Project Work III. - 2025/26/1

Decomposing the activations of Large Language Models

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Introduction

Large Language Models have exploded in popularity in the last 10 years. However — as is the nature of neural networks — it is difficult to decipher how a model figures out the output, what matters and what is "irrelevant" throughout the calculation.

Most causal language models are trained on a corpus which is mostly English. Yet they seem to possess advanced multilingual capabilities, oftentimes matching their English generation "skills". Furthermore, it is a usual observation that when prompting an LLM with the same instruction in different languages results in generated texts which are almost literal translations of each other in the specified languages. This leads us to believe that "the information said" and "the language used" is not entirely intertwined in the inner representations of a causal language model.

In this semester's project work we will explore this topic on a deeper level. Mainly building on the work of Dumas et al. [1], we will attempt to extract the representations of concepts and languages over a translation task examining a transformer-based language model trained for causal generation.

A note on failed experiments

Our original intention for the topic of the project work was different initially. We planned on following the **Conclusion** section of our second semester project work report. This would have included the continued pretraining of a causal language model, with a mixed dataset to improve Hungarian language specific knowledge.

Executing this plan we were met with multiple difficulties. First, there are numerous precautions that are needed for the prolonged training of an LLM, since the infrastructure can fail. Second, even though we tried to minimize custom solutions and focus on using well documented, widely utilized tools and packages, our training process did not seem to progress as the generation loss was stagnating as opposed to decreasing.

For this reason, we postponed the original aim, and started working on exploring the inner representations themselves, resulting in the current topic of the report. However we plan on continuing, once we are able to assess and repair the insufficient training pipeline.

Activation patching

Our main method for conducting our experiments is a technique called activation patching, introduced by Meng et al. [2]. The central idea is the following: override the activations ***during*** the execution of a neural net, and measure the changes in the output. In more details

1. Take a neural network, an input, an activation location and a dirty activation.
2. Start the computation with the neural net using the input.
3. When reaching the activation at the specified location is calculated, overwrite it with the dirty activation.
4. Continue the computation normally, and gather the output.

Of course this idea (and pipeline) may be extended to patching multiple activations in one run with ease.

In our initial experiments, we mostly apply activation patching in the following form:

1. Take a causal language model, one or multiple reference prompts, a test prompt, and a layer index j.
2. For each reference prompt: calculate the next token with the LM, and extract the activation of the last token at the specified layer. At the end, average the reference activations, this will be our "mean reference activation at layer j" (MRA_j).
3. Execute the test prompt with patching applied at layer j to the activation of the last token with MRA_j in the role of "dirty activation".
4. Observe the token distribution at the end of the test run.

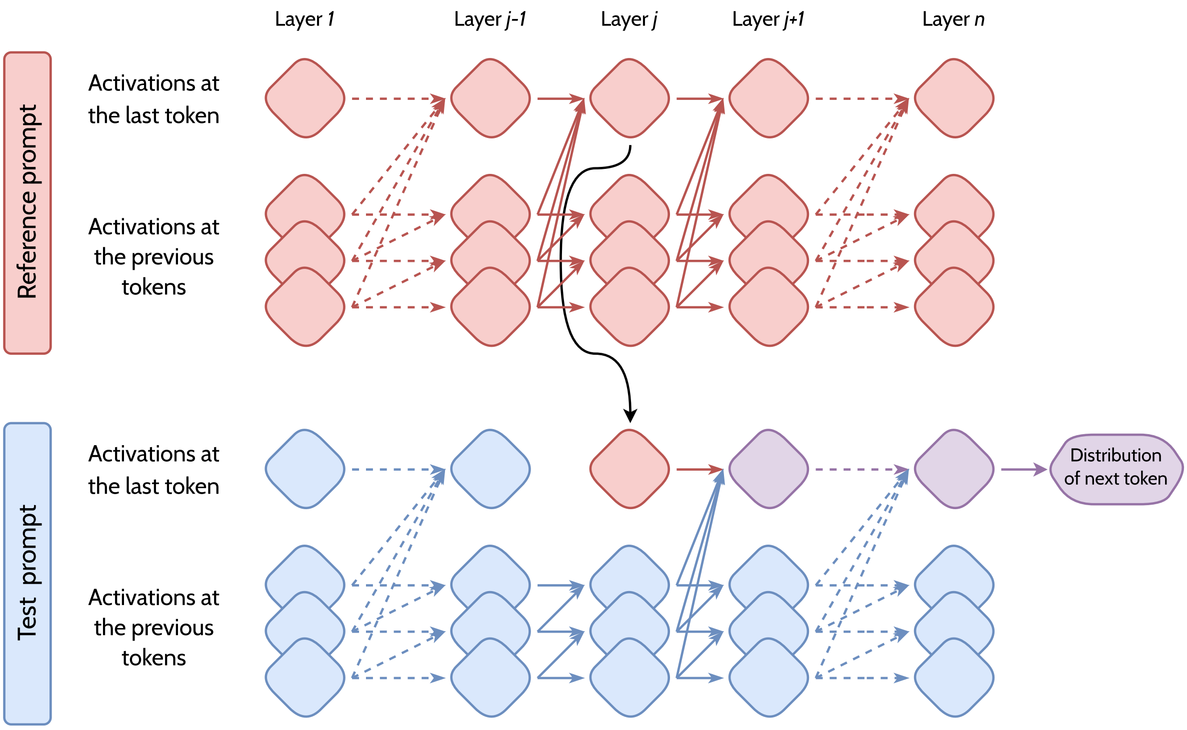

Figure 1: Activation patching with a single reference prompt

Problem setting

As we mentioned in the introduction, the main focus of this project work is to extend on the results of Dumas et al. [1]. They conducted multiple experiments, each on the Llama 2 [3] model by Meta. The central question of their experiments was the following:

"Given a single-word translation task, can we observe a separation of ***concept*** *and* ***target language*** *in the activations of the last token at some layer?"*

They used activation patching to study the activations extensively through multiple languages, allowing to derive roughly the following findings (for the specified model):

1. The target language of the translation can be overridden without modifying the concept. This can be achieved with patching a single activation of the last token at layers 12-16.
2. The concept can be overridden without modifying the target language. This can be achieved with patching an activation at layer 17 and each subsequent one.

For the second finding, roughly speaking, the technique was using MRA_i at $i \in 17, \ldots, 31$, with reference prompts translating the same concept from and to different languages. The idea behind this is that if there exists a layer k at where the concept can be extracted from the latent representation with no language attached, then averaging activations translating the same concept across different languages isolates the "component" of the concept, and leaves everything else as noise. This strategy proved to be effective in our experiments.

Remark. *Using MRA_i to described their methodology is inaccurate, since they patched not at the last token of the input, rather at the last token of the word representing the concept in the source language.*

Remark. *It is worth noting that these are not the only findings in the paper. In a third experiment, they observe that the "concept vectors" calculated as MRA_i in the translation task can be utilized in another task. Namely, if they prompt the same model to generate definitions, inserting the same "concept vectors" of a single concept (each to their respective layers), the generated definition changes accordingly. The result described is quite powerful, since it hints that activations can be untangled in a way to provide a task-independent concept vector. We will not explore a parallel of this claim.*

In conclusion Dumas et al. were able to inject (or *override*) a concept and a language into a translation task, though with different methods, and utilizing multiple layers. We suspect this can be simplified, based on the following notions.

Decomposition Hypothesis. *We're given a translation task and model with n layers. Then the following stand:*

1. *There is a layer with index ℓ_L at which the last token's activation* $\mathbf{x}$ *can be decomposed into 2 parts* $\mathbf{x} = \mathbf{x}_L + \mathbf{r}_L$ in a way that $\mathbf{x}_L$ fully controls the target language of the translation, and it does not interfere with the concept.

2. *There is a layer with index ℓ_C at which the last token's activation* $\mathbf{y}$ *can be decomposed into 2 parts* $\mathbf{y} = \mathbf{y}_C + \mathbf{r}_C$ in a way that $\mathbf{y}_C$ fully controls the concept of the translation, and it does not interfere with the target language.

In the hypothesis we think about $\mathbf{x}_L$ as the "language component", $\mathbf{y}_C$ as the "concept component", and the $\mathbf{r}$ vectors as arbitrary remainders. We also theorize the following augmentation of the hypotheses.

Subspatial Decomposition Hypothesis. *The decomposition hypothesis stands. Moreover the decomposition at layer ℓ_L is such that the $\mathbf{x}_L$ components across all possible translations span a subspace, while the $\mathbf{r}_L$ components span its orthogonal. Similarly, the decomposition at layer ℓ_C is such that the $\mathbf{y}_C$ components across all possible translations span a subspace, while the $\mathbf{r}_C$ components span its orthogonal.*

We attempt to prove or refute these claims by utilizing carefully selected reference prompts and the injection of a single MRA_i vector. Our main model for the experiments will be the **Llama 3.1 8B** [4].

The Dataset – BabelNet

To carry out the experiments, we need a translation dataset. However we run into the following challenges:

- There is no universal mapping of words: a word in one language may have multiple representations in an other, or even none.
- We need multitudes of languages, preferably from different language families, to be able to properly isolate or filter the "language" part of an activation.

BabelNet is a large multilingual dictionary with the goal of identifying concepts across many languages. It organizes data into units called "synset" (derived from "synonym set"), each of which contain the possible textual representations of a concept, in multiple languages.

The aim of BabelNet aligns with our use-case. Fortunately, the repository of the paper [5] of Dumas et al. contains a small, clean sample of 123 synsets across 13 languages (which we partially extended with Hungarian). We process this further into a dataset where each concept has a "main representation" (notated with r_C^L), and a "set of possible representations" R_c^L. The first is only given if there is a word in the language which unambiguously defines the concept, and it is used in the construction of prompts. The second is useful when identifying which concept the LLM is translating.

The following languages appear in the dataset: German (DE), English (EN), Spanish (ES), Estonian (ET), Finnish (FI), French (FR), Hindi (HI), Hungarian (HU), Italian (IT), Japanese (JA), Korean (KO), Dutch (NL), Russian (RU) and Chinese (ZH). We refrained from using English in our initial experiments, since the pretraining data is largely English, which could interfere with our findings. We also avoided Chinese, considerig the tokenization appeared to be causing issues using the Llama 3 tokenizer.

Prompt format and unambiguity

Throughout our experiments we use a simple 5-shot translation prompt, which is identical to the one utilized by Dumas et al. [1]. The 5 examples are sampled randomly for each prompt.

Deutsch: "Division" - Italiano: "divisione"
Deutsch: "Norden" - Italiano: "nord"
Deutsch: "Bekleidung" - Italiano: "vestiti"
Deutsch: "Maschine" - Italiano: "macchina"
Deutsch: "Abbild" - Italiano: "pittura"
Deutsch: "Herz" - Italiano: "

Français: "yeux" - Suomi: "silmämuna"
Français: "danse" - Suomi: "tanssi"
Français: "fringue" - Suomi: "vaatetus"
Français: "temps" - Suomi: "aika"
Français: "peinture" - Suomi: "kuva"
Français: "porte" - Suomi: "

Figure 2: Two prompt examples: translating "heart" from German to Italian, and "door" from French to Finnish

For the evaluation, it is essential to calculate probabilities of events like "according to the generated content, the LLM translated the concept C to language L". We will refer to this as "generating C in L", and denote it with E_C^L. Determining $P(E_C^L)$, we follow the methodology of Dumas et al. [1]: we generate the probability distribution of a single token, and sum the probabilities over possible representations of C in the target language L (a.k.a R_C^L).

This evaluation technique could lead to inconsistencies if utilized improperly. Let's say we have a concept C and 2 languages L_1 and L_2. If $R_C^{L_1} \cap R_C^{L_2}$ is non-empty, then the probability of a token t in the intersection is counted twice. This phenomenon is especially prominent if L_1 and L_2 are closely related (e.g FR and IT). Therefore it is important to construct such experiments where the first tokens of the possible representations do not clash for the observed outputs. The methods we use to generate samples takes this into account.

Experiment 0 – Replicating the original results

First, our aim was to replicate the initial results of Dumas et al. [1]. The goal of the experiment is to show that the translation language can be influenced without changing the translated concept.

We take 2 distinct translation tasks: the first translating the concept C^1 from source language L_s^1 to target language L_t^1, and the second translating a distinct C^2 from L_s^2 to L_t^2. We chose $L_s^1 = \textsc{De}$, $L_t^1 = \textsc{It}$, $L_s^2 = \textsc{Fr}$, and $L_t^2 = \textsc{Ru}$, matching the original experiment. Let us notate the generated prompts with $\mathcal{P}^1$ and $\mathcal{P}^2$.

Next, we apply the activation patching with reference prompt $\mathcal{P}^1$ and test prompt $\mathcal{P}^2$, at each layer, one by one. Then record the probabilities of generating C^1 and C^2 in L_t^1 and L_2^t.

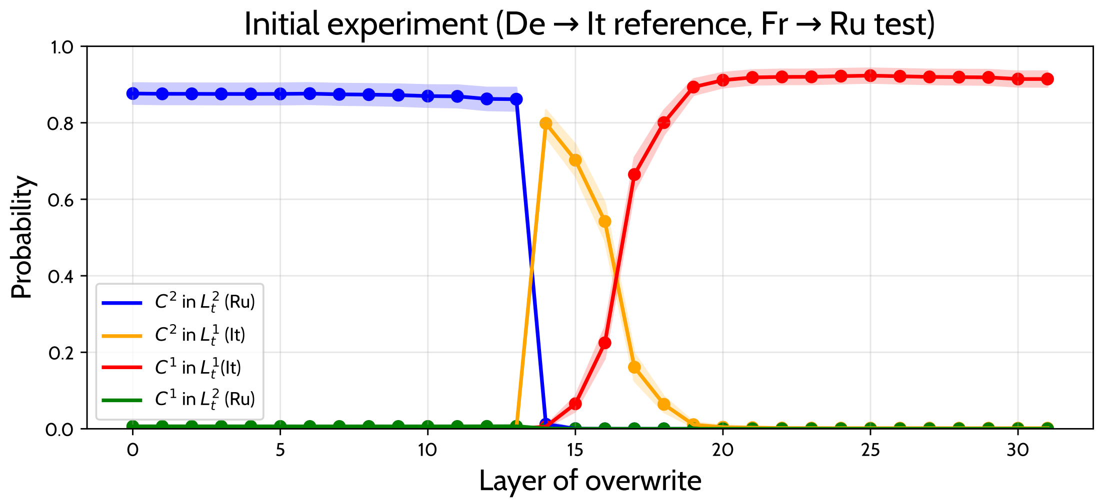

Figure 3: Probabilities of generating C^1 and C^2 in the target languages, averaged over 200 samples, depicting a 95% confidence interval.

Observing Figure 3, our results match the ones demonstrated in the original paper (despite us utilizing the Llama 3 family of models). Patching at the first 13 layers of the model seems to leave the output unaffected, while patching in the last 16 both the language and the concept change. The pure Linguistic influence is strongest at layers 14-16, with the target language changing to the reference's (L_t^1), while the concept staying at the test's (C^2).

Experiment 1 – Decoupling the language

We now take a closer look at the first claim of the decomposition hypothesis, stating the target language can be extracted from the activation of the last token at a specific layer ℓ_L.

We take inspiration from the "disambiguation experiment" of Dumas et al. [1], and construct our experiment the following way. In practice, we used $k = 20$.

1. Take an L_t^1 target language, k (distinct) concepts $C_1^1, \ldots, C_k^1$ and k corresponding source languages $L_{s_1}^1, \ldots, L_{s_k}^1$ (not necessarily distinct). We construct the reference prompts $\mathcal{P}_1^1, \ldots, \mathcal{P}_k^1$ accordingly.
2. Take an L_s^2 source and L_t^2 target language and construct the $\mathcal{P}^2$ test prompt with a C^2 concept.
3. Run the reference prompts, and calculate the MRA_i for every layer i.
4. Run the test prompt with the MRA_i injected at the i-th layer, for each layer, one-by-one.
5. Record the probabilities of generating C^2 in L_t^1 and L_t^2.

Since we average the reference activations across multiple concepts and source languages, the only information we hope to retain is the target language. By this reasoning, we're not interested in recording the probabilities of generating $C_1^1, \cdots, C_k^1$, for they serve the purpose of noise when averaged.

Initial results

The recorded probabilities display a curious behaviour. As seen on the figure, if we inject at earlier layers, the language (and the concept) of the generation remains undisturbed. At layer 14 to 19, injecting modifies the generation by changing the language. This aligns with our expectation, however the range exceeds the one which we initially expected based on the replicated experiments, where the language seemed to have the strongest individual effect at a 2-3-layer range.

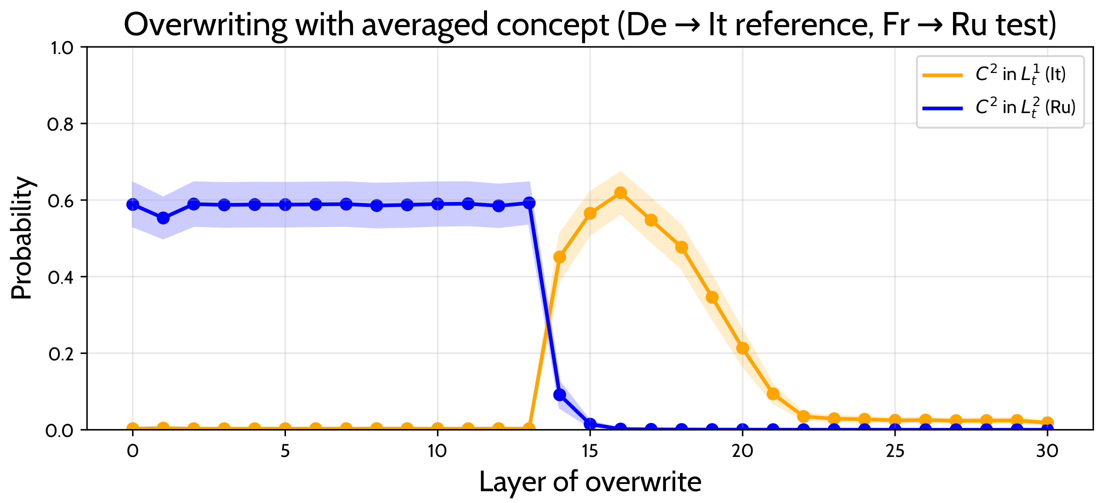

Figure 4: Probabilities of generating a given concept C^2 in the original language and the one patched. The figure shows reference translation German ⇝ Italian and test translation French ⇝ Russian, with probabilities averaged over 93 samples, depicting a 95% confidence interval.

Extracting vector representations

Taking the experiment described, let us notate the vector MRA$_i$ for a given common L target language as $\mathfrak{L}_i^L$. Running the experiment with every language as $L (\equiv L_t^1)$, we are able to extract "language vectors" $\mathfrak{L}_i^L$ for every L language and i layer.

The initial results show that with a translation concept C and target language L_0, if we take a layer index i in the range of 14 and 19, and override the last token activation at layer i with $\mathfrak{L}_i^L$, then the model generates C in L with a high probability.

We suspect that at layer i the 1st statement of the decomposition hypothesis stands (in some form), utilizing these "language vectors". More precisely, if we take a translation of C to L, then the activation x at layer can be decomposed into an $\mathfrak{L}_i^L + \mathbf{r}$ form, where **r** does not hold any information regarding the target language.

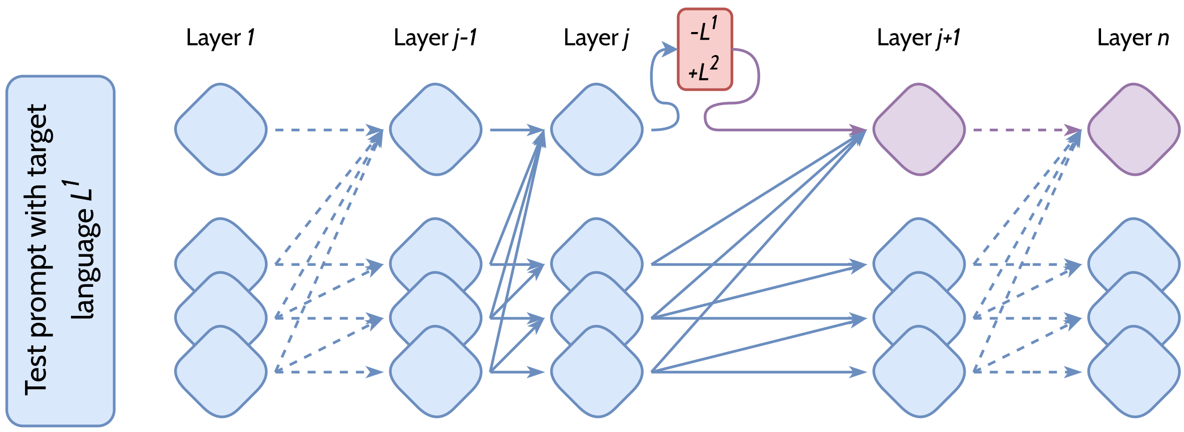

Figure 5: Arithmetic injection of a language

In an attempt to refute this, we try the following: instead of overriding the whole activation at layer i, only override the "language part". Suppose we have an original translation target L^1, concept C, and a new target L^2. Having last token activation **a** at layer i, we replace it with $\mathbf{a} - \mathfrak{L}_i^{L^1} + \mathfrak{L}_i^{L^2}$. If the decomposition hypothesis stands, this operation should yield $\mathfrak{L}_i^{L^2} + \mathbf{r}$, and then generate C in L^2 with high probability. We will refer to this technique as **arithmetic injection**.

The measurements (seen in Figure 6) partially adhere to our expectations, with the model generating C in L^2 if injected into any layer from index 18 to 27, with this arithmetic method. This interval is wider and slightly shifted compared to the one observed in the previous result.

Experiment 2 – Decoupling the concept

An important observation about our 0-th experiment is that the probability of generating C^1 in L_t^2 is low to none. Dumas et al. [1] built their disambiguation experiment such way that they were able to get the model to generate C^1 in L_t^2. In their

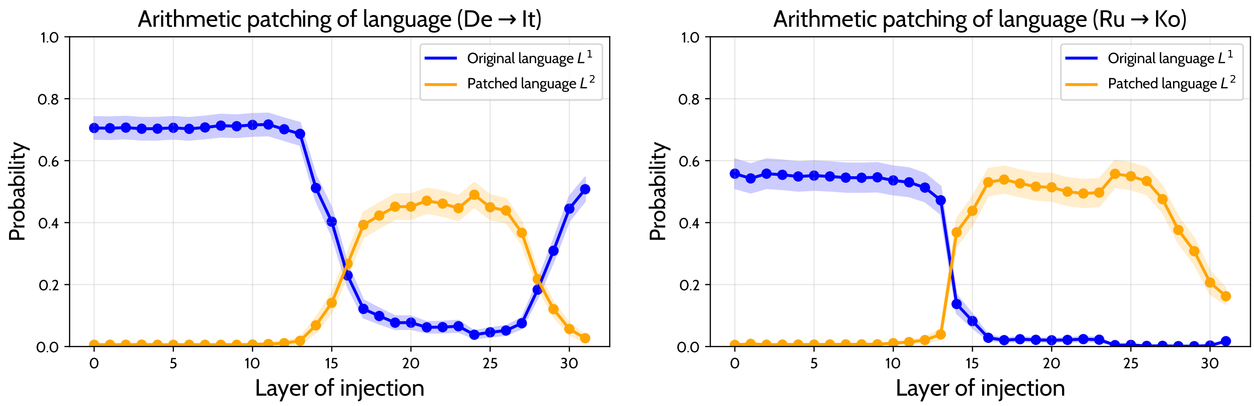

Figure 6: Probabilities of generating a given concept in the original language and the one injected arithmetically (*patched*). The figures show translations German ⇝ Italian and Russian ⇝ Korean, with probabilities averaged over 200 samples, depicting a 95% confidence interval.

experiment they injected MRA_i throughout multiple layers simultaneously, with prompts translating the same concept from and to different input and output languages. Their attempt was successful, the model generated C^1 in L^2_t with high probability, proving the concept and the language is distinct in the activation.

Our 2nd experiment's aim is to provide similar results without needing to patch at multiple layers. We construct our experiment the following way.

1. Take a C^1 concept, and $(L^1_{s_1}, L^1_{t_1}), \ldots, (L^1_{s_k}, L^1_{t_k})$ language pairs (with the source languages not necessarily distinct, and similarly for the targets). We construct the reference prompts $\mathcal{P}^1_1, \ldots, \mathcal{P}^1_k$ accordingly.
2. Take an L^2_s source and L^2_t target language and construct the $\mathcal{P}^2$ test prompt with a C^2 concept.
3. Run the reference prompts, and calculate the MRA_i for every layer i.
4. Run the test prompt with the MRA_i injected at the i-th layer, for each layer, one-by-one.
5. Record the probabilities of generating C^1 and C^2 in L^2_t.

Initial results

Similar to experiment 1, there is a clear interval of layer indices where in case of injection, the model clearly favours generating C^1 in L^2_t as opposed to C^2, namely the range 17 to 22, as seen in Figure 7.

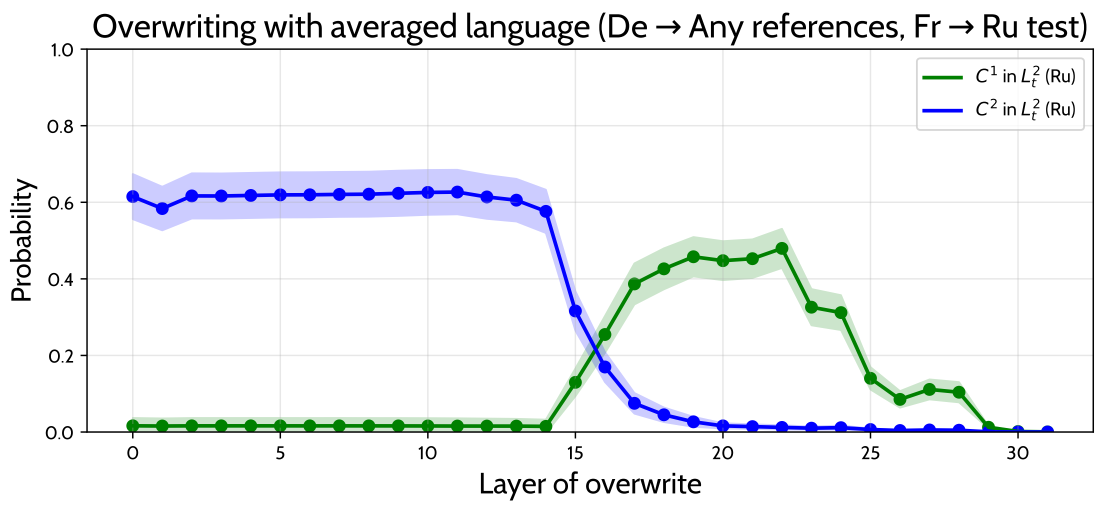

Figure 7: Probabilities of generating concepts C^1 and C^2 in the original language. The figure shows reference translation German ⇝ Italian and test translation French ⇝ Russian, with probabilities averaged over 93 samples, depicting a 95% confidence interval.

It is worth noting that the index range here has an intersection with the one observed at experiment 1. This hints us that — if the decomposition hypothesis stands — a common layer index $\ell = \ell_L = \ell_C$ can be chosen.

Extracting vector representations

As with experiment 1, we attempt to extract "concept vectors", taking MRA$_i$ as $\mathfrak{C}_i^C$ with a fixed concept C. Our suspicion is similar: if we take a layer index i in the range observed, then the activation y at layer i when translating C to L can be decomposed into a $\mathfrak{C}_i^C + \mathbf{r}$ form, where $\mathbf{r}$ does not hold any information regarding the concept.

We again attempt to refute this with arithmetic injection. Analogously, taking concepts C^1 and C^2 with target language L, the injection at layer i is expected to yield activation $\mathfrak{C}_i^{C^2} + \mathbf{r}$, with the model generating C^2 in L with high probability.

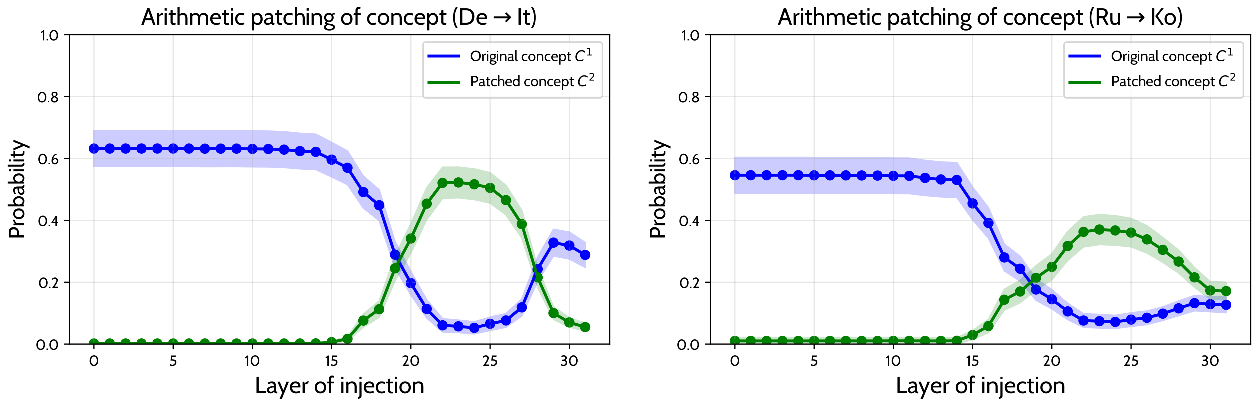

Figure 8: Probabilities of generating the original concept and the one injected arithmetically (*patched*) in a given language. The figures show translations German ⇝ Italian and Russian ⇝ Korean, with probabilities averaged over 200 samples, depicting a 95% confidence interval.

After experiment 1 and the initial results, it takes us by no surprise that the generation probabilities align with our expectation: the model generates C^2 in L with a high probability at layers 20 to 27, while C^1 in L is more prominent in earlier layers.

Experiment 3 – Complete redirection

After both experiments 1 and 2 we observed that if **we're given a set of representations** — stripped to preserve only a specific aspect (e.g only the language or only the concept) — a targeted modification of the output is possible with overwriting at a specific layer with the corresponding vector. Moreover, the modification is also achievable with arithmetic injection.

Of course in these experiments we only injected one activation. Using overwriting, more is not possible (at the token), since any information propagated is lost at the next overwrite. Arithmetic injection acts differently. If the decomposition hypothesis stands, the effect of arithmetically injecting a language at ℓ_L and a concept at ℓ_C is tangential, one does not influence the other.

We now construct an experiment based on this notion. Our goal is to run experiments 1 and 2 "simultaneously", with arithmetic injection, over samples of shape (L_t^1, C^1, L_t^2, C^2), at each layer-pair one-by-one, with recording the probabilities the model generating C^1 and C^2 in L_t^1 and L_t^2.

Results

In Figure 9 we display the 4 sets of generation probabilities in a 2-dimensional heatmap, where the horizontal axis notates the layer index where the language injection, while the vertical axis shows where the concept injection happens. Accurate results can be found in appendices A and B, where we plot each colour of the heatmap separately, with the values attached.

The experiment shows that our assumption stands: the extracted concept and language vectors act independently. Furthermore — in line with our earlier expectation — there are layers (around 21-26) where both modifications are possible, even simultaneously.

Interpreting the results of experiments

We now executed 3 experiments, each constructed to tackle a behaviour which should stand if the decomposition hypothesis is true, and fail otherwise. In all cases, the results align with the expected behaviour under the hypothesis.

These provide strong arguments in favour of the decomposition hypothesis. In fact, with extracting the vector representations themselves, and successfully utilizing them as the basis of arithmetic injection, we conclude that at least a partial form of the decomposition hypothesis stands.

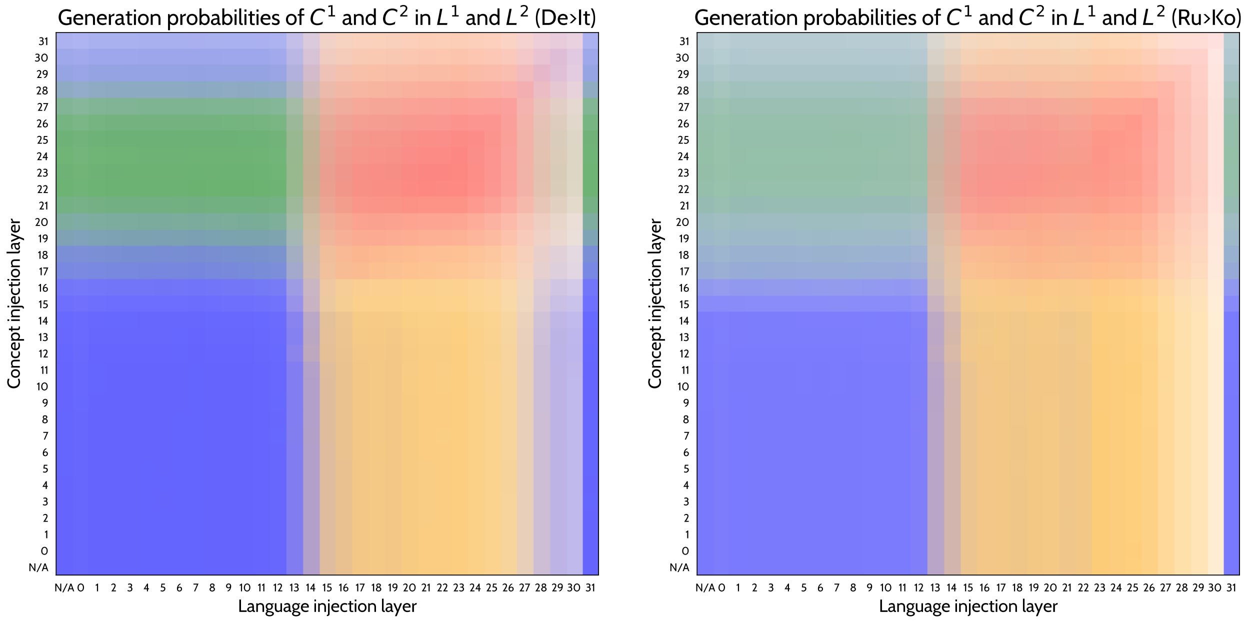

Figure 9: Probabilities of generating C^1 in L^1 (blue), C^1 in L^2 (orange), C^2 in L^1 (green) and C^2 in L^2 (red). The strength of the colours represent the corresponding probability. The figures show translations German $\rightsquigarrow$ Italian and Russian $\rightsquigarrow$ Korean, with probabilities averaged over 200 samples. N/A means no injection happened. For reference, the deepest blue represents ~0.6

The reason we only identify a partial form of the hypothesis lies in the generation probabilities. Even though the probabilities of generating the modified translation are high (if we choose the injection layer appropriately), they are far from certain; the values mostly fall in the interval from 0.4 to 0.5. In contrast, generating the probability of generating the original translation (without any injection) usually falls between 0.6 and 0.8.

The phenomenon can originate from multiple causes, including but not limited to the following.

- Our prompt generation method might be faulty. We applied multitudes of scripts to run the experiments, and along the semester the prompt generation got updated multiple times. One of these updates may have resulted in an improper filtering. The drop of the baseline probability from 0.9 of experiment 0 to 0.6 at subsequent experiments is suspected to be the consequence of this. We were too late to notice this, and while it does not invalidate the results, we might be able to extract stronger representations if we revise the prompt generation methods.
- Our dataset is small and possibly skewed. We attempt to "guess" the components of the language and concept by randomly generating prompts, then averaging the corresponding representations. There is no guarantee nevertheless, that the results will completely align with the actual component we're looking for.

  The assumption is that given enough "seemingly well distributed" references, the remainder parts of the decomposition average to a minimal noise. However we did not check the "conceptual skew" of our dataset (e.g there might be a large quantity of words related to "the spatial displacement of the self", such as "walking", "running", "driving", etc...).

  The same stands with languages: the remainder part of languages of the same family may be closer, which means we need a quite large number of languages to make sure the averaging results in noise at the remainder component.
- The concept or target language of the translation might require multiple layers to be "fully understood" by the model. We disturb the inference in the middle, which may interfere with an "understanding" which requires multiple layers.
- The models used are small. Models with a lower parameter count can have trouble understanding an input to the full extent; this effect may manifest itself as the activations being "more fuzzy" and "less defined".

These are speculations, we did not conduct experiments to determine the cause of the "lower" probabilities.

The shape of the decomposition

So far we have only addressed the original decomposition hypothesis. In the remainder of the project report we will explore the nature of the spatial region occupied by the extracted representations. This is directly related to the subspatial decomposition hypothesis, where we hypothesize that the representations of a kind span a subspace at the appropriate layer.

In our investigation, we use layer 24 for the language and layer 22 for the concept representations. These are based on our previous observations, where the injection at the respective layers had the highest probability of modifying the generation output.

We note that our analysis is expected to be limited, since we only have 14 languages and 123 concepts at our disposal, while the Llama 3.1 8B has inner representation dimensionality of 4096.

First we apply an SVD transformation to the concept representations, and observe both their distribution projected to the singular vectors and the decay of the singular values. As seen in Figure 10, the first singular vector is quite prominent, but later the decay seems to be linear, all the way to ~1-2 at σ_{120}. As the vector space is 4096 dimensional, 123 vectors prove to be insufficient to determine if there is a subspace which contains these vectors.

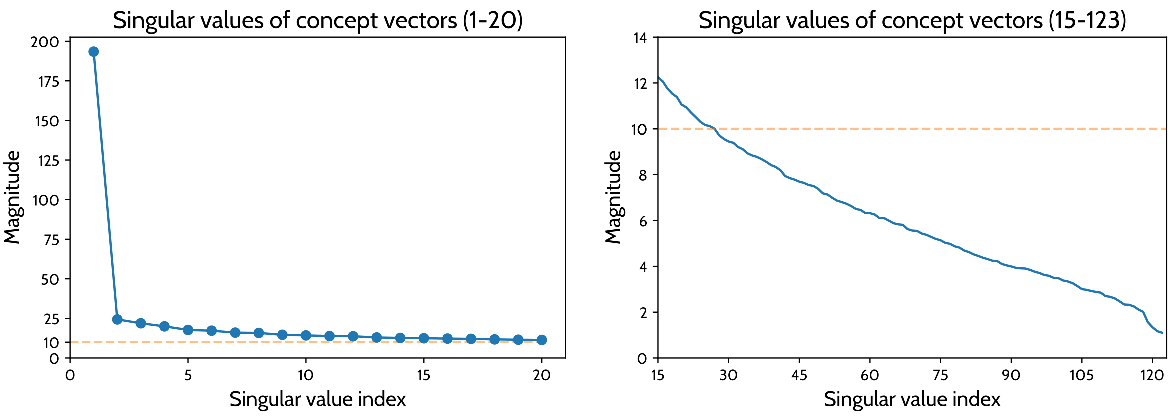

Figure 10: Singular values of the concept vectors

Observing the projections to the singular vectors, we examine an interesting pattern. The vectors appear to exist in a spherical (rather ellipsoidal) section of the space. This hints that the subspatial decomposition hypothesis may not stand in the described form.

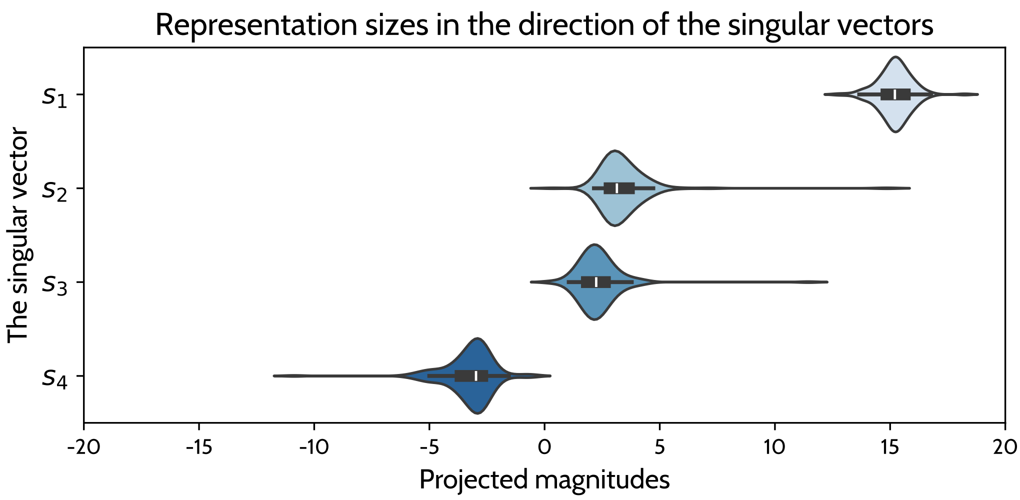

Figure 11: Concept vector sizes projected to the top 4 singular vectors

We inspected the language vectors in a similar manner. Since there are only have 14 language, the analysis of singular values is found to be inconclusive again. Likewise, the projected representation sizes show a comparable behaviour, with appearing to be distributed not in a subspace, rather in an ellipsoid.

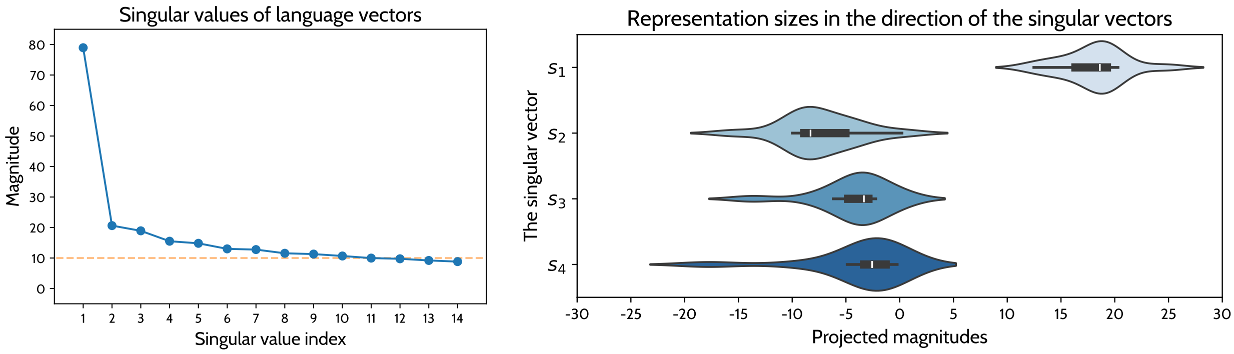

Figure 12: Concept vector sizes projected to the top 4 singular vectors

In summary, the representations do not seem to form subspaces neither in the case of languages, nor the concepts. However we are able to guess "shapes" which contain the vectors, hinting some kind of "definable" separation of space exists both with the language and concept representations.

Conclusion and future work

In this semester's project work our main goal was to determine whether it is possible to attribute different aspects of a query to different components in the inner activations of a causal LLM. The base of our search was a translation task, which is well suited to explore this topic since it's main components (from a generative perspective) are well defined: a **target language** and a **concept**.

First we replicated the results of Dumas et al., concluding a separation of language and concept is indeed feasible. Then we designed extraction methods and experiments to test these, which verified that the created vectors represent the languages and concepts in some way.

Lastly, we examined the shape of the space the extracted vectors lie in. Here we deduced that the representations do not define a subspace, however they still seem to take up a structured segment of the space.

These results raise several intriguing research questions. These include diving deeper into the spatial structure of the target language and concept vectors, improving the precision of the representations, experimenting with multi-token generation using similar arithmetic injection-like modifications, examining other tasks, exploring the genericity of the vectors, etc...

Furthermore, our focus in this project work was modifying the output of a causal LLM, and while doing so, we did not see a significant change when injecting to the first half of the layers. We suspect some kind of "interpretation" takes place in this segment, and intervening with such may lead to rather powerful discoveries.

References

[1] Clément Dumas, Chris Wendler, Veniamin Veselovsky, Giovanni Monea, and Robert West. Separating tongue from thought: Activation patching reveals language-agnostic concept representations in transformers, 2025.

[2] Kevin Meng, David Bau, Alex Andonian, and Yonatan Belinkov. Locating and editing factual associations in gpt, 2023.

[3] Llama 2 Team. Llama 2: Open foundation and fine-tuned chat models, 2023.

[4] Llama 3 Team. The Llama 3 herd of models, 2024.

[5] Butanium. llm-lang-agnostic. `https://github.com/Butanium/llm-lang-agnostic`, 2024.

Appendices

A Complete redirection probabilities – translating German to Italian

Probabilities of generating C^1 in L^1 (De → It)

	N/A	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
31	0.27	0.26	0.27	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.27	0.26	0.19	0.11	0.03	0.02	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.06	0.08	0.07	0.27
30	0.30	0.30	0.30	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.30	0.30	0.22	0.12	0.04	0.02	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.08	0.11	0.10	0.30
29	0.30	0.30	0.30	0.30	0.31	0.31	0.31	0.31	0.31	0.31	0.30	0.31	0.30	0.30	0.22	0.12	0.04	0.02	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.04	0.09	0.11	0.09	0.30
28	0.21	0.22	0.21	0.21	0.21	0.21	0.21	0.21	0.22	0.21	0.21	0.21	0.21	0.21	0.16	0.08	0.02	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.06	0.07	0.06	0.21
27	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.07	0.03	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.02	0.02	0.02	0.08
26	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.04	0.04	0.04	0.04	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.05
25	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.03	0.03	0.03	0.04	0.03	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.04
24	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.03
23	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.03
22	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.03
21	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.06	0.06	0.06	0.06	0.05	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.07
20	0.13	0.15	0.13	0.13	0.13	0.13	0.14	0.13	0.14	0.13	0.12	0.12	0.12	0.12	0.08	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.02	0.02	0.13
19	0.21	0.23	0.21	0.21	0.21	0.22	0.22	0.21	0.22	0.21	0.20	0.20	0.20	0.19	0.12	0.05	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.04	0.03	0.21
18	0.36	0.36	0.36	0.35	0.35	0.36	0.36	0.36	0.36	0.35	0.34	0.34	0.33	0.32	0.20	0.09	0.02	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.03	0.07	0.09	0.08	0.36
17	0.41	0.40	0.41	0.40	0.40	0.41	0.41	0.40	0.41	0.40	0.39	0.38	0.38	0.37	0.23	0.11	0.03	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.03	0.08	0.11	0.10	0.41
16	0.52	0.52	0.52	0.53	0.53	0.53	0.53	0.53	0.53	0.52	0.52	0.51	0.51	0.50	0.34	0.19	0.05	0.03	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.05	0.13	0.17	0.17	0.52
15	0.56	0.55	0.56	0.56	0.56	0.56	0.56	0.56	0.57	0.56	0.56	0.56	0.55	0.54	0.39	0.21	0.07	0.03	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.02	0.06	0.14	0.20	0.20	0.56
14	0.59	0.58	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.58	0.46	0.26	0.10	0.07	0.03	0.03	0.03	0.02	0.01	0.01	0.01	0.01	0.01	0.02	0.08	0.18	0.24	0.24	0.59
13	0.59	0.58	0.59	0.59	0.59	0.59	0.59	0.59	0.60	0.59	0.59	0.59	0.59	0.58	0.47	0.26	0.10	0.07	0.04	0.03	0.04	0.02	0.02	0.01	0.01	0.01	0.01	0.03	0.08	0.19	0.25	0.25	0.59
12	0.59	0.59	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.59	0.59	0.45	0.25	0.10	0.07	0.04	0.04	0.04	0.03	0.02	0.02	0.01	0.01	0.01	0.03	0.09	0.19	0.26	0.25	0.59
11	0.60	0.59	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.59	0.49	0.29	0.12	0.08	0.04	0.04	0.04	0.02	0.02	0.02	0.01	0.01	0.01	0.03	0.09	0.19	0.25	0.25	0.60
10	0.60	0.59	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.59	0.49	0.30	0.12	0.08	0.04	0.04	0.04	0.02	0.02	0.02	0.01	0.01	0.01	0.03	0.09	0.19	0.25	0.24	0.60
9	0.60	0.59	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.59	0.49	0.30	0.12	0.08	0.04	0.04	0.04	0.02	0.02	0.02	0.01	0.01	0.01	0.03	0.09	0.19	0.25	0.24	0.60
8	0.60	0.59	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.59	0.49	0.30	0.12	0.08	0.04	0.04	0.04	0.02	0.02	0.02	0.01	0.01	0.01	0.03	0.09	0.19	0.26	0.24	0.60
7	0.60	0.59	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.59	0.48	0.29	0.12	0.08	0.04	0.04	0.04	0.02	0.02	0.02	0.01	0.01	0.01	0.03	0.09	0.19	0.25	0.24	0.60
6	0.60	0.59	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.59	0.49	0.30	0.12	0.08	0.04	0.04	0.04	0.02	0.02	0.02	0.01	0.01	0.01	0.03	0.09	0.19	0.26	0.24	0.60
5	0.60	0.59	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.59	0.49	0.30	0.12	0.08	0.04	0.04	0.04	0.02	0.02	0.02	0.01	0.01	0.01	0.03	0.09	0.19	0.26	0.24	0.60
4	0.60	0.59	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.59	0.49	0.30	0.12	0.08	0.04	0.04	0.04	0.02	0.02	0.02	0.01	0.01	0.01	0.03	0.09	0.19	0.26	0.24	0.60
3	0.60	0.59	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.59	0.49	0.30	0.12	0.08	0.04	0.04	0.04	0.02	0.02	0.02	0.01	0.01	0.01	0.03	0.09	0.19	0.26	0.24	0.60
2	0.60	0.59	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.59	0.49	0.30	0.12	0.08	0.04	0.04	0.04	0.02	0.02	0.02	0.01	0.01	0.01	0.03	0.09	0.19	0.26	0.24	0.60
1	0.60	0.59	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.59	0.49	0.30	0.12	0.08	0.04	0.04	0.04	0.02	0.02	0.02	0.01	0.01	0.01	0.03	0.09	0.19	0.26	0.24	0.60
0	0.60	0.59	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.59	0.49	0.30	0.12	0.08	0.04	0.04	0.04	0.02	0.02	0.02	0.01	0.01	0.01	0.03	0.09	0.19	0.26	0.24	0.60
N/A	0.60	0.59	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.59	0.49	0.30	0.12	0.08	0.04	0.04	0.04	0.02	0.02	0.02	0.01	0.01	0.01	0.03	0.09	0.19	0.26	0.24	0.60

Probabilities of generating C^2 in L^1 (De → It)

	N/A	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
31	0.06	0.05	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.05	0.05	0.04	0.03	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.06
30	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.05	0.03	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.07
29	0.11	0.09	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.10	0.10	0.08	0.05	0.03	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.11
28	0.23	0.21	0.23	0.23	0.23	0.23	0.23	0.23	0.23	0.23	0.23	0.23	0.23	0.22	0.16	0.10	0.05	0.04	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.03	0.03	0.23
27	0.41	0.39	0.41	0.42	0.42	0.42	0.42	0.42	0.42	0.42	0.42	0.42	0.41	0.40	0.29	0.17	0.07	0.05	0.03	0.03	0.03	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.03	0.06	0.08	0.08	0.41
26	0.49	0.47	0.49	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.49	0.48	0.34	0.21	0.08	0.06	0.03	0.03	0.03	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.04	0.09	0.11	0.10	0.49
25	0.53	0.51	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.54	0.54	0.53	0.52	0.37	0.21	0.08	0.06	0.03	0.03	0.03	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.05	0.10	0.13	0.12	0.52
24	0.53	0.52	0.53	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.53	0.38	0.22	0.08	0.06	0.03	0.03	0.03	0.02	0.01	0.01	0.00	0.01	0.01	0.01	0.05	0.10	0.14	0.12	0.53
23	0.54	0.52	0.54	0.54	0.54	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.53	0.38	0.21	0.08	0.05	0.03	0.02	0.03	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.05	0.10	0.14	0.12	0.54
22	0.54	0.53	0.54	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.56	0.55	0.54	0.38	0.21	0.08	0.05	0.02	0.02	0.02	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.05	0.10	0.14	0.12	0.54
21	0.48	0.46	0.48	0.48	0.48	0.48	0.48	0.49	0.49	0.49	0.49	0.49	0.49	0.48	0.33	0.18	0.07	0.04	0.02	0.02	0.02	0.01	0.00	0.01	0.00	0.00	0.01	0.01	0.03	0.08	0.11	0.09	0.47
20	0.37	0.35	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.39	0.39	0.40	0.40	0.39	0.28	0.15	0.05	0.03	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.05	0.07	0.06	0.37
19	0.29	0.26	0.29	0.30	0.30	0.30	0.30	0.30	0.29	0.30	0.31	0.32	0.32	0.31	0.23	0.13	0.05	0.02	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.03	0.05	0.04	0.28
18	0.16	0.15	0.16	0.17	0.17	0.17	0.17	0.17	0.17	0.18	0.18	0.19	0.19	0.19	0.16	0.09	0.03	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.02	0.02	0.16
17	0.12	0.12	0.12	0.13	0.13	0.13	0.12	0.13	0.12	0.13	0.14	0.14	0.15	0.15	0.13	0.07	0.02	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.02	0.02	0.11
16	0.02	0.02	0.02	0.02	0.03	0.02	0.02	0.02	0.02	0.03	0.03	0.03	0.04	0.03	0.04	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.02
15	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N/A	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Probabilities of generating C^1 in L^2 (De → It)

	N/A	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
31	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.04	0.11	0.12	0.14	0.14	0.13	0.13	0.13	0.13	0.13	0.12	0.11	0.09	0.04	0.02	0.01	0.01	0.00
30	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.04	0.11	0.12	0.14	0.14	0.13	0.14	0.13	0.13	0.14	0.12	0.11	0.08	0.04	0.02	0.01	0.01	0.00
29	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.05	0.11	0.13	0.14	0.14	0.14	0.14	0.13	0.13	0.13	0.12	0.10	0.08	0.03	0.02	0.01	0.01	0.00
28	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.04	0.09	0.11	0.12	0.12	0.11	0.11	0.11	0.10	0.10	0.09	0.07	0.05	0.02	0.02	0.02	0.01	0.00
27	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.06	0.07	0.08	0.07	0.07	0.07	0.06	0.06	0.06	0.05	0.04	0.03	0.02	0.02	0.02	0.01	0.00
26	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.05	0.05	0.06	0.05	0.05	0.05	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.00
25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.04	0.05	0.05	0.05	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.00
24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.04	0.04	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.00
23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.03	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.00
22	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.03	0.04	0.03	0.02	0.02	0.00
21	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.04	0.07	0.07	0.07	0.07	0.07	0.06	0.07	0.07	0.07	0.07	0.06	0.06	0.06	0.04	0.04	0.03	0.00
20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.07	0.10	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.12	0.11	0.11	0.10	0.08	0.07	0.05	0.04	0.00
19	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.10	0.15	0.16	0.16	0.15	0.16	0.17	0.17	0.17	0.17	0.17	0.16	0.14	0.11	0.09	0.07	0.05	0.00
18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.14	0.22	0.23	0.24	0.26	0.26	0.27	0.27	0.27	0.27	0.26	0.25	0.22	0.16	0.11	0.08	0.06	0.00
17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.15	0.24	0.26	0.27	0.29	0.30	0.31	0.31	0.30	0.30	0.29	0.27	0.24	0.18	0.12	0.09	0.07	0.00
16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.19	0.31	0.36	0.38	0.40	0.40	0.41	0.40	0.40	0.40	0.38	0.35	0.31	0.22	0.14	0.09	0.07	0.00
15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.22	0.36	0.41	0.43	0.44	0.44	0.44	0.44	0.43	0.44	0.41	0.38	0.33	0.23	0.14	0.09	0.06	0.00
14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.22	0.39	0.42	0.46	0.46	0.46	0.46	0.46	0.46	0.47	0.44	0.41	0.36	0.25	0.14	0.09	0.07	0.00
13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.23	0.40	0.43	0.46	0.47	0.46	0.46	0.47	0.46	0.48	0.45	0.42	0.36	0.25	0.14	0.09	0.06	0.00
12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.25	0.40	0.43	0.46	0.47	0.46	0.47	0.47	0.47	0.49	0.45	0.42	0.37	0.25	0.14	0.09	0.06	0.00
11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.20	0.38	0.43	0.46	0.47	0.46	0.47	0.47	0.47	0.49	0.45	0.43	0.37	0.26	0.15	0.09	0.07	0.00
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.20	0.38	0.43	0.46	0.47	0.46	0.47	0.47	0.47	0.49	0.46	0.43	0.37	0.26	0.15	0.09	0.07	0.00
9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.20	0.38	0.43	0.46	0.47	0.46	0.47	0.47	0.47	0.49	0.46	0.43	0.37	0.26	0.15	0.09	0.07	0.00
8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.20	0.38	0.43	0.46	0.47	0.46	0.47	0.47	0.47	0.49	0.46	0.43	0.38	0.26	0.15	0.09	0.07	0.00
7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.20	0.38	0.43	0.46	0.47	0.46	0.47	0.47	0.47	0.49	0.46	0.43	0.38	0.26	0.15	0.09	0.07	0.00
6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.20	0.38	0.43	0.46	0.47	0.46	0.47	0.47	0.47	0.49	0.46	0.43	0.38	0.26	0.15	0.09	0.07	0.00
5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.20	0.38	0.43	0.46	0.47	0.46	0.47	0.47	0.47	0.49	0.46	0.43	0.38	0.26	0.15	0.09	0.07	0.00
4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.20	0.38	0.43	0.46	0.47	0.46	0.47	0.47	0.47	0.49	0.46	0.43	0.38	0.26	0.15	0.09	0.07	0.00
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.20	0.38	0.43	0.46	0.47	0.46	0.47	0.47	0.47	0.49	0.46	0.43	0.38	0.26	0.15	0.09	0.07	0.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.20	0.38	0.43	0.46	0.47	0.46	0.47	0.47	0.47	0.49	0.46	0.43	0.38	0.26	0.15	0.09	0.07	0.00
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.20	0.38	0.43	0.46	0.47	0.46	0.47	0.47	0.47	0.49	0.46	0.43	0.38	0.26	0.15	0.09	0.07	0.00
0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.20	0.38	0.43	0.46	0.47	0.46	0.47	0.47	0.47	0.49	0.46	0.43	0.38	0.26	0.15	0.09	0.07	0.00
N/A	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.20	0.38	0.43	0.46	0.47	0.46	0.47	0.47	0.47	0.49	0.46	0.43	0.38	0.26	0.15	0.09	0.07	0.00

Probabilities of generating C^2 in L^2 (De → It)

	N/A	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
31	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.07	0.09	0.10	0.11	0.12	0.12	0.13	0.14	0.14	0.14	0.14	0.14	0.13	0.13	0.12	0.11	0.10	0.00
30	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.08	0.12	0.13	0.14	0.15	0.15	0.16	0.17	0.17	0.18	0.17	0.17	0.17	0.17	0.15	0.13	0.09	0.00
29	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.10	0.15	0.16	0.18	0.18	0.19	0.20	0.21	0.21	0.22	0.21	0.22	0.21	0.21	0.18	0.13	0.09	0.00
28	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.13	0.19	0.21	0.23	0.24	0.24	0.25	0.26	0.27	0.28	0.27	0.28	0.28	0.27	0.19	0.13	0.09	0.00
27	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.15	0.24	0.27	0.29	0.30	0.31	0.33	0.34	0.34	0.35	0.35	0.35	0.35	0.26	0.18	0.12	0.09	0.00
26	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.16	0.27	0.31	0.34	0.35	0.35	0.37	0.38	0.38	0.40	0.40	0.40	0.36	0.27	0.18	0.12	0.09	0.00
25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.17	0.29	0.33	0.37	0.37	0.38	0.40	0.42	0.42	0.43	0.43	0.40	0.35	0.26	0.17	0.11	0.08	0.00
24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.18	0.30	0.35	0.38	0.39	0.40	0.42	0.43	0.44	0.45	0.43	0.40	0.35	0.26	0.17	0.11	0.09	0.00
23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.19	0.32	0.37	0.40	0.41	0.41	0.44	0.45	0.45	0.45	0.43	0.40	0.35	0.26	0.17	0.11	0.08	0.00
22	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.19	0.32	0.37	0.40	0.41	0.42	0.44	0.45	0.44	0.45	0.42	0.39	0.34	0.26	0.17	0.11	0.08	0.00
21	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.17	0.29	0.33	0.37	0.38	0.38	0.40	0.40	0.40	0.39	0.37	0.34	0.30	0.23	0.16	0.11	0.08	0.00
20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.14	0.24	0.28	0.31	0.32	0.32	0.32	0.31	0.31	0.30	0.28	0.26	0.23	0.18	0.13	0.09	0.06	0.00
19	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.11	0.20	0.23	0.26	0.27	0.26	0.25	0.24	0.24	0.24	0.22	0.21	0.18	0.15	0.10	0.07	0.05	0.00
18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.08	0.14	0.18	0.19	0.18	0.16	0.16	0.14	0.14	0.14	0.13	0.13	0.11	0.10	0.07	0.05	0.03	0.00
17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.07	0.12	0.15	0.16	0.14	0.13	0.12	0.11	0.11	0.11	0.10	0.10	0.09	0.07	0.05	0.04	0.03	0.00
16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.01	0.01	0.00
15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.00
14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00
13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00
12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00
11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00
9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00
8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00
7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00
6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00
5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00
4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00
0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00
N/A	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00

B Complete redirection probabilities – translating Russian to Korean

Probabilities of generating C^1 in L^1 (Ru → Ko)

	N/A	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
31	0.11	0.10	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.05	0.03	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.11
30	0.12	0.11	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.11	0.05	0.03	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.12
29	0.13	0.11	0.13	0.13	0.12	0.12	0.12	0.12	0.12	0.12	0.13	0.13	0.13	0.12	0.05	0.03	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13
28	0.11	0.10	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.05	0.03	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.11
27	0.10	0.09	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.09	0.04	0.03	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.10
26	0.09	0.08	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.04	0.03	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.09
25	0.08	0.07	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.09	0.09	0.08	0.04	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08
24	0.08	0.07	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.03	0.02	0.01	0.00	0.00	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08
23	0.08	0.07	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.03	0.02	0.01	0.00	0.00	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08
22	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.02	0.01	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08
21	0.12	0.10	0.12	0.12	0.12	0.12	0.11	0.11	0.11	0.11	0.12	0.12	0.12	0.11	0.04	0.02	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.12
20	0.14	0.13	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.13	0.14	0.14	0.14	0.13	0.04	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.14
19	0.17	0.16	0.17	0.17	0.17	0.17	0.17	0.16	0.16	0.16	0.17	0.17	0.17	0.16	0.06	0.03	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.17
18	0.21	0.20	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.20	0.21	0.21	0.21	0.21	0.08	0.05	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.21
17	0.25	0.23	0.25	0.25	0.25	0.25	0.25	0.24	0.24	0.24	0.25	0.25	0.25	0.25	0.10	0.06	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.25
16	0.37	0.36	0.37	0.37	0.36	0.36	0.36	0.36	0.36	0.36	0.37	0.37	0.37	0.36	0.16	0.10	0.03	0.02	0.02	0.02	0.01	0.01	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.37
15	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.43	0.43	0.43	0.44	0.44	0.44	0.42	0.20	0.12	0.04	0.03	0.02	0.03	0.02	0.02	0.03	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.45
14	0.51	0.50	0.51	0.51	0.51	0.51	0.50	0.50	0.50	0.51	0.50	0.50	0.50	0.48	0.26	0.17	0.06	0.05	0.04	0.05	0.04	0.04	0.05	0.04	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.51
13	0.51	0.50	0.51	0.51	0.51	0.51	0.51	0.51	0.51	0.51	0.50	0.51	0.50	0.49	0.26	0.16	0.06	0.04	0.04	0.05	0.04	0.04	0.06	0.04	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.51
12	0.51	0.50	0.51	0.51	0.51	0.51	0.51	0.51	0.51	0.51	0.51	0.51	0.51	0.49	0.25	0.15	0.05	0.04	0.04	0.05	0.04	0.04	0.06	0.05	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.51
11	0.52	0.51	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.51	0.51	0.51	0.49	0.27	0.17	0.07	0.05	0.04	0.06	0.05	0.04	0.06	0.05	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.52
10	0.52	0.51	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.51	0.51	0.51	0.49	0.28	0.18	0.07	0.05	0.04	0.06	0.05	0.04	0.06	0.05	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.52
9	0.52	0.51	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.51	0.51	0.51	0.49	0.28	0.17	0.07	0.05	0.04	0.06	0.05	0.04	0.06	0.04	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.52
8	0.52	0.51	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.51	0.51	0.51	0.49	0.27	0.17	0.07	0.05	0.04	0.06	0.05	0.04	0.06	0.04	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.52
7	0.52	0.51	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.51	0.51	0.51	0.49	0.27	0.17	0.07	0.05	0.04	0.05	0.05	0.04	0.06	0.04	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.52
6	0.52	0.51	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.51	0.51	0.51	0.49	0.27	0.17	0.07	0.05	0.04	0.06	0.05	0.04	0.06	0.04	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.52
5	0.52	0.51	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.51	0.51	0.51	0.49	0.27	0.17	0.07	0.05	0.04	0.06	0.05	0.04	0.06	0.04	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.52
4	0.52	0.51	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.51	0.51	0.51	0.49	0.27	0.17	0.07	0.05	0.04	0.06	0.05	0.04	0.06	0.04	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.52
3	0.52	0.51	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.51	0.51	0.51	0.49	0.27	0.17	0.07	0.05	0.04	0.06	0.05	0.04	0.06	0.04	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.52
2	0.52	0.51	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.51	0.51	0.51	0.49	0.27	0.17	0.07	0.05	0.04	0.06	0.05	0.04	0.06	0.04	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.52
1	0.52	0.51	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.51	0.51	0.51	0.49	0.27	0.17	0.07	0.05	0.04	0.06	0.05	0.04	0.06	0.04	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.52
0	0.52	0.51	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.51	0.51	0.51	0.49	0.27	0.17	0.07	0.05	0.04	0.06	0.05	0.04	0.06	0.04	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.52
N/A	0.52	0.51	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.51	0.51	0.51	0.49	0.27	0.17	0.07	0.05	0.04	0.06	0.05	0.04	0.06	0.04	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.52

Probabilities of generating C^2 in L^1 (Ru → Ko)

	N/A	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
31	0.17	0.16	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.16	0.16	0.16	0.09	0.07	0.03	0.02	0.02	0.03	0.02	0.02	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.17
30	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.17	0.17	0.10	0.07	0.03	0.02	0.02	0.03	0.02	0.02	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.18
29	0.21	0.21	0.21	0.20	0.20	0.20	0.20	0.21	0.20	0.20	0.20	0.20	0.20	0.19	0.12	0.08	0.04	0.03	0.03	0.03	0.02	0.02	0.03	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.21
28	0.26	0.25	0.26	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.24	0.14	0.09	0.04	0.03	0.03	0.03	0.02	0.02	0.03	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.25
27	0.30	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.28	0.28	0.27	0.15	0.10	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.29
26	0.32	0.32	0.32	0.32	0.32	0.32	0.32	0.32	0.32	0.32	0.31	0.31	0.31	0.29	0.16	0.10	0.04	0.03	0.03	0.03	0.03	0.02	0.03	0.02	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.32
25	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.32	0.32	0.32	0.30	0.16	0.11	0.04	0.03	0.02	0.03	0.02	0.02	0.03	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33
24	0.34	0.34	0.34	0.33	0.33	0.33	0.33	0.34	0.33	0.33	0.33	0.32	0.32	0.30	0.16	0.11	0.04	0.03	0.02	0.03	0.02	0.02	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.34
23	0.34	0.33	0.34	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.32	0.32	0.30	0.16	0.10	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.34
22	0.33	0.32	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.32	0.32	0.31	0.30	0.15	0.10	0.03	0.02	0.02	0.02	0.01	0.01	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33
21	0.30	0.30	0.29	0.29	0.29	0.29	0.29	0.30	0.30	0.30	0.29	0.29	0.28	0.27	0.14	0.09	0.02	0.02	0.01	0.01	0.01	0.01	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.29
20	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.23	0.23	0.23	0.22	0.12	0.07	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.24
19	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.22	0.22	0.22	0.21	0.21	0.20	0.19	0.11	0.06	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.21
18	0.18	0.19	0.19	0.18	0.18	0.18	0.18	0.19	0.19	0.19	0.18	0.17	0.17	0.16	0.09	0.05	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.18
17	0.16	0.16	0.16	0.15	0.16	0.16	0.15	0.16	0.16	0.16	0.15	0.15	0.15	0.13	0.07	0.04	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.15
16	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.07	0.07	0.07	0.06	0.05	0.05	0.05	0.03	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06
15	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02
14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N/A	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Probabilities of generating C^1 in L^2 (Ru → Ko)

	N/A	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
31	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.08	0.14	0.16	0.17	0.17	0.18	0.18	0.17	0.18	0.21	0.20	0.19	0.15	0.09	0.05	0.04	0.02	0.00
30	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.10	0.16	0.18	0.18	0.18	0.19	0.19	0.19	0.20	0.22	0.21	0.20	0.16	0.09	0.06	0.04	0.03	0.00
29	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.10	0.15	0.17	0.17	0.17	0.18	0.18	0.18	0.19	0.21	0.20	0.19	0.15	0.09	0.06	0.06	0.03	0.00
28	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.07	0.11	0.12	0.13	0.13	0.14	0.15	0.15	0.16	0.18	0.16	0.15	0.13	0.08	0.07	0.06	0.04	0.00
27	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.04	0.06	0.07	0.07	0.07	0.09	0.09	0.10	0.11	0.13	0.12	0.11	0.08	0.08	0.07	0.06	0.04	0.00
26	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.03	0.05	0.05	0.05	0.05	0.06	0.07	0.08	0.09	0.10	0.09	0.08	0.08	0.08	0.07	0.06	0.04	0.00
25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.03	0.04	0.04	0.04	0.05	0.06	0.07	0.08	0.08	0.09	0.08	0.08	0.08	0.08	0.08	0.06	0.04	0.00
24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.03	0.04	0.04	0.04	0.04	0.05	0.06	0.08	0.08	0.08	0.08	0.09	0.08	0.08	0.08	0.07	0.04	0.00
23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.04	0.04	0.04	0.04	0.05	0.06	0.07	0.10	0.09	0.09	0.09	0.09	0.09	0.08	0.08	0.07	0.04	0.00
22	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.04	0.05	0.05	0.05	0.05	0.07	0.08	0.09	0.09	0.10	0.10	0.10	0.09	0.09	0.09	0.08	0.04	0.00
21	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.05	0.06	0.07	0.07	0.08	0.09	0.12	0.13	0.12	0.12	0.13	0.13	0.13	0.12	0.11	0.10	0.09	0.05	0.00
20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.08	0.11	0.12	0.13	0.13	0.16	0.18	0.17	0.17	0.17	0.18	0.17	0.17	0.16	0.15	0.13	0.11	0.06	0.00
19	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.11	0.15	0.17	0.18	0.19	0.21	0.21	0.21	0.21	0.20	0.21	0.20	0.20	0.18	0.17	0.15	0.13	0.07	0.00
18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.15	0.21	0.25	0.27	0.27	0.25	0.25	0.25	0.25	0.25	0.26	0.25	0.25	0.22	0.20	0.17	0.15	0.08	0.00
17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.17	0.24	0.30	0.31	0.30	0.29	0.29	0.29	0.29	0.29	0.31	0.29	0.29	0.26	0.23	0.20	0.17	0.09	0.00
16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.23	0.31	0.39	0.39	0.39	0.38	0.40	0.40	0.39	0.40	0.42	0.40	0.40	0.36	0.31	0.25	0.21	0.12	0.00
15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.24	0.32	0.43	0.44	0.44	0.43	0.45	0.45	0.44	0.45	0.48	0.46	0.46	0.42	0.36	0.29	0.25	0.14	0.00
14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.22	0.31	0.44	0.45	0.46	0.45	0.47	0.46	0.45	0.46	0.51	0.49	0.49	0.45	0.38	0.32	0.27	0.16	0.00
13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.22	0.33	0.44	0.45	0.46	0.45	0.47	0.46	0.45	0.46	0.51	0.49	0.49	0.45	0.38	0.32	0.27	0.16	0.00
12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.23	0.34	0.45	0.46	0.47	0.45	0.47	0.46	0.45	0.46	0.51	0.50	0.49	0.46	0.39	0.32	0.28	0.16	0.00
11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.22	0.32	0.43	0.46	0.47	0.45	0.47	0.47	0.45	0.47	0.51	0.50	0.50	0.46	0.39	0.32	0.28	0.16	0.00
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.21	0.31	0.43	0.45	0.47	0.45	0.47	0.47	0.45	0.47	0.51	0.50	0.50	0.46	0.39	0.32	0.28	0.16	0.00
9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.21	0.31	0.43	0.46	0.47	0.46	0.47	0.47	0.45	0.47	0.52	0.50	0.50	0.46	0.39	0.32	0.28	0.16	0.00
8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.21	0.32	0.43	0.46	0.47	0.46	0.47	0.47	0.45	0.47	0.52	0.51	0.50	0.46	0.39	0.32	0.28	0.17	0.00
7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.21	0.32	0.43	0.46	0.47	0.46	0.47	0.47	0.45	0.47	0.52	0.51	0.50	0.46	0.39	0.32	0.28	0.17	0.00
6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.21	0.32	0.43	0.46	0.47	0.46	0.47	0.47	0.45	0.47	0.52	0.51	0.50	0.46	0.39	0.32	0.28	0.17	0.00
5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.21	0.32	0.43	0.46	0.47	0.46	0.47	0.47	0.45	0.47	0.52	0.51	0.50	0.46	0.39	0.32	0.28	0.17	0.00
4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.22	0.32	0.43	0.46	0.47	0.46	0.47	0.47	0.45	0.47	0.52	0.51	0.50	0.46	0.39	0.32	0.28	0.17	0.00
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.22	0.32	0.43	0.46	0.47	0.46	0.47	0.47	0.45	0.47	0.52	0.51	0.50	0.46	0.39	0.32	0.28	0.17	0.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.22	0.32	0.43	0.46	0.47	0.46	0.47	0.47	0.45	0.47	0.52	0.51	0.50	0.46	0.39	0.32	0.28	0.17	0.00
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.22	0.32	0.43	0.46	0.47	0.46	0.47	0.47	0.45	0.47	0.52	0.51	0.50	0.46	0.39	0.32	0.28	0.17	0.00
0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.22	0.32	0.43	0.46	0.47	0.46	0.47	0.47	0.45	0.47	0.52	0.51	0.50	0.46	0.39	0.32	0.28	0.17	0.00
N/A	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.22	0.32	0.43	0.46	0.47	0.46	0.47	0.47	0.45	0.47	0.52	0.51	0.50	0.46	0.39	0.32	0.28	0.17	0.00

Probabilities of generating C^2 in L^2 (Ru → Ko)

	N/A	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
31	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.04	0.06	0.07	0.08	0.08	0.08	0.08	0.08	0.07	0.07	0.08	0.08	0.08	0.09	0.10	0.11	0.12	0.11	0.00
30	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.06	0.08	0.10	0.11	0.11	0.11	0.11	0.11	0.10	0.10	0.12	0.12	0.12	0.13	0.14	0.15	0.16	0.09	0.00
29	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.07	0.11	0.14	0.15	0.15	0.14	0.14	0.14	0.14	0.14	0.16	0.16	0.17	0.17	0.19	0.20	0.16	0.09	0.00
28	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.10	0.16	0.20	0.21	0.21	0.20	0.20	0.20	0.19	0.19	0.21	0.22	0.23	0.23	0.26	0.21	0.17	0.09	0.00
27	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.14	0.21	0.27	0.29	0.29	0.28	0.29	0.28	0.26	0.27	0.30	0.30	0.31	0.32	0.26	0.21	0.18	0.09	0.00
26	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.17	0.24	0.31	0.33	0.34	0.33	0.33	0.33	0.31	0.31	0.34	0.35	0.37	0.33	0.27	0.22	0.18	0.09	0.00
25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.18	0.25	0.34	0.36	0.36	0.35	0.36	0.35	0.33	0.34	0.37	0.37	0.36	0.32	0.26	0.21	0.18	0.09	0.00
24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.18	0.25	0.34	0.36	0.37	0.36	0.37	0.36	0.33	0.34	0.38	0.36	0.35	0.32	0.26	0.21	0.18	0.10	0.00
23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.19	0.26	0.36	0.38	0.38	0.38	0.38	0.37	0.34	0.36	0.37	0.36	0.35	0.32	0.26	0.21	0.18	0.10	0.00
22	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.19	0.26	0.36	0.38	0.39	0.38	0.37	0.36	0.34	0.35	0.36	0.35	0.34	0.31	0.26	0.21	0.18	0.10	0.00
21	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.17	0.24	0.33	0.35	0.35	0.34	0.32	0.31	0.30	0.31	0.32	0.31	0.31	0.28	0.23	0.19	0.16	0.09	0.00
20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.14	0.19	0.28	0.29	0.28	0.27	0.26	0.26	0.24	0.25	0.26	0.25	0.25	0.23	0.19	0.15	0.13	0.07	0.00
19	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.11	0.15	0.23	0.23	0.23	0.22	0.23	0.23	0.21	0.22	0.23	0.22	0.22	0.20	0.16	0.13	0.12	0.07	0.00
18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.10	0.16	0.16	0.17	0.18	0.19	0.19	0.18	0.18	0.19	0.18	0.18	0.17	0.14	0.11	0.10	0.06	0.00
17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.07	0.12	0.13	0.13	0.15	0.15	0.15	0.14	0.14	0.15	0.14	0.14	0.13	0.11	0.09	0.08	0.05	0.00
16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.04	0.05	0.06	0.06	0.06	0.06	0.05	0.06	0.06	0.06	0.06	0.06	0.05	0.04	0.04	0.03	0.00
15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.00
14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00
13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00
12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00
11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00
9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00
8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00
7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00
6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00
5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00
4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00
0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00
N/A	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00