{'word':'go','shape':1,'colour':'orange','amount':1,'
communicativeSuccess':1}
{'word':'kakafa','shape':2,'colour':'green','amount':2,'
communicativeSuccess':1}
{'word':'goa','shape':1,'colour':'blue','amount':1,'
communicativeSuccess':1}
{'word':'kakamama','shape':2,'colour':'green','amount':3,'
communicativeSuccess':1}
{'word':'tego','shape':3,'colour':'blue','amount':1,'
communicativeSuccess':1}
{'word':'kaka','shape':2,'colour':'blue','amount':1,'
communicativeSuccess':1}
{'word':'tegoma','shape':3,'colour':'orange','amount':2,'
communicativeSuccess':0}
{'word':'gofamama','shape':1,'colour':'green','amount':3,'
communicativeSuccess':1}
{'word':'kakamama','shape':2,'colour':'blue','amount':3,'
communicativeSuccess':1}
{'word':'gofama','shape':1,'colour':'orange','amount':2,'
communicativeSuccess':1}
{'word':'tega','shape':3,'colour':'green','amount':1,'
communicativeSuccess':1}
{'word':'tegomama','shape':3,'colour':'blue','amount':3,'
communicativeSuccess':1}
{'word':'gofamama','shape':1,'colour':'orange','amount':3,'
communicativeSuccess':1}
{'word':'tegama','shape':'<|eot_id|><|start_header_id|>assistant<|
end_header_id|>
[PREFILLED WITH DISTRACTOR ATTRIBUTES]
```

Prompt D.1.3: An example guessing prompt during communication. Here the human speaker has produced the label *'tegama'* which was correctly interpreted by the listener.

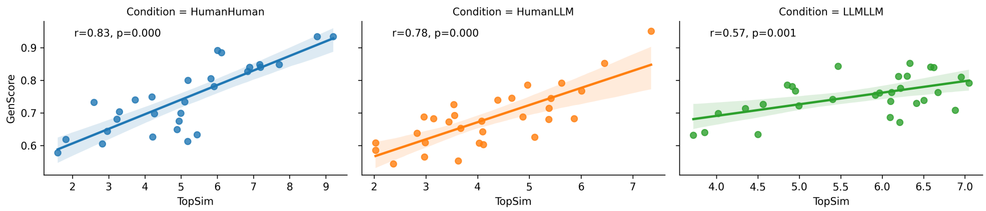


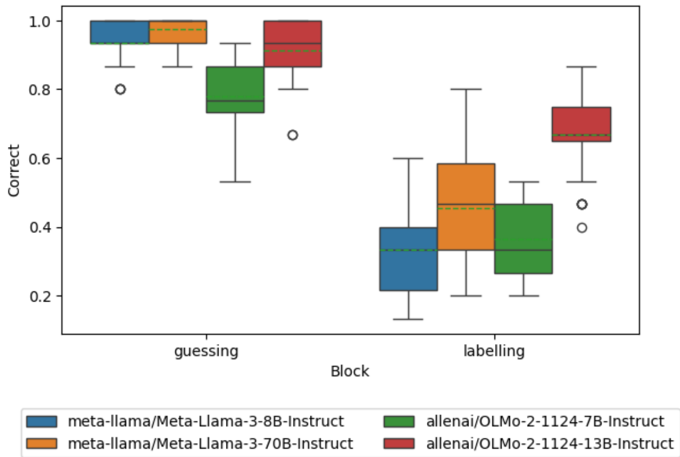
Figure D.1: Across conditions, generalisation to novel stimuli was more consistent with known samples when the labels produced during the last round of communication showed a higher degree of *TopSim*.

D.2 Generalisation to novel stimuli

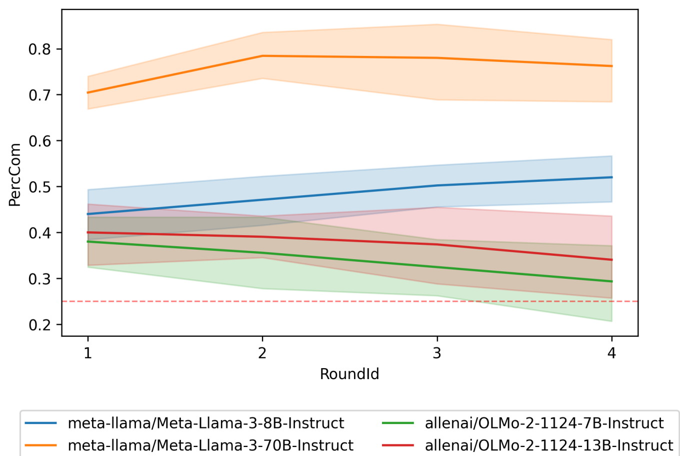
In the testing block of our experiments, we examined whether the participants and LLMs could generalise to novel stimuli. Figure D.1 shows the relationship between *TopSim* and *GenScore* that was modelled by a mixed effects model in Chapter 7. It reveals clearly that generalisation to novel items happened more consistently when the vocabulary evolved to be more structured.

D.3 Testing additional LLMs

To extend the findings of Chapter 6, we ran additional simulations with three different LLMs, Llama-3-8B (Llama Team, 2024), OLMo-2 7B, and OLMo-2 13B (Walsh et al., 2025) using the same 15 seeds. Figure D.2a shows that learning the artificial languages is also possible for smaller and different LLMs. Interestingly, out of all models, agents comprised of a OLMo-2 13B model perform best during the labelling task. While agents with OLMo-2 13B can also communicate reliably above change performance ($t(13) = 1.96, p = .036$), they struggle much more (*PercCom* $\approx 35\%$, Figure D.2b, chance performance amounts to 25%). Moreover, we observe that compared to their larger versions, smaller models struggle more. Llama-3 8B achieves $\approx 50\%$ of successful communication and OLMo-2 8B only 30%. The latter is not significantly above chance ($t(14) = 1.04, p = .158$). We take these results as additional evidence that our setup can be used to discover LLM-specific constraints and indicating that larger LLMs benefit more from instruction following Lou et al. (2024). We leave the precise dynamics of both to future work.



(a) Performance on the guessing and labelling task. The newly tested LLMs can learn the languages equally well or better (e.g. OLMO-2 13B outperforms Llama-3 70B).



(b) Communicative performance across rounds for different models. Note that the dashed red line indicates chance performance.

Figure D.2: The results of learning and using languages for two different LLMs with two different sizes. Figure D.2a shows the degree to which LLMs can learn the languages and Figure D.2b shows how well these models can use the language during communication.

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