REPRESENTATIONS OF COMPUTER PROGRAMS IN THE HUMAN BRAIN

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Paper under double-blind review

ABSTRACT

We present the first study relating representations of computer programs generated by unsupervised machine learning (ML) models and representations of computer programs in the human brain. We analyze recordings—brain representations—from functional magnetic resonance imaging (fMRI) studies of people comprehending Python code. We discover brain representations, in different and specific regions of the brain, that encode static and dynamic properties of code such as abstract syntax tree (AST)-related information and runtime information. We also map brain representations to representations of a suite of ML models that vary in their complexity. We find that the Multiple Demand system, a system of brain regions previously shown to respond to code, contains information about multiple specific code properties, as well as machine learned representations of code. We make all the corresponding code, data, and analysis publicly available.[1]

1 INTRODUCTION

Unsupervised machine learning (ML) models trained on computer code are increasingly being used in software engineering workflows (Allamanis et al., 2018a). Dubbed *code models*, they have been shown to perform well on tasks like code summarization (Alon et al., 2019), detecting variable misuse (Bichsel et al., 2016), and more recently, code auto-completion (Chen et al., 2021). These models process large corpora of code to produce *ML model representations* of computer programs. These representations likely encode syntax and semantics of programs (Bichsel et al., 2016; Allamanis et al., 2018b; Srikant et al., 2021).

A question of interest, as yet uninvestigated, is whether these ML model representations faithfully reflect brain representations of computer code during comprehension. One way to address this question is by comparing representations from ML models to the code-related information encoded in the human brain. Yamins et al. (2013) first showed how information encoded in our visual system resembles what convolutional neural networks learn when trained to recognize images. Could it then be possible that common code properties and semantics of programs are also reflected in brain activity patterns? More directly, do the current model architecture choices used to reason about code faithfully capture what is encoded by our brains? These questions form the focus of this work.

A few prior works have investigated the neural bases of programming (Siegmund et al., 2017; Floyd et al., 2017; Peitek et al., 2018; Castelhano et al., 2019; Huang et al., 2019; Krueger et al., 2020; Prat et al., 2020; Ivanova et al., 2020; Liu et al., 2020; Ikutani et al., 2021; Peitek et al., 2021). These works use analysis techniques like functional magnetic resonance imaging (fMRI) and electroencephalography (EEG) to investigate brain regions involved in coding tasks like code comprehension, code writing, and data structure manipulation. The primary quest of these works though, has been to locate physical regions in the brain involved in these activities, with the goal of determining whether code-related activity joins other activities supported by those brain regions. It remains unclear what specific code-related information these regions encode. Do these regions encode specific syntactic or semantic code properties? Further, are different regions involved in encoding different such properties? Likewise, how brain activity data—*brain representations*—of code relate to what ML models of code learn is an open question. To date, no systematic method exists to generate the evidence from which to draw answers.

In this work, we study the task of code comprehension, and utilize the fMRI recordings dataset from Ivanova et al. (2020) to investigate human brain representations of code. We establish two major directions of investigation—the probing of brain region representations for specific code properties, and an analysis of the mapping of these representations onto various code models with

[1]Project URL - `https://github.com/anonmyous-author/anonymous-code`

differing model complexity. We learn affine maps from brain representations to predict code representations of different code models, and similarly predict code properties which summarize the syntactic and semantic behavior of programs. We investigate the effects that brain regions, the nature of code properties, and the complexity of the code models have on the accuracies with which we decode brain representations. We find that we can decode code-related information from brain representations, and can map representations of code models from brain representations. We find the Multiple Demand system, a system of brain regions, to consistently encode specific code properties and map with machine learned representations of code. We provide an open-source framework to replicate our experiments, and we release our data and analysis publicly. Link - `https://github.com/anonmyous-author/anonymous-code`. The framework allows both brain data and program metrics to be easily added to extend the current set of experiments. This should enable authors from other neuroimaging studies or code model developers to collaborate and analyze data across these works, which will also help amortize the high costs of carrying out such experiments.

2 Related Work

Of the prior works that have investigated the neural bases of programming through fMRI and EEG techniques (Siegmund et al., 2017; Floyd et al., 2017; Peitek et al., 2018; Castelhano et al., 2019; Huang et al., 2019; Krueger et al., 2020; Ivanova et al., 2020; Liu et al., 2020; Ikutani et al., 2021; Peitek et al., 2021) and through behavioral studies (Prat et al., 2020; Casalnuovo et al., 2020; Crichton et al., 2021), the following probe brain recordings for program properties encoded in them.

Floyd et al. (2017) learn a linear model to successfully classify whether an observed brain activity corresponds to reading code or reading text. Ikutani et al. (2021) study expert programmers and show that it is possible to classify code into the four problem categories–math, search, sort, and string from the brain activations corresponding to the code. Similarly, Liu et al. (2020) classify whether a brain signal corresponds to code implementing an `if` condition or not. Peitek et al. (2021) analyze correlations between brain recordings of participants reading code and a set of code complexity metrics.

In testing for code properties, our work uses a similar methodology (a linear model trained on fMRI data), but we evaluate a larger set of static and dynamic code properties. We also systematically test whether key programming constructs like control flow and data operations are encoded by these brain representations. A systematic analysis of multiple such properties has not been performed in any of these works. Further, we perform these tests in those brain regions identified by Liu et al. (2020) and Ivanova et al. (2020) as being responsive specifically to code comprehension. This gives us a finer insight into how different regions encode these properties. In addition to these tests, we study representations generated by a suite of ML models with varying model complexity and compare those representations to brain representations.

Brain representations have also been studied in domains like natural language, vision, and motor control. Among related works in natural language, a domain that resembles programming languages, Mitchell et al. (2008); Pallier et al. (2011); Brennan & Pylkkänen (2017); Jain & Huth (2018); Gauthier & Levy (2019); Schwartz et al. (2019); Wang et al. (2020); Schrimpf et al. (2020); Cao et al. (2021) have studied brain representations of words and sentences by relating them to representations produced by language models. While the broader tools we use to investigate these representations, like multi-voxel pattern analysis (MVPA), are similar to some of these prior works, our focus is on properties specific to code and not natural language.

3 Background

We provide a brief background on fMRI signals as a proxy for brain representations and describe the brain systems that we probe in this work.

Measuring brain activity with fMRI. Functional magnetic resonance imaging (fMRI) is a brain imaging technique used to measure brain activity in specific brain regions. When a brain region is active, blood flows into the region to aid its processing. An MRI machine measures this change in blood flow, and reports BOLD (blood oxygen level dependent) values sampled at the machine's frequency (Glover, 2011, usually 2 seconds). The smallest unit of brain tissue for which BOLD signal is recorded is called a voxel (an equivalent of a 3D pixel); it comprises several cubic millimeters of brain tissue. For our analyses, we select subsets of voxels belonging to specific brain systems. Following common practice, the parameters of a general linear model, fit to time-varying BOLD values, are used as a measure of the overall activation in each voxel in response to a given

input. It is the values of these parameters that, according the neuroscience community, are brain representations.

Brain systems. A system of brain regions can span different areas of the brain but behaves as a holistic unit, showing similar patterns of engagement across a given cognitive task. We probe the following systems of regions in our work. See Appendix A for a detailed description of these systems along with relevant references.

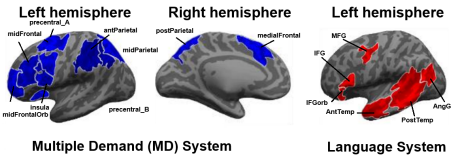

Figure 1: The approximate locations of MD and the Language systems in the human brain. The regions depicted are used as a starting point to functionally localize these systems in individual participants.

• **Multiple Demand (MD) system.** This system of regions is known to engage in cognitively demanding, domain agnostic tasks like general problem solving, logic, and spatial memory tasks. Liu et al. (2020) and Ivanova et al. (2020) reported that this system is active during code comprehension.

• **Language system (LS).** This system responds during language production and comprehension across modalities (speech, text) and languages (across 10 language families, including American sign language). Siegmund et al. (2014; 2017) reported activity in regions resembling the LS during code comprehension, whereas Floyd et al. (2017); Liu et al. (2020); Krueger et al. (2020) concluded that brain regions processing language and code are distinct. Ivanova et al. (2020) reported moderate levels of activity within the LS in response to Python, but not to code in a visual programming language, ScratchJr.

We also probe brain representations in two brain systems responsible for perception.

• **Visual system.** These regions respond primarily to visual inputs. We expect activity in this system to reflect low-level visual properties of the code (*e.g.* code length and indentation).

• **Auditory system.** These regions respond primarily to auditory inputs. We do not expect activity in this system to reflect code-related properties.

4 Brain and Model Representations

We describe in this section the method we follow to gather representations of code in the brain (Section 4.1), evaluate the different code properties they encode (Section 4.2), and how we compare brain representations to those generated by ML models (Section 4.3).

4.1 Brain representations and decoding

We provide a summary of how we process activation signals in the brain elicited by code comprehension, to probe whether they encode any specific code properties. We provide details in Appendix B.

Dataset. We use the publicly available brain recordings released as part of the study by Ivanova et al. (2020). It contains brain recordings of 24 participants reading 72 programs from a set of 108 unique Python programs. The 72 programs were presented in 12 blocks of 6 programs each. These programs were 3-10 lines in length and contained simple Python constructs, such as lists, *for* loops and *if* statements. The task required the participants to read the code and mentally compute the expected output.

From dataset to brain representations. The original dataset contains 3D images of the brain of each participant. Each voxel value in these images is an estimate of the response strength in this voxel when a particular code (or sentence) problem is presented. To determine which brain systems contain information about particular code properties, we focus our analyses to four systems – MD, Language, Visual, and Auditory (Section 3). A vector of voxels' activation values in each brain system is then taken to constitute that system's *representation* of a computer program and serves as an input to all our analyses. See Appendix B for details on data processing and voxel selection.

Analyzing brain representations of code. We probe brain representations from each participant separately. We do not average data across participants since the regions which respond to any task (comprehending code in our case) need not align anatomically. For each of two experiments—decoding different code properties, and mapping to code model representations—we train ridge regression models which take as input normalized brain representations per participant. We hence learn 24 different regression models, for each code property or code model (one per participant), and then report the mean performance of these models across participants. This procedure is also referred to as multi-voxel pattern analysis (MVPA) (Norman et al., 2006). Linear regression models are conventionally preferred for probes into brain representations since there has been evidence supporting the idea that other brain areas linearly map information from such brain representations

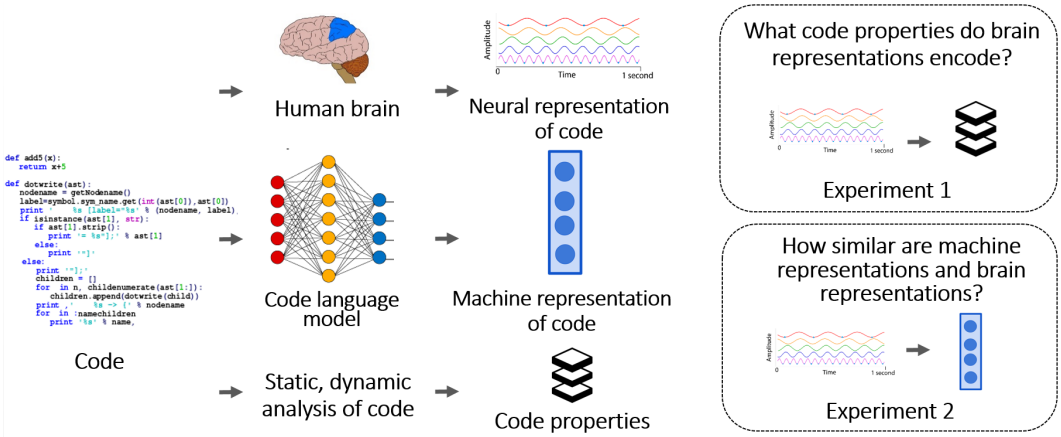

Figure 2: **Overview.** The goal of this work is to relate brain representations of code to (1) specific code properties and (2) representations of code produced by language models trained on code. In Experiment 1, we predict different static and dynamic analysis metrics from the brain MRI recordings of 24 human subjects reading 72 unique Python programs. In Experiment 2, we learn affine maps from brain representations to the corresponding representations generated by code language models on these 72 programs.

(Kamitani & Tong, 2005; Kriegeskorte, 2011). We choose a linear model primarily to control for over-fitting in light of the relatively small dataset.

A remark on data scarcity. We train a ridge regression model for every participant on unique cross-validated leave-one-run-out folds of the 72 programs they attempted, or 48 programs when sentences are removed. On the order of 1000 voxels were selected for each brain region responding to any given program per participant. As a baseline for the model predictions, we use the accuracy of a null permutation distribution generated from sampling 1000 random assignments of the labels.

4.2 Code properties

We attempt to decode multiple code properties from brain representations. This original dataset has the following conditions, which enable testing for specific code properties:

- ***Code vs. sentences.*** A control condition in this dataset is code problems that are described in English sentences (referred to as *sentences*). See Figure B, Appendix B for an example. Each participant saw 48 code problems and 24 sentence problems.
- ***Variable language.*** To test the effect English words may have on code comprehension, there are English-like variable names within half of the programs and Japanese variable names (which are semantically obscure to an English speaker) within the other half of the programs.
- ***Control flow.*** A third of the programs in this dataset have one loop (`for` loop), a third have one branch (`if` condition), and a third have sequential instructions without any control branching or loops.
- ***Data type.*** Half of the programs in the dataset have string operations within them, while the other half have numeric operations within them.

Additionally, we test two broad categories of code properties–those obtained from *static analysis* and *dynamic analysis*.

Static analysis provides information about the code without having access to any of its execution behavior. We test for *token count* (number of tokens in the program) and *node count* (number of AST nodes. We also consider *cyclomatic complexity*, and *Halstead difficulty* (details in Appendix B). These two properties have been used by software engineering practitioners to quantify the complexity of code, and to quantify the difficulty a human would experience when comprehending code respectively. Both these properties are functions of the number of nodes in the program's abstract syntax tree (AST) and tokens that appear in a program. We defer exploring other advanced static analysis metrics such as tracking abstract interpretation joins, data flow analysis-related metrics, *etc*. to future work.

Dynamic analysis provides information about the code's execution behavior. We evaluate two properties–*runtime steps* (number of instructions executed in the program) and *bytecode ops* (number of bytecode operations executed in running the program). Both these properties should align with the number of *mental instructions* needed to arrive at the output. While *runtime steps* should particularly align with the number of coarse lines executed mentally, *bytecode ops* should resemble the number of actual operations performed mentally across those lines to arrive at an output.

We measured how correlated these different properties were across the included programs and found that the four *static analysis* properties were highly correlated to each other and to *bytecode ops* (details in Appendix G). They are, by their definitions, expected to be correlated to the length of a program. We hence use one representative metric each from the two categories of properties for the rest of our analysis–*token count* for *static analysis*, and *runtime steps* for *dynamic analysis*.

The brain representations (Section 4.1) are mapped to each of the code properties by training a ridge regression model each for every participant-property pair. To evaluate model performance, we use classification accuracy when the predicted values are categorical (*e.g.* string vs. numeric data types), and the Pearson correlation coefficient when the predicted values are continuous (*e.g.* number of runtime steps). When testing for the significance of these predictions, we perform false discovery rate (FDR) correction for the number of brain systems tested and the number of properties tested. See Appendix B for a detailed description of model hyper-parameters and cross-validation settings employed.

4.3 Model representations and decoding.

We evaluate a bench of unsupervised language models, spanning from count-based language models to transformer neural networks (Vaswani et al., 2017). These models were all trained on large ($\sim$1M programs) Python datasets (Husain et al., 2019; Puri et al., 2021). We use the output of the trained encoders in each of the neural network models as representations of the code input to the model. We vary the general complexity of these models to test whether that variation is meaningful in establishing the quality of brain to model fits. We evaluate the following models, ordered by their increasing model complexity: simple frequency-based language models—*bag-of-words*, *TF-IDF*; auto-encoder based unsupervised models—*seq2seq* (Sutskever et al., 2014), *CodeTransformer* (Zügner et al., 2021), *CodeBERTa* (HuggingFace, 2020); auto-regressive model with a model complexity similar to that of transformers and *CodeBERTa—XLNet*(Yang et al., 2019).

We compare the results of the above models against an aggressive baseline (relative to the null-distribution labeling baseline) provided by using unique Gaussian-distributed random vectors for the token embeddings in a vocabulary, and returning the sum of these token embeddings across a program. The resultant embedding is not transformed by any model or any weights–it instead serves as a proxy for the tokens that appear in the program.

The brain representations (Section 4.1) are mapped to code representations by training another set of ridge regression models to learn an affine map, and a ranked accuracy metric is used to compare outputs. When reporting result significance, we perform false discovery rate (FDR) correction for the number of brain systems and the number of models. See Appendix B for a detailed discussion of the implemented code models.

5 Experiments & Results

Our experiments address two research questions:

- **Experiment 1.** How well do the different brain systems encode specific code properties?
- **Experiment 2.** How do the brain representations of code correspond to the representations learned by computational language models of code?

5.1 Experiment 1 - How well do the different brain systems encode specific code properties?

Here, we analyze the classification models and regressions trained on brain representations to predict each of the code properties described in Section 4.2. The results of our analyses are summarized in Figure 3. The classification and regression tests are marked on the x-axis of the left and right subplots respectively; the classification accuracy or Pearson correlation for each of the tasks is marked on the y-axes. We plot dynamic and static properties separately from the others because their baselines are different due to a difference in the similarity metric (classification accuracy vs. Pearson correlation). The empirical baselines for the categorical code properties differ from each other due to variation in the number of target classes, and in the case of *code vs sentences*, an imbalance in class size.

Auditory and Visual systems. The Auditory system serves as a negative control for the other systems. Given that the code comprehension task we use is visual, we do not expect to decode any meaningful information from it. We find that, out of 6 tested properties, only *code vs sentences* can be decoded from the Auditory system, and even then the decoding performance is much lower than in other systems. The Visual system also serves as a control for low-level visual properties of the code (as opposed to abstract semantic or syntactic features). Given the visual attributes of a program such as the layout and indentation of the code, the length of the program, and the presence of letters and alphabets in the programs (Park et al., 2012; Roux et al., 2008; Polk et al., 2002), this system

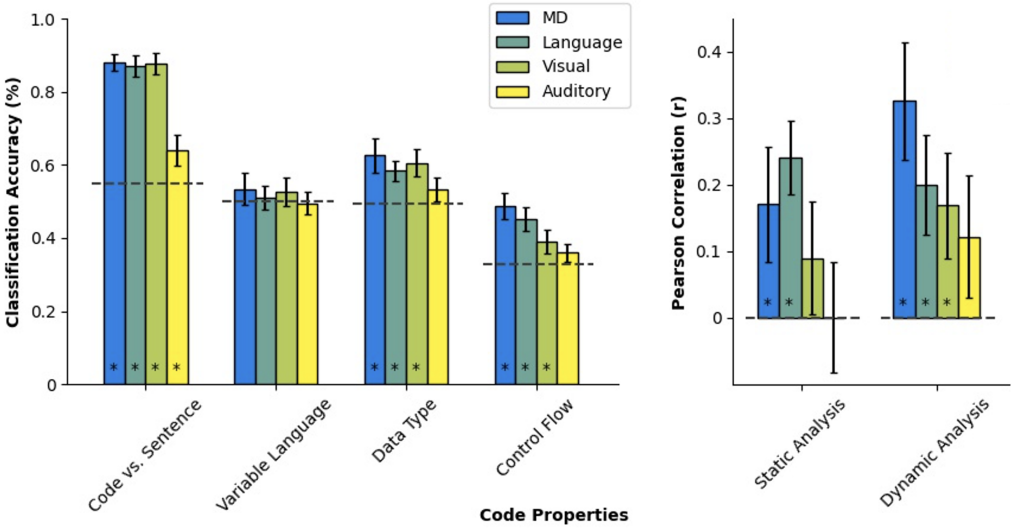

Figure 3: In Experiment 1, a linear model is trained on brain representations to predict each of the code properties described in Section 4.2. Error bars represent 95% confidence interval of individual subject scores. Dotted lines signify the empirical baseline for a null permutation distribution on shuffled labels. All results were compared to this permuted null distribution, and p-values for the number of comparisons in this experiment were corrected for false discovery rates (FDR). Statistically significant results are denoted with a $*$, marked at the base of the bars.

might reflect at least some of the properties we evaluate. This is indeed what we observe: 4 out of 6 tested properties can be decoded from the visual system above-chance. The MD and the Language systems yield the following specific observations -

Analysis 1 - How accurately are different properties predicted by MD and LS? We analyze how accurately each of MD and LS predict all the properties in our suite of tasks. For ease of viewing, we re-plot in Figure 4 the results from a selection of code properties for just the LS and MD from Figure 3. We plot the z-scores to normalize the different scales used in the two sets of code properties shown in Figure 3.

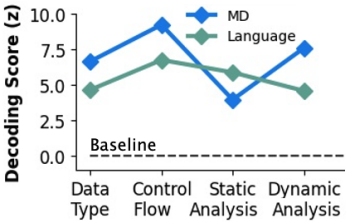

Figure 4: Predicting code properties from MD and LS.

• *Code vs. sentences* Code and sentence properties are decoded most accurately among all the properties we test. Both MD and LS decode with $\sim 90\%$ accuracy. This is an interesting result. The underlying operations required to solve both types of programming problems were the same (*e.g.* both might have required summing elements in a list). Yet, despite the *mental operations* remaining mostly the same, the MD system is able to discriminate between the two contrasting conditions. This supports the claims made by Liu et al. (2020) and Ivanova et al. (2020) that the MD system is responsible for code comprehension in addition to being responsive to mentally tracing the execution flow of code snippets–a typical working memory task.

• *Variable language* This analysis requires distinguishing between sets of nearly identical programs, with the only variation being in the language of the variable names (English vs. Japanese). We hence expect the Language system will most accurately encode this information, since it is sensitive to the presence of words in a foreign language. However, no such effect is observed–no brain region shows any significant decoding. This unexpected finding is however consistent with Ivanova et al. (2020), who show a lack of any significant difference in the aggregate neural activity between the two variations. Both suggest that these brain systems do not seem to rely on variable names as a meaningful feature, consistent with the fact that a change in variable names does not alter the expected output of the program.

• *Control flow* and *data type* Both *control flow* and *data type* tasks are most accurately predicted by the MD, followed by the LS. In the case of *control flow*, the more accurate predictions by the MD can possibly be explained by the larger number of mental operations needed for programs with loops when compared to programs with one or no branches. The difference seen in *data type* prediction is unclear. While programs with string operations contain more literals and words from the English alphabet, we do not see any preference in the LS being able to decode this property more accurately.

• *Static* and *Dynamic analysis* We observe the LS predicts *static analysis* properties with the highest accuracy. This is expected, since activity in the LS is known to be sensitive to the length of any text being read (independent of any specific program instructions in our case).

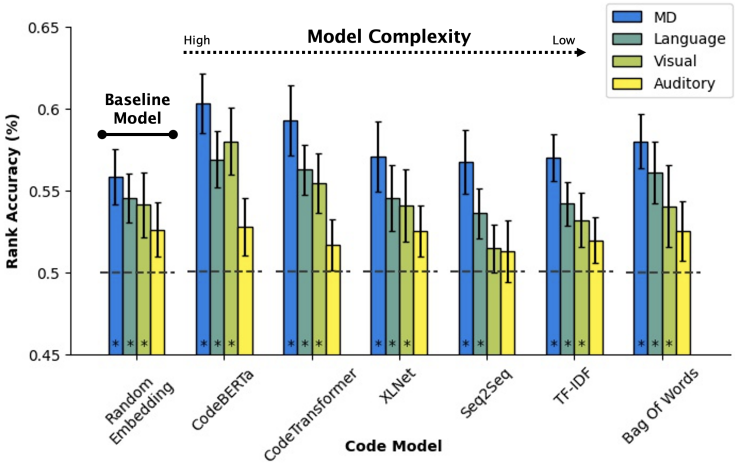

Figure 5: In Experiment 2, an affine map is learned from brain representations to the representations produced by machine learning models. Error bars represent 95% confidence interval of individual subject scores. Dotted lines signify the empirical baseline from a null permutation distribution on shuffled labels. *Random embedding* is an aggressive baseline of using random but unique embeddings for vocabulary tokens. Statistically significant results are denoted with a $*$, marked at the base of the bars.

For the *dynamic analysis* property *runtime steps*, we see the MD system has the highest accuracy. This again is reflective of the workings of the MD system, which is sensitive to working memory tasks, and the number of steps executed by a program matches the number of mental calculations performed by a person tracing through the program to calculate its output.

Analysis 2 - How accurately do MD and LS encode different properties? We compare the accuracies of all the code properties predicted by each system, to see if there is meaningful variation across brain systems for any code property.
We first test whether the distribution of accuracies across brain systems for each code property varies significantly. It could well be the case that the accuracies seen across the brain systems originate from the same distribution for a given property, which would then imply that the accuracies we observe are independent of the system being evaluated. We test for this, and find that the decoding accuracies corresponding to all code properties barring *variable language* vary significantly across brain regions (ANOVA; $F = 53.56$ (*code vs sentences*), $F = 6.96 \pm 1.94$ (other properties); $p < 0.05$; Appendix D).
We follow this up by using t-tests to examine whether any one brain region decodes any given property more significantly than another, but find no differences between the MD system and the Language system for any properties (Table 8, Appendix E).
We additionally test if any brain region has a preference for a specific code property over another. For instance, is the evidence seen in Figure 4, of MD more accurately decoding *dynamic analysis* properties than *static analysis* properties, statistically significant? Likewise, does the LS predict *static analysis* properties significantly more accurately than the *dynamic analysis* properties? We do not find any significant differences (Table 9, Appendix E).
This suggests that while we observe evidence of MD predicting runtime execution-related properties more accurately, and LS predicting program-length related properties more accurately (Figure 6), these results do not reach statistical generalization, and merit further investigation.

5.2 Experiment 2 - How do the brain representations of code correspond to the representations learned by computational language models of code?

Here, we train ridge regression models with brain representations of programs from a specific brain system to predict code model representations of the same programs. The full set of results from this experiment are summarized in Figure 5.

Auditory and Visual systems. Similar to Experiment 1, the Auditory system performs as expected, exhibiting the lowest decoding performance across all code models. The Visual system exhibits the second lowest performance across code models with the exception of *CodeBERTa* to which it maps more accurately to than LS, but not MD. However, this result is not statistically significant (Table 10, Appendix E).

Analysis 1 - How well do brain representations in MD and LS map to code model representations? To ease our analysis of the MD and LS systems, we re-plot in Figure 6 the decoding accuracies of just these two brain systems from Figure 5. We find that the MD system and Language system map to all the models in our suite significantly more accurately than the null permutation baseline (baseline accuracy of 50% in Figures 5 and 6). Further, from Figure

6, we see the MD maps more accurately than the LS across all code models. We test the significance of the differences between the two systems and find that the MD rank accuracy is higher than LS for *CodeBERTa*, *seq2seq*, and *TF-IDF*, while in the rest of the models, the differences are not significant (Table 10, Appendix E). These results suggest that while we see a strong evidence for the MD system to map more accurately with code models, we will need future works to confirm these results by studying the neural responses from a larger number of participants.

We followed this by investigating the distribution of brain to model mapping accuracies. As in Experiment 1, we test whether the mapping accuracies observed are dependent on brain system and code model choice. We find that these scores vary significantly across brain systems for all models (ANOVA; $F = 8.19 \pm 1.31$; $p < 0.05$; Table 6, Appendix D), and vary significantly across models in the MD system but not in the Language system (ANOVA; $F = 2.72$; $p < 0.05$; Table 7, Appendix D). This suggests that the choice of brain region used when mapping to any model in our set is significant, but the model scores only significantly vary from each other within the MD system.

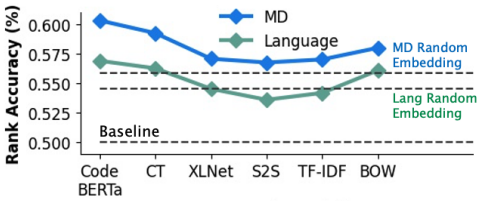

Figure 6: Mapping MD and LSto code model representations.

Analysis 2 - The effect of model complexity on brain-code model mapping. We investigate the impact model complexity has on the quality of the mapping between brain and code representations. Model complexity here is the number of a model's learnable parameters. In analysis 1 above, we saw that the MD system mapped to the representations of *CodeBERTa*, *seq2seq*, and *TF-IDF* significantly more accurately than the Language system. These three models vary substantially in their complexity, thus suggesting the lack of any relationship between model complexity and brain systems.

We also compare each of these code models against the *Random embedding* model. This baseline model assigns a random vector of numbers to every unique token that appears in the training vocabulary, and sums the vectors of all the tokens that appear in a program. By its design, this model encodes only the presence of specific tokens in programs. The mapping accuracies of random embeddings in the MD and the Language systems are marked in blue and green horizontal lines in Figure 6. We find that the Multiple Demand system maps to all the models more accurately than the *Random embedding*. This is not seen in the LS, which confirms the lack of variabilility of rank accuracies observed in the LS.

In a set of pairwise significance tests, we find that the MD maps to *CodeBERTa* significantly more accurately than *Random embedding* while other systems are more accurate numerically, but not significantly (Table 11, Appendix E). The fact that MD maps to other complex models other than *CodeBERTa*, like *CodeTransformer* and *seq2seq*, as accurately as the *Random embedding* model is a strong indicator that the representations in these brain systems is strongly driven by token-level information in the input programs. For the set of programs we evaluate, it seems that encoding individual tokens is sufficient to represent these programs uniquely. Future work should experiment with datasets of programs designed to be indistinguishable using tokens alone to test this hypothesis.

6 Discussion

We have discovered a correspondence between brain representations and code models. Further, we have developed a framework to understand what properties of computer programs are encoded in the human brain.

Key among our contributions is demonstrating that it is possible to map brain representations to representations produced by code models. We show that it is possible to perform zero-shot decoding of the computer program being comprehended using a proxy representation produced by a suite of code models. Although our decoding accuracies are relatively modest, they are comparable with similar decoding results from the domain of language (Pereira et al., 2018; Wang et al., 2020; Schrimpf et al., 2020). Moreover, unlike most prior decoding works in cognitive neuroscience, our decoders are trained on individual trials (rather than on averages of multiple recorded responses), a task that is difficult due to inherent noise present in fMRI data. Thus, our result demonstrates the feasibility of investigating the specifics of code comprehension in the brain without the need to present the same program multiple times to a participant.

We find that code representations in the Multiple Demand system can be mapped to code model representations more accurately than brain representations in other systems. This finding matches the known functional properties of the Multiple Demand system (*e.g.* its sensitivity to tasks involving logic, reasoning, and working memory) and its sensitivity to code comprehension shown by Liu

et al. (2020) and Ivanova et al. (2020).
In addition to the Multiple Demand system, the Language system also encoded information about multiple code properties. This is an intriguing result indicating that the Language system does contain some information about Python code. Further work should investigate the functional role of these responses and their relationship to the functions performed by the Multiple Demand system.
Among code models, *CodeBERTa*, a state-of-the-art code model, is most accurately aligned with Multiple Demand system representations. This result complements recent work in language research that has revealed a match between transformer architectures and brain representations of language (Toneva & Wehbe, 2019; Schrimpf et al., 2020). In other brain systems, however, the mapping accuracy was comparable across models, indicating that it is likely driven by token-level code properties. The relationship between model complexity and the mapping quality between brain and model representations merits a detailed study.

Another key contribution is demonstrating it is possible to predict a range of code properties from brain system activity (representations). Runtime information of programs is encoded most strongly in the Multiple Demand system, while code properties related to the length of a program are weakly encoded in Language system. The Multiple Demand system also encodes other static code properties, which suggests that the it is responsible both for parsing code and simulating it and calculating its outcome. Future work should test a larger set of programs that vary in the complexity of the properties they possess.

Limitations. The average program in any software project exhibits non-trivial control and data dependencies, object manipulation, function calls, types, and state changes. A portion of our study was made possible by the presence of a controlled set of conditions and properties in the dataset we analyze. However, the programming tasks in Ivanova et al. (2020) are short snippets of procedural code with limited program properties. Longer, more realistic programs should be studied in the future, building on the understanding of simpler snippets provided by our work. Further, while there are equally important aspects like designing solutions, selecting appropriate data structures, and writing programs, we have chosen to study a very specific activity related to programming—comprehending programs.
The sample size we analyze in our work (N=24; 72 code responses per participant) is the norm in the neuroimaging community; however, the robustness of our results is limited by the relatively small number of program responses and participants. Obtaining brain response recordings on carefully designed conditions using fMRI is expensive in terms of the effort to set up experiments and the cost associated with using MRI machines.
One aspect that cannot be inferred from these results, is whether the MD and LS are using the same or different underlying features of code to discriminate between code properties, and to map to different code models. It is possible that the MD encodes code and sentences based on a set of features entirely different from the LS while it is also possible that there is a large overlap in the features which drive both MD and LS. These opposing options arise because it has been shown that brain systems specializing in one cognitive skill (LS in our case) may exhibit redundancy and process information from a cognitive skill it is not known to process (Decharms & Zador, 2000). Unfortunately, the ability to decode various properties from these different brain systems provides no insight on the underlying mechanisms driving the organization of information in these systems.

Broader impact. Our findings have the potential to improve our understanding of the organization of the human brain, which can in turn lead to the design of better code models. In computer vision, recent results by Tschopp et al. (2018) show how deep network architectures that mimic the visual system in fruit flies exhibit superior image classification rates on image recognition tasks. One immediate outcome is reconsidering the current design of ML models of code. Extant code model architectures do not explicitly model the Multiple Demand system in any way–they only model syntactic information and infer dependency information from program ASTs. Taking inspiration from the role of the Multiple Demand system we identified in this work, modeling both static and dynamic information should be explored.
This work could perhaps also enhance *code prosthetics*–artificial interfaces in the body that can help the physically challenged engage with programming environments. Such systems generally rely on brain decoders–models that convert brain activity data to electrical impulses modulating external devices. An open challenge is to improve them. See the discussion in Nuyujukian et al. (2018) and Andersen et al. (2019) for details.
Finally, our aspiration is that the framework we release in this work will bring together the neuroscience and machine learning communities to better understand the cognitive and neural bases of programming.

7 REPRODUCABILITY STATEMENT

All the results, and corresponding tables, plots, and intermediate results we introduce in this paper are fully reproducible. We have made the source code to our work publicly available through this anonymized code repository - `https://github.com/anonmyous-author/anonymous-code/`

The repository contains detailed instructions for setting up the source code and running the two main experiments we introduce in this work. Further, we also release the dataset that we analyze along with the source code.

All the intermediate results which we use to arrive at our conclusions are available in Appendix A through Appendix G.

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A BRAIN REGIONS

Regions of Interest (ROIs). We investigate the representations of code in well-studied systems of brain regions–the MD system, Language system, Visual system, and the Auditory system (details below). A *region* (also referred to as *parcel*) here denotes a contiguous chunk of brain mass involved in a cognitive task. A *system* of regions (also referred to as a *network*) can comprise multiple disjoint regions that exhibit shared activity patterns across a range of tasks. For many cognitive tasks, a region marks only the approximate location of voxel populations involved in a cognitive task. *Functional* ROIs (fROIs) are voxels within these broad regions that respond most strongly to a given task (language, working memory, *etc*.). The use of fROIs enables accounting for the exact anatomical locations of these task-sensitive voxels, which vary across individuals.

Multiple Demand (MD) system. Located in the prefrontal and parietal areas of the brain, this system of regions is active in a host of tasks requiring working memory and general problem solving skills, including math and logic (Duncan, 2010; Fedorenko et al., 2013; Amalric & Dehaene, 2019).

Language system. These regions have been identified to respond to both comprehension and production of language across modalities (written, speech, sign language), respond to typologically diverse languages (>50 languages, from across 10 language families), form a functionally integrated system, reliably and robustly track linguistic stimuli, and have been shown to be causally important for language (Clark & Cummings, 2003; Fedorenko et al., 2010; Blank & Fedorenko, 2017; Ayyash et al., 2021).

Visual system. These regions in the occipital lobe of the brain respond to visual input, ranging from low-level features like lines and edges, through intermediate categories like shapes, letters, and numbers, through higher order structures like faces and scenes. (Hubel & Wiesel, 1959; Polk et al., 2002; Epstein & Kanwisher, 1998; Kanwisher et al., 1997).

Auditory system. The auditory system is located in the superior temporal region of the brain. This region uniquely encodes pitch, speech, and music, but is not involved in high-level language comprehension and production (Norman-Haignere et al., 2015; 2019). In our experiments pertaining to programming language comprehension, we use the activity seen in the auditory system as a negative control.

B METHOD - DETAILS

Selecting brain representations. For each trial in the fMRI experiment, stimulus responses in each voxel were extracted from the parameters of a General Linear Model (GLM) fit to the time-varying BOLD signal. The predictors for the GLM included trial ID (equivalent to problem ID), run number, and motion regressors. The voxels were then filtered using gray-matter masking and (for MD and the Language systems) network localization. Although fMRI measurements return whole brain responses, only a thin layer of cortex dubbed gray matter contains BOLD signal of interest to these analyses. Gray matter voxels were selected using a Bayesian segmentation of the anatomical brain image into standard tissue types, and then returning the set of indices where the posterior gray matter probability exceeds 0.70 (Ashburner et al., 1999). Next, these sets of voxels were filtered separately for each of the brain regions outlined in Appendix A. For the visual and auditory networks, primary sensory areas were identified using an anatomical atlas (Rolls et al., 2020). For the MD and the Language systems, voxels were functionally localized as those containing the top 10% of responses to their respective functional localizer tasks, as described in Ivanova et al. (2020). See Fedorenko et al. (2010) for a discussion of the functional localization approach as it pertains to the language network. GLM modeling and gray matter segmentation was performed using SPM12; functional localization was performed using the toolbox released by Ivanova et al. (2020). Once voxel responses within each brain region were extracted for each trial of each run, some additional preprocessing was required before finalizing the brain representations, and passing them to downstream models. Due to differences in MRI sensitivity across runs, each of the 12 runs of 6 programs for a given subject appeared with nonuniform mean and variance. In order to normalize these signals, so as to leverage data across a participant's entire scanning session, brain representations were z-transformed within each run to achieve a common scale. In order to avoid data-leakage from this preprocessing step, all downstream analyses were cross-validated via a leave-one-run-out approach, such that no intra-run rescaling could be used for prediction.

MVPA cross-validation and hyperparameters. For each brain system and each code property or code model, we run a separate MVPA analysis. For each subject, we train a separate ridge regression model on each cross-validated leave-one-run-out fold, and then predict the remaining targets using the brain representations from the left-out run. We use L2 regularization to control for model complexity, and employ a leave-one-out cross validation scheme to select λ. We score resulting predictions using a series of different metrics to maximize interpretability. For the categorical code properties, we report classification accuracy of model estimates. For the continuously scaled code properties, we report Pearson correlation between the model estimates and true targets. For the model representations, we report rank accuracy between model representation predictions and the true model representations of left-out samples. We calculate rank accuracy as the percentile of a predicted and true target pairing within the full set of possible pairings sorted by a Euclidean distance metric. Rank accuracy was chosen for this experiment as it returns a more interpretable 50% baseline through which to evaluate the brain to model mappings. Following metric calculation on each cross-validation fold, we take the mean of those estimates to report an out-of-sample score over the entire dataset for each subject. We then take the mean of those scores across subjects to derive an overall performance measure. As a baseline, we repeat the above process in its entirety 1000 times for each MVPA analysis, to provide a null permutation distribution against which to compare scores. These null distributions are fit with a univariate Gaussian and used to calculate z-statistics and p-values for MVPA scores. All statistical tests were corrected for false discovery rate. The code to run our MVPA analysis is available in `https://github.com/anonmyous-author/anonymous-code`.

Code properties. The code properties we consider are the following –

- ***Token count.*** The total number of tokens that appear in the program. This is a sanity check to measure brain activity against, since it is natural to expect the activity in the brain to be correlated to the length of a program, and in general, the amount of content being comprehended. By their design, the dataset had program lengths with a small standard deviation.
- ***Node count.*** The total number of AST nodes that appear in a program. Similar to the number of tokens, we verify if brain activity correlates to a proxy for the amount of syntactic content in it.
- ***Runtime steps.*** We execute the programs and measure the number of instructions the program steps through. While two programs can have the same program length, the number of instructions executed can differ (*e.g.*`for 1:10` vs. `for 1:50`). We measure if any brain regions capture the number of *mental operations* needed to compute the output of a program.
- ***Bytecode ops.*** We execute the programs and count the number of bytecode operations performed. This metric should mimic the number of *mental operations* performed needed to compute the output of a program.
- ***Cyclomatic complexity.*** This metric (McCabe, 1976) is used to measure the general complexity of software systems. It is defined as a function of the number of nodes, edges, and the connected

components in a program's control flow graph. While its efficacy as a metric to measure software complexity has been contested (Shepperd, 1988), we include it to see if brain activity is correlated to any explicit syntactic constructs of a program.
- ***Halstead difficulty.*** This metric (Halstead, 1977) was defined to measure how difficult any piece of software would be for a programmer to comprehend or write. It is defined as a function of the number of tokens, operations, vocabulary that appears in a program.

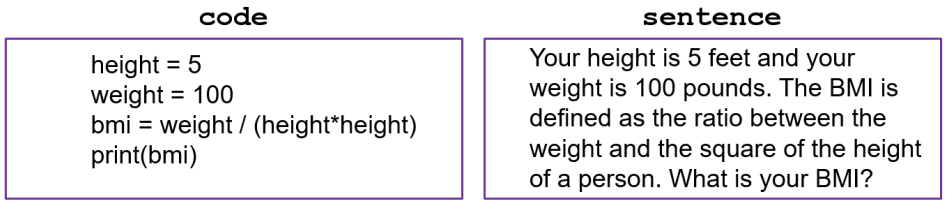

Figure 7: An example of a code problem and its sentence equivalent from Ivanova et al. (2020)

The inter-correlations between these metrics have been tabulated in Table 17, Appendix G.

Code models - Model details. We evaluate the following models in this work–
- ***bag-of-words***, ***TF-IDF***. These are count-based language models. They predict the likelihood of a token appearing in a program based on vocabulary statistics and frequencies.
- ***seq2seq*** (Sutskever et al., 2014), ***CodeTransformer*** (Zügner et al., 2021), ***CodeBERTa*** (HuggingFace, 2020). We evaluate these three autoencoder (AE) models with increasing model complexity. AE based pretraining reconstructs the original program from corrupted input.
- ***XLNet*** (Yang et al., 2019). We evaluate an auto-regressive (AR) model with a model complexity similar to that of transformers and *CodeBERTa*. AR language modeling estimates the probability distribution of a text corpus in one direction–either forward or backward, while AE models capture dependencies in both directions. We use an AR model to mimic a top-down, single pass comprehension style by humans.
- ***Random embedding***. We compare the results of the above models against an aggressive baseline provided by using unique Gaussian-distributed random vectors for the token embeddings in a vocabulary, and returning the sum of these token embeddings across a program. The resultant embedding is not transformed by any model or any weights–it instead serves as a proxy for the tokens that appear in the program. This sets a higher bar than the null-distribution labeling baseline (Section 5.2).

Code models - Configuration details. In setting up our code model bench, we aimed to select a collection of models ranging in their complexity, namely *bag-of-words*, *TF-IDF* (Term frequency-Inverse document frequency), *seq2seq*, *XLNet*, *CodeTransformer*, and *CodeBERTa*, as well as a *Random embedding* embedding model.
- The *bag-of-words*, *TF-IDF*, *seq2seq*, and *Random embedding* models all use the same custom tokenizer defined by the current authors, whereas *XLNet*, *CodeTransformer*, and *CodeBERTa* use tokenizers defined by the original training authors (Zügner et al., 2021; HuggingFace, 2020).
- The tokenizer set up for the models trained by the current authors establishes a unique token in the vocabulary for each Python keyword, each Python builtin function, one token for all numeric types, one token for all string types, and N tokens for each of the N variables in a given program.
- In the case of the *Random embedding* baseline, this tokenizer was used to map each token in a piece of source code to an index in the vocabulary, which in turn was used to index a Gaussian distributed random matrix ($D = 128$). The sum of these random token projections was calculated to return a unique embedding for each program.
- For *bag-of-words* and *TF-IDF*, the validation split of the *code-search-net* Python dataset (Husain et al., 2019) was used to enumerate vocabulary and token occurrence statistics. These data were then used to transform each program to a vector where each dimension represented the raw (*bag-of-words*) or document-weighted (*TF-IDF*) count of the unique items in the vocabulary.
- If a given set of programs viewed by a subject never included a specific token, leading that column to equal the zero vector, then those dimensions would be filtered out.
- We used the dataset released by Project Codenet (Puri et al., 2021) to pretrain a *seq2seq* model (Sutskever et al., 2014). The dataset contains Python programs that are solutions to olympiad-style programming problems in data structures and algorithms. We trained a seq2seq model with a GRU unit for 15 epochs, with a dropout probability of 0.2, dot product attention, and a maximum sentence length of 500.

- For *XLNet*, *CodeTransformer*, and *CodeBERTa*, each program was passed through that model's tokenizer and model pipeline as defined by the original authors. The representations of each program were extracted from the pretrained encoders. *XLNet* and *CodeTransformer* were originally trained on the Python subset of the *code-search-net* dataset, whereas *CodeBERTa* was originally trained on the full *code-search-net* dataset, which also incorporates *go*, *java*, *javascript*, *php*, and *ruby*.

C ADDITIONAL RESULTS

C.1 EXPERIMENT 1

Using representations from localized brain regions, we attempt to decode static and dynamic properties of comprehended code, and learn maps to code model representations of that same code. We report decoding performance of each brain region to the original Ivanova et al. (2020) code properties in Table 1, the complexity-related code properties in Table 2, and the code model mappings in Table 3. We find that the MD system and the Language system decode all code properties and code models except *variable language* significantly above baseline, as established through a null permutation test. The Visual system decodes 4 of the 6 code properties and 6 of the 7 code models, whereas the Auditory system only decodes the *code vs sentences* property.

Brain Representation Code Properties	Empirical Baseline	MD	Language	Visual	Auditory
Code vs. Sentence	0.55	0.88 (+0.33)	0.87 (+0.32)	0.88 (+0.33)	0.64 (+0.09)
Control Flow	0.33	0.49 (+0.16)	0.45 (+0.12)	0.39 (+0.06)	0.36 (+0.03)
Data Type	0.49	0.63 (+0.14)	0.58 (+0.09)	0.61 (+0.12)	0.53 (+0.04)
Variable Language	0.50	0.53 (+0.03)	0.51 (+0.01)	0.53 (+0.03)	0.50 (-0.00)

Table 1: Brain region decoding performance on original Ivanova et al. (2020) code properties. Scores represent classification accuracy and are contrasted with an empirical baseline from the null permutation analysis. Values in parentheses are units above baseline.

Brain Representation Code Properties	MD	Language	Visual	Auditory
Static Analysis	0.17	0.24	0.09	0.00
Dynamic Analysis	0.33	0.20	0.17	0.12

Table 2: Brain region decoding performance on *static analysis* and *dynamic analysis* code properties. Scores represent Pearson correlation between predicted and true code properties.

C.2 EXPERIMENT 2

Brain Representation Code Models	Empirical Baseline	MD	Language	Visual	Auditory
Random Embedding	0.50	0.56 (+0.06)	0.55 (+0.05)	0.54 (+0.04)	0.53 (+0.03)
Bag Of Words	0.50	0.58 (+0.08)	0.56 (+0.06)	0.54 (+0.04)	0.52 (+0.02)
TF-IDF	0.50	0.57 (+0.07)	0.54 (+0.04)	0.53 (+0.03)	0.52 (+0.02)
Seq2Seq	0.50	0.57 (+0.07)	0.54 (+0.04)	0.51 (+0.01)	0.51 (+0.01)
XLNet	0.50	0.57 (+0.07)	0.55 (+0.05)	0.54 (+0.04)	0.52 (+0.02)
CodeTransformer	0.50	0.59 (+0.09)	0.56 (+0.06)	0.55 (+0.05)	0.52 (+0.02)
CodeBERTa	0.50	0.60 (+0.10)	0.57 (+0.07)	0.58 (+0.08)	0.53 (+0.03)

Table 3: Brain region decoding performance on code model mappings. Scores represent rank accuracy and are contrasted with an empirical baseline from the null permutation analysis. Values in parentheses are units above baseline.

We additionally evaluate whether code models contain linearly decodable information about the code properties we explore in this work (Section 4.2). The models decode with near perfect accuracy on most classification tasks (avg. accuracy= 0.96 ± 0.01), and with high correlations on the regression tasks (avg. $r = 0.89 \pm 0.02$). This is expected for the classification tasks, since the dataset contains tokens which help with perfectly separable decision boundaries. For example, for the *control flow* code property, the dataset contains programs with `if`, `for`, or neither, but never both. These results suggest that the code models we evaluate faithfully encode the set of properties we evaluate them on.

Code Properties Empirical Baseline Model Representation	Control Flow 0.31	Data Type 0.48	Dynamic Analysis 0.00	Static Analysis 0.00
Random Embedding	1.00	0.94	0.88	1.00
Bag Of Words	1.00	0.92	0.93	0.98
TF-IDF	1.00	0.94	0.94	0.89
Seq2Seq	0.95	0.97	0.87	0.91
XLNet	0.92	0.92	0.76	0.88
CodeTransformer	1.00	0.95	0.90	0.91
CodeBERTa	0.96	0.98	0.81	0.79

Table 4: Decoding performance of all models on all tasks. Scores represent classification accuracy for *control flow* and *data type*, and Pearson correlation for the remaining benchmarks. These can be contrasted with an empirical baseline from the null permutation analysis.

D ANALYSIS OF VARIANCE

We run a series of one-way ANOVA statistical tests to assess whether decoding performance varies across brain regions for each code property and code model, and whether decoding performance varies across code models for each brain region. We report these results in Tables 5, 6, and 7. We find that decoding performance varies across brain region for all code properties and code models, except the *variable language* property and the *Random embedding* model, and decoding performance varies across code models for the MD system and the Visual system.

Code Property	F	p	p (corrected)	Is Significant?
Code vs. Sentence	53.57	4.03e-20	2.42e-19	1
Control Flow	12.52	6.13e-07	1.84e-06	1
Static Analysis	6.71	3.82e-04	7.65e-04	1
Data Type	4.46	5.66e-03	8.50e-03	1
Dynamic Analysis	4.15	8.38e-03	1.01e-02	1
Variable Language	0.82	4.84e-01	4.84e-01	0

Table 5: Results from statistical testing of variance across brain regions for each code property.

Code Model	F	p	p (corrected)	Is Significant?
CodeTransformer	11.85	1.25e-06	7.95e-06	1
CodeBERTa	11.28	2.27e-06	7.95e-06	1
TF-IDF	8.46	5.08e-05	9.48e-05	1
Seq2Seq	8.40	5.42e-05	9.48e-05	1
Bag Of Words	5.66	1.33e-03	1.86e-03	1
XLNet	3.48	1.90e-02	2.22e-02	1
Random Embedding	2.32	8.04e-02	8.04e-02	0

Table 6: Results from statistical testing of variance across brain regions for each code model.

Brain Region	F	p	p (corrected)	Is Significant?
Visual	4.00	9.17e-04	3.67e-03	1
MD	2.72	1.54e-02	3.08e-02	1
Language	2.18	4.70e-02	6.27e-02	0
Auditory	0.43	8.57e-01	8.57e-01	0

Table 7: Results from statistical testing of variance across code models for each brain region.

E PAIRWISE ANALYSIS

To extend the findings from the ANOVA analyses towards specific pairwise comparisons between brain regions and code models, we compare scores between brain regions for each code property or code model, and compare scores between code models and a subset of code properties for each brain region, using two-sample two-tail t-tests with unequal variance. We report all pairwise brain region comparisons in Tables 8 and 10, and report all pairwise code property and model comparisons in Tables 9 and 11. To highlight a few key results from code properties, we find that the MD system decodes *runtime steps* and *control flow* significantly better than the Visual system (Table 8). Additionally, the Language system decodes *static analysis* and *control flow* significantly better than the Visual system. Moving onto code models, we find that the MD system decodes *CodeBERTa*, *seq2seq*, and *TF-IDF* significantly more accurately than the Language system, and additionally decodes *CodeTransformer*, *seq2seq*, *TF-IDF*, and *bag-of-words* significantly more accurately than the Visual system (Table 10). Finally, an investigation into model complexity reveals that *CodeBERTa* is significantly more accurately decoded from the MD system than the *Random embedding* model.

Code Property	Brain Region A	Brain Region B	t	p	p (corrected)	Is Significant?
Code vs. Sentence	Language	Auditory	8.82	5.33e-11	6.40e-10	1
Code vs. Sentence	MD	Auditory	9.79	1.28e-11	4.62e-10	1
Code vs. Sentence	Visual	Auditory	9.06	2.65e-11	4.78e-10	1
Control Flow	Language	Auditory	4.28	1.02e-04	6.10e-04	1
Control Flow	Language	Visual	2.60	1.26e-02	3.30e-02	1
Control Flow	MD	Auditory	5.59	1.65e-06	1.49e-05	1
Control Flow	MD	Visual	3.92	2.95e-04	1.52e-03	1
Data Type	MD	Auditory	3.16	2.98e-03	1.21e-02	1
Data Type	Visual	Auditory	2.93	5.33e-03	1.88e-02	1
Dynamic Analysis	MD	Auditory	3.13	3.03e-03	1.21e-02	1
Dynamic Analysis	MD	Visual	2.59	1.28e-02	3.30e-02	1
Static Analysis	Language	Auditory	4.70	2.97e-05	2.14e-04	1
Static Analysis	Language	Visual	2.92	5.75e-03	1.88e-02	1
Static Analysis	MD	Auditory	2.79	7.68e-03	2.30e-02	1
Code vs. Sentence	Language	Visual	-0.28	7.83e-01	8.30e-01	0
Code vs. Sentence	MD	Language	0.49	6.27e-01	6.84e-01	0
Code vs. Sentence	MD	Visual	0.18	8.55e-01	8.55e-01	0
Control Flow	MD	Language	1.44	1.58e-01	2.84e-01	0
Control Flow	Visual	Auditory	1.50	1.40e-01	2.81e-01	0
Data Type	Language	Auditory	2.30	2.62e-02	6.30e-02	0
Data Type	Language	Visual	-0.94	3.55e-01	4.91e-01	0
Data Type	MD	Language	1.48	1.47e-01	2.81e-01	0
Data Type	MD	Visual	0.64	5.24e-01	6.18e-01	0
Dynamic Analysis	Language	Auditory	1.29	2.03e-01	3.04e-01	0
Dynamic Analysis	Language	Visual	0.57	5.73e-01	6.45e-01	0
Dynamic Analysis	MD	Language	2.11	4.01e-02	9.03e-02	0
Dynamic Analysis	Visual	Auditory	0.75	4.55e-01	5.85e-01	0
Static Analysis	MD	Language	-1.34	1.89e-01	3.04e-01	0
Static Analysis	MD	Visual	1.32	1.94e-01	3.04e-01	0
Static Analysis	Visual	Auditory	1.47	1.48e-01	2.81e-01	0
Variable Language	Language	Auditory	0.66	5.15e-01	6.18e-01	0
Variable Language	Language	Visual	-0.63	5.32e-01	6.18e-01	0
Variable Language	MD	Auditory	1.40	1.68e-01	2.88e-01	0
Variable Language	MD	Language	0.84	4.06e-01	5.41e-01	0
Variable Language	MD	Visual	0.23	8.20e-01	8.44e-01	0
Variable Language	Visual	Auditory	1.23	2.26e-01	3.25e-01	0

Table 8: Results from pairwise t-tests of brain regions for each code property. $+t$ reflects $A > B$, whereas $-t$ reflects $A < B$.

Brain Region	Code Property A	Code Property B	t	p	p (corrected)	Is Significant?
Auditory	Static Analysis	Dynamic Analysis	-1.93	6.00e-02	1.20e-01	0
Language	Static Analysis	Dynamic Analysis	0.85	4.00e-01	4.00e-01	0
MD	Static Analysis	Dynamic Analysis	-2.45	1.80e-02	7.18e-02	0
Visual	Static Analysis	Dynamic Analysis	-1.34	1.88e-01	2.51e-01	0

Table 9: Results from pairwise t-tests of continuous code metrics across brain regions. Only this subset of properties was selected so as to evaluate scores with a consistent metric and baseline. $+t$ reflects $A > B$, whereas $-t$ reflects $A < B$.

Code Model	Brain Region A	Brain Region B	t	p	p (corrected)	Is Significant?
Bag Of Words	Language	Auditory	2.70	9.69e-03	2.60e-02	1
Bag Of Words	MD	Auditory	4.42	6.03e-05	6.33e-04	1
Bag Of Words	MD	Visual	2.61	1.26e-02	2.93e-02	1
CodeBERTa	Language	Auditory	3.29	1.94e-03	7.41e-03	1
CodeBERTa	MD	Auditory	5.80	5.85e-07	2.46e-05	1
CodeBERTa	MD	Language	2.67	1.05e-02	2.60e-02	1
CodeBERTa	Visual	Auditory	3.80	4.28e-04	2.25e-03	1
CodeTransformer	Language	Auditory	4.12	1.55e-04	1.09e-03	1
CodeTransformer	MD	Auditory	5.61	1.42e-06	2.99e-05	1
CodeTransformer	MD	Visual	2.67	1.05e-02	2.60e-02	1
CodeTransformer	Visual	Auditory	3.09	3.40e-03	1.19e-02	1
Random Embedding	MD	Auditory	2.69	9.95e-03	2.60e-02	1
Seq2Seq	MD	Auditory	3.94	2.72e-04	1.63e-03	1
Seq2Seq	MD	Language	2.48	1.71e-02	3.78e-02	1
Seq2Seq	MD	Visual	4.25	1.16e-04	9.71e-04	1
TF-IDF	MD	Auditory	4.95	1.06e-05	1.48e-04	1
TF-IDF	MD	Language	2.86	6.39e-03	2.06e-02	1
TF-IDF	MD	Visual	3.42	1.33e-03	6.20e-03	1
XLNet	MD	Auditory	3.39	1.53e-03	6.45e-03	1
Bag Of Words	Language	Visual	1.29	2.03e-01	2.80e-01	0
Bag Of Words	MD	Language	1.50	1.40e-01	2.03e-01	0
Bag Of Words	Visual	Auditory	0.98	3.33e-01	3.88e-01	0
CodeBERTa	Language	Visual	-0.81	4.20e-01	4.65e-01	0
CodeBERTa	MD	Visual	1.66	1.04e-01	1.62e-01	0
CodeTransformer	Language	Visual	0.69	4.92e-01	5.30e-01	0
CodeTransformer	MD	Language	2.21	3.23e-02	6.46e-02	0
Random Embedding	Language	Auditory	1.70	9.56e-02	1.54e-01	0
Random Embedding	Language	Visual	0.32	7.52e-01	7.81e-01	0
Random Embedding	MD	Language	1.13	2.63e-01	3.18e-01	0
Random Embedding	MD	Visual	1.28	2.07e-01	2.80e-01	0
Random Embedding	Visual	Auditory	1.16	2.53e-01	3.18e-01	0
Seq2Seq	Language	Auditory	1.87	6.85e-02	1.20e-01	0
Seq2Seq	Language	Visual	1.98	5.36e-02	1.02e-01	0
Seq2Seq	Visual	Auditory	0.14	8.87e-01	8.87e-01	0
TF-IDF	Language	Auditory	2.28	2.71e-02	5.69e-02	0
TF-IDF	Language	Visual	0.92	3.64e-01	4.13e-01	0
TF-IDF	Visual	Auditory	1.13	2.65e-01	3.18e-01	0
XLNet	Language	Auditory	1.58	1.22e-01	1.83e-01	0
XLNet	Language	Visual	0.30	7.62e-01	7.81e-01	0
XLNet	MD	Language	1.71	9.49e-02	1.54e-01	0
XLNet	MD	Visual	1.91	6.25e-02	1.14e-01	0
XLNet	Visual	Auditory	1.13	2.64e-01	3.18e-01	0

Table 10: Results from pairwise t-tests of brain regions for each code model. $+t$ reflects $A > B$, whereas $-t$ reflects $A < B$.

Brain Region	Code Model A	Code Model B	t	p	p (corrected)	Is Significant?
MD	Random Embedding	CodeBERTa	-3.53	9.65e-04	2.70e-02	1
Visual	CodeBERTa	Seq2Seq	5.13	7.01e-06	5.89e-04	1
Visual	CodeBERTa	TF-IDF	3.60	7.93e-04	2.70e-02	1
Visual	CodeTransformer	Seq2Seq	3.35	1.68e-03	3.53e-02	1
Auditory	Bag Of Words	TF-IDF	0.47	6.39e-01	8.14e-01	0
Auditory	CodeBERTa	Bag Of Words	0.23	8.23e-01	9.48e-01	0
Auditory	CodeBERTa	CodeTransformer	0.94	3.51e-01	6.82e-01	0
Auditory	CodeBERTa	Seq2Seq	1.15	2.58e-01	6.37e-01	0
Auditory	CodeBERTa	TF-IDF	0.73	4.68e-01	7.40e-01	0
Auditory	CodeBERTa	XLNet	0.24	8.10e-01	9.48e-01	0
Auditory	CodeTransformer	Bag Of Words	-0.69	4.93e-01	7.40e-01	0
Auditory	CodeTransformer	Seq2Seq	0.30	7.64e-01	9.44e-01	0
Auditory	CodeTransformer	TF-IDF	-0.27	7.87e-01	9.45e-01	0
Auditory	CodeTransformer	XLNet	-0.75	4.57e-01	7.40e-01	0
Auditory	Random Embedding	Bag Of Words	0.07	9.45e-01	1.00e+00	0
Auditory	Random Embedding	CodeBERTa	-0.16	8.70e-01	9.75e-01	0
Auditory	Random Embedding	CodeTransformer	0.80	4.29e-01	7.35e-01	0
Auditory	Random Embedding	Seq2Seq	1.02	3.14e-01	6.82e-01	0
Auditory	Random Embedding	TF-IDF	0.58	5.68e-01	7.74e-01	0
Auditory	Random Embedding	XLNet	0.08	9.40e-01	1.00e+00	0
Auditory	Seq2Seq	Bag Of Words	-0.91	3.65e-01	6.82e-01	0
Auditory	Seq2Seq	TF-IDF	-0.56	5.81e-01	7.74e-01	0
Auditory	XLNet	Bag Of Words	0.00	1.00e+00	1.00e+00	0
Auditory	XLNet	Seq2Seq	0.98	3.33e-01	6.82e-01	0
Auditory	XLNet	TF-IDF	0.52	6.07e-01	7.85e-01	0
Language	Bag Of Words	TF-IDF	1.64	1.10e-01	3.29e-01	0
Language	CodeBERTa	Bag Of Words	0.63	5.35e-01	7.72e-01	0
Language	CodeBERTa	CodeTransformer	0.54	5.90e-01	7.74e-01	0
Language	CodeBERTa	Seq2Seq	2.82	7.17e-03	1.15e-01	0
Language	CodeBERTa	TF-IDF	2.48	1.70e-02	1.33e-01	0
Language	CodeBERTa	XLNet	1.77	8.27e-02	2.89e-01	0
Language	CodeTransformer	Bag Of Words	0.14	8.89e-01	9.83e-01	0
Language	CodeTransformer	Seq2Seq	2.40	2.06e-02	1.33e-01	0
Language	CodeTransformer	TF-IDF	2.02	4.91e-02	2.37e-01	0
Language	CodeTransformer	XLNet	1.35	1.83e-01	4.81e-01	0
Language	Random Embedding	Bag Of Words	-1.28	2.09e-01	5.32e-01	0
Language	Random Embedding	CodeBERTa	-2.05	4.61e-02	2.37e-01	0
Language	Random Embedding	CodeTransformer	-1.59	1.20e-01	3.47e-01	0
Language	Random Embedding	Seq2Seq	0.85	4.02e-01	7.03e-01	0
Language	Random Embedding	TF-IDF	0.34	7.33e-01	9.19e-01	0
Language	Random Embedding	XLNet	0.00	1.00e+00	1.00e+00	0
Language	Seq2Seq	Bag Of Words	-2.01	5.08e-02	2.37e-01	0
Language	Seq2Seq	TF-IDF	-0.56	5.77e-01	7.74e-01	0
Language	XLNet	Bag Of Words	-1.12	2.69e-01	6.46e-01	0
Language	XLNet	Seq2Seq	0.72	4.75e-01	7.40e-01	0
Language	XLNet	TF-IDF	0.29	7.76e-01	9.45e-01	0
MD	Bag Of Words	TF-IDF	0.88	3.81e-01	6.82e-01	0
MD	CodeBERTa	Bag Of Words	1.84	7.18e-02	2.87e-01	0
MD	CodeBERTa	CodeTransformer	0.74	4.61e-01	7.40e-01	0
MD	CodeBERTa	Seq2Seq	2.60	1.27e-02	1.28e-01	0
MD	CodeBERTa	TF-IDF	2.77	8.21e-03	1.15e-01	0
MD	CodeBERTa	XLNet	2.25	2.95e-02	1.77e-01	0
MD	CodeTransformer	Bag Of Words	0.90	3.71e-01	6.82e-01	0
MD	CodeTransformer	Seq2Seq	1.68	1.00e-01	3.11e-01	0
MD	CodeTransformer	TF-IDF	1.69	9.84e-02	3.11e-01	0
MD	CodeTransformer	XLNet	1.40	1.67e-01	4.53e-01	0
MD	Random Embedding	Bag Of Words	-1.81	7.67e-02	2.89e-01	0
MD	Random Embedding	CodeTransformer	-2.46	1.81e-02	1.33e-01	0
MD	Random Embedding	Seq2Seq	-0.70	4.86e-01	7.40e-01	0
MD	Random Embedding	TF-IDF	-1.05	2.99e-01	6.82e-01	0
MD	Random Embedding	XLNet	-0.89	3.76e-01	6.82e-01	0
MD	Seq2Seq	Bag Of Words	-0.95	3.45e-01	6.82e-01	0
MD	Seq2Seq	TF-IDF	-0.21	8.35e-01	9.48e-01	0
MD	XLNet	Bag Of Words	-0.67	5.05e-01	7.44e-01	0
MD	XLNet	Seq2Seq	0.21	8.31e-01	9.48e-01	0
MD	XLNet	TF-IDF	0.04	9.65e-01	1.00e+00	0
Visual	Bag Of Words	TF-IDF	0.55	5.84e-01	7.74e-01	0
Visual	CodeBERTa	Bag Of Words	2.43	1.94e-02	1.33e-01	0
Visual	CodeBERTa	CodeTransformer	1.86	6.97e-02	2.87e-01	0
Visual	CodeBERTa	XLNet	2.56	1.38e-02	1.28e-01	0
Visual	CodeTransformer	Bag Of Words	0.89	3.80e-01	6.82e-01	0
Visual	CodeTransformer	TF-IDF	1.79	8.08e-02	2.89e-01	0
Visual	CodeTransformer	XLNet	0.93	3.57e-01	6.82e-01	0
Visual	Random Embedding	Bag Of Words	0.05	9.58e-01	1.00e+00	0
Visual	Random Embedding	CodeBERTa	-2.67	1.04e-02	1.25e-01	0
Visual	Random Embedding	CodeTransformer	-0.95	3.48e-01	6.82e-01	0
Visual	Random Embedding	Seq2Seq	2.11	4.07e-02	2.28e-01	0
Visual	Random Embedding	TF-IDF	0.70	4.87e-01	7.40e-01	0
Visual	Random Embedding	XLNet	0.04	9.70e-01	1.00e+00	0
Visual	Seq2Seq	Bag Of Words	-1.76	8.74e-02	2.94e-01	0
Visual	Seq2Seq	TF-IDF	-1.55	1.29e-01	3.60e-01	0
Visual	XLNet	Bag Of Words	0.02	9.86e-01	1.00e+00	0
Visual	XLNet	Seq2Seq	1.92	6.20e-02	2.74e-01	0
Visual	XLNet	TF-IDF	0.61	5.42e-01	7.72e-01	0

Table 11: Results from pairwise t-tests of code models for each brain region. $+t$ reflects $A > B$, whereas $-t$ reflects $A < B$.

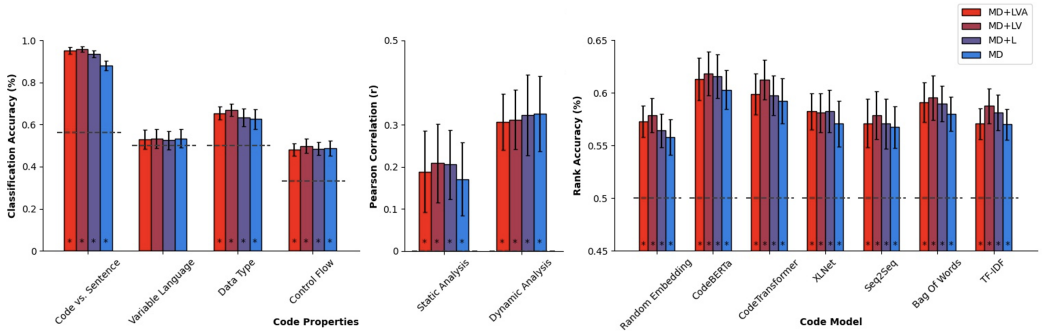

Figure 8: In the supplemental ablation study, we investigate the extent to which merging brain regions improves their performance on decoding code properties and code models. Error bars represent 95% confidence interval of individual subject scores. Dotted lines signify the empirical baseline from a null permutation distribution on shuffled labels. Statistically significant results are denoted with a $*$, marked at the base of the bars.

F Ablation Study: Scores and Significance

In order to investigate whether each of the brain regions included contribute unique variance towards the decoding tasks, we combine brain representations from different regions in various combinations and observe changes in downstream decoding performance across all experiments. We find that the addition of the Language system representations to the MD system baseline leads to a significant increase in decoding performance of *code vs sentences* (two-sample t-test; $t = 3.83$; $p < 0.05$), and numerical increases for *static analysis*, whereas the subsequent addition of the Visual system leads to a numerical increase in *data type* decoding. These data suggest that the MD system and Language system represent unique variance related to the *code vs sentences* property, although we cannot conclude significance of other effects from the current data.

Brain Representation Code Properties	Empirical Baseline	MD	MD+L	MD+LV	MD+LVA
Code vs. Sentence	0.56	0.88 (+0.32)	0.94 (+0.38)	0.96 (+0.40)	0.95 (+0.39)
Control Flow	0.33	0.49 (+0.16)	0.49 (+0.16)	0.50 (+0.17)	0.48 (+0.15)
Data Type	0.50	0.63 (+0.13)	0.63 (+0.13)	0.67 (+0.17)	0.65 (+0.15)
Variable Language	0.50	0.53 (+0.03)	0.53 (+0.03)	0.53 (+0.03)	0.53 (+0.03)

Table 12: Ablation analysis on original Ivanova et al. (2020) code properties. Scores represent classification accuracy and are contrasted with an empirical baseline from the null permutation analysis. Values in parentheses are units above baseline.

Brain Representation Code Properties	MD	MD+L	MD+LV	MD+LVA
Static Analysis	0.17	0.21	0.21	0.19
Dynamic Analysis	0.33	0.32	0.31	0.31

Table 13: Ablation analysis on static and dynamic code properties. Scores represent Pearson correlation between predicted and true code properties.

Brain Representation Code Models	Empirical Baseline	MD	MD+L	MD+LV	MD+LVA
Random Embedding	0.50	0.56 (+0.06)	0.56 (+0.06)	0.58 (+0.08)	0.57 (+0.07)
Bag Of Words	0.50	0.58 (+0.08)	0.59 (+0.09)	0.60 (+0.10)	0.59 (+0.09)
TF-IDF	0.50	0.57 (+0.07)	0.58 (+0.08)	0.59 (+0.09)	0.57 (+0.07)
Seq2Seq	0.50	0.57 (+0.07)	0.57 (+0.07)	0.58 (+0.08)	0.57 (+0.07)
XLNet	0.50	0.57 (+0.07)	0.58 (+0.08)	0.58 (+0.08)	0.58 (+0.08)
CodeTransformer	0.50	0.59 (+0.09)	0.60 (+0.10)	0.61 (+0.11)	0.60 (+0.10)
CodeBERTa	0.50	0.60 (+0.10)	0.62 (+0.12)	0.62 (+0.12)	0.61 (+0.11)

Table 14: Ablation analysis on code model mappings. Scores represent rank accuracy and are contrasted with an empirical baseline from the null permutation analysis. Values in parentheses are units above baseline.

Code Property	Brain Region A	Brain Region B	t	p	p (corrected)	Is Significant?
Code vs. Sentence	MD+L	MD	3.83	4.33e-04	5.20e-03	1
Code vs. Sentence	MD+LV	MD	5.71	1.62e-06	5.84e-05	1
Code vs. Sentence	MD+LVA	MD	4.99	1.12e-05	2.02e-04	1
Code vs. Sentence	MD+LV	MD+L	2.15	3.67e-02	3.31e-01	0
Code vs. Sentence	MD+LVA	MD+L	1.50	1.41e-01	8.48e-01	0
Code vs. Sentence	MD+LVA	MD+LV	-0.49	6.29e-01	9.79e-01	0
Control Flow	MD+L	MD	-0.11	9.16e-01	9.79e-01	0
Control Flow	MD+LV	MD	0.40	6.90e-01	9.79e-01	0
Control Flow	MD+LV	MD+L	0.55	5.87e-01	9.79e-01	0
Control Flow	MD+LVA	MD	-0.28	7.77e-01	9.79e-01	0
Control Flow	MD+LVA	MD+L	-0.20	8.45e-01	9.79e-01	0
Control Flow	MD+LVA	MD+LV	-0.73	4.66e-01	9.79e-01	0
Data Type	MD+L	MD	0.24	8.11e-01	9.79e-01	0
Data Type	MD+LV	MD	1.51	1.40e-01	8.48e-01	0
Data Type	MD+LV	MD+L	1.36	1.80e-01	9.26e-01	0
Data Type	MD+LVA	MD	0.98	3.33e-01	9.79e-01	0
Data Type	MD+LVA	MD+L	0.78	4.37e-01	9.79e-01	0
Data Type	MD+LVA	MD+LV	-0.68	5.02e-01	9.79e-01	0
Dynamic Analysis	MD+L	MD	-0.05	9.63e-01	9.79e-01	0
Dynamic Analysis	MD+LV	MD	-0.24	8.11e-01	9.79e-01	0
Dynamic Analysis	MD+LV	MD+L	-0.18	8.59e-01	9.79e-01	0
Dynamic Analysis	MD+LVA	MD	-0.33	7.40e-01	9.79e-01	0
Dynamic Analysis	MD+LVA	MD+L	-0.27	7.92e-01	9.79e-01	0
Dynamic Analysis	MD+LVA	MD+LV	-0.10	9.21e-01	9.79e-01	0
Static Analysis	MD+L	MD	0.57	5.68e-01	9.79e-01	0
Static Analysis	MD+LV	MD	0.58	5.63e-01	9.79e-01	0
Static Analysis	MD+LV	MD+L	0.05	9.63e-01	9.79e-01	0
Static Analysis	MD+LVA	MD	0.27	7.88e-01	9.79e-01	0
Static Analysis	MD+LVA	MD+L	-0.26	7.94e-01	9.79e-01	0
Static Analysis	MD+LVA	MD+LV	-0.29	7.72e-01	9.79e-01	0
Variable Language	MD+L	MD	-0.27	7.86e-01	9.79e-01	0
Variable Language	MD+LV	MD	-0.03	9.79e-01	9.79e-01	0
Variable Language	MD+LV	MD+L	0.24	8.11e-01	9.79e-01	0
Variable Language	MD+LVA	MD	-0.13	8.94e-01	9.79e-01	0
Variable Language	MD+LVA	MD+L	0.13	8.94e-01	9.79e-01	0
Variable Language	MD+LVA	MD+LV	-0.10	9.17e-01	9.79e-01	0

Table 15: Results from pairwise t-tests of brain regions for each code property. $+t$ reflects $A > B$, whereas $-t$ reflects $A < B$.

G ALL CODE PROPERTIES: SCORES AND CORRELATIONS

We analyzed a series of code properties as part of the static and dynamic code analysis. As several of these properties (*token count*, *node count*, *Halstead difficulty*, *cyclomatic complexity*, and *bytecode ops*) were revealed to be highly correlated in a post-hoc analysis, we report only one measure for this subset in Experiment 1, *token count*, but include all scores here for completeness (Table 16). We also report the correlation matrix between all code properties that led us to select *token count* as the representative property for this subset (Table 17).

Brain Representation Code Properties	MD	Language	Visual	Auditory
Token Count	0.17	0.24	0.09	0.00
Node Count	0.12	0.20	0.03	0.01
Halstead Difficulty	0.11	0.17	0.10	-0.01
Cyclomatic Complexity	0.18	0.24	0.10	0.01
Bytecode Operations	0.15	0.18	0.03	0.02
Runtime Steps	0.33	0.20	0.17	0.12

Table 16: Brain region decoding performance on all *static analysis* and *dynamic analysis* code properties. Scores represent Pearson correlation between predicted and true code properties.

	Datatype	Conditional	Iteration	Tokens	Nodes	Halstead	Cyclomatic	Runtime	Bytecode
Datatype	1.00	0.00	0.00	0.41	0.33	0.39	0.18	0.13	0.28
Conditional	-	1.00	-0.50	0.44	0.46	0.50	0.61	-0.41	0.49
Iteration	-	-	1.00	-0.10	-0.14	-0.35	-0.09	0.90	0.01
Tokens	-	-	-	1.00	0.97	0.89	0.80	0.08	0.95
Nodes	-	-	-	-	1.00	0.86	0.79	0.00	0.96
Halstead	-	-	-	-	-	1.00	0.74	-0.17	0.80
Cyclomatic	-	-	-	-	-	-	1.00	0.02	0.84
Runtime	-	-	-	-	-	-	-	1.00	0.13
Bytecode	-	-	-	-	-	-	-	-	1.00

Table 17: Correlation matrix across all code properties. The *control flow* property was split into two binary properties here, *conditional* and *iteration*. Of relevance is that *token count* presents with $r > 0.8$ for all *static analysis* properties in the set and as such is used as the representative *static analysis* code property in Experiment 1.