Abstract

Forming and interpreting abstraction is a core process in human communication. In particular, when giving and performing complex instructions stated in natural language (NL), people may naturally evoke abstract constructs such as objects, loops, conditions and functions to convey their intentions in an efficient and precise way. Yet, interpreting and grounding abstraction stated in NL has not been systematically studied in NLP/AI. To elicit naturally-occurring abstractions in NL we develop the HEXAGONS referential game, where players describe increasingly complex images on a two-dimensional HEXAGONS board, and other players need to follow these instructions to recreate the images. Using this game we collected the HEXAGONS dataset, which consists of 164 images and over 3000 naturally-occurring instructions, rich with diverse abstractions. Results of our baseline models on an instruction-to-execution task derived from the HEXAGONS dataset confirm that higher-level abstractions in NL are indeed more challenging for current systems to process. Thus, this dataset exposes a new and challenging dimension for grounded semantic parsing, and we propose it for the community as a future benchmark to explore more sophisticated and high-level communication within NLP applications.

1 Introduction

When humans provide or follow complex instructions in situated environments, they often evoke abstraction, which is defined in the broader sense of human cognition as the reference to a set of elements all at once, by appealing to a shared property and discarding irrelevant distinctions (Wing, 2011). To illustrate, Table 1 presents instructions to draw an image, involving various cases of abstraction. For instance, to express the condition in step 4, the user has to ignore irrelevant properties such as location and capture all target tiles as centers of flowers. On the other hand, she has to focus attention on a property that does matter, the color, to define a partition of the set. Thus, emerging objects, loops, conditions and functions in NL are all abstract structures that humans evoke in their thought process, in order to convey their intentions effectively and efficiently.

Table 1: Grounded Instructions in HEXAGONS. On the left are four instructions for drawing the target (bottom-right) image, paired with their grounding on the HEXAGONS board on the right. Italics mark expressions of abstraction.
So, understanding and interpreting human-generated abstractions is a core capability that would be needed for systems that attempt to follow non-trivial human instructions. However, detecting and grounding such abstractions has not yet been systematically studied in NLP/AI. Previous studies in grounded semantic parsing commonly use situated collaborative scenarios where two players engage in a referential game, in order to elicit challenging instructions for systems to process (e.g., Jayannavar et al., 2020; Bisk et al., 2016a,b; Long et al., 2016; Wang et al., 2016, 2017). While they all successfully elicit linguistically interesting instructions, they do not purposefully aim to control for the existence of abstraction or different levels thereof.

In this work we introduce the HEXAGONS game and a respective dataset, which are aimed at studying abstraction informally stated in NL, and its grounding to the concrete elements that are referred to. HEXAGONS is a two-player referential game in which a player describes the construction process of increasingly complex figures on a two-dimensional board, and another player needs to reconstruct the image on her empty board. Table 1 shows an example of a 4-step drawing procedure where all steps refer to an emerging object (a flower), the first three steps include three iterations (loops), and the final step states a condition.

Using HEXAGONS we collected human instructions rich with abstract constructs (objects, loops, conditions, functions, etc.), coupled with their grounded executional semantics in a concrete visual world. The HEXAGONS dataset we deliver comprises 164 images and over 3000 naturally-provided instructions, exposing a new and exciting dimension of natural language understanding. Our experiments on an instruction-to-execution task we devise based on the HEXAGONS dataset confirm that, for models based on contextualized embeddings of the instructions, utterances with higher-level abstractions are indeed harder to process. We thus offer HEXAGONS as a new and novel benchmark for grounded semantic parsing.

Our contribution is then manifold. First, we propose abstraction in natural language as a critical challenge in grounded semantic parsing, and deliver a game and dataset reflecting the variety of ways abstraction is expressed in NL. Second, we deliver an abstraction elicitation methodology geared towards eliciting a variety of abstract structures as loops, conditions, and functions expressed by novices, via a setting of a situated collaborative game. Finally, we present strong baseline results on an instruction-to-execution task we derived from our data, setting the stage for further investigation of abstractions and towards the development of natural yet precise and efficient interfaces for human-computer interaction.

2 The Challenge: Abstraction in NL

In order to deliver complex instructions in efficient and precise ways, human speakers often employ various levels of abstraction. To illustrate, consider the image in Figure 1(a). Imagine you are given the task to instruct a remote friend who cannot see your board, how to draw this specific image on her empty HEXAGONS board, Figure 1(b).

Table 2 presents four different ways of stating the requested procedure. The first is a tile-by-tile procedure, which consists of 7 steps, each specifying the position and color of the different tiles. In the second procedure, which we call a scanning approach, each instruction specifies the actions to be performed on a single column. The third procedure, which we refer to as iteration (or, loop) provides a condition, and then an action to be performed on a set of tiles meeting a given criterion. Finally, the fourth procedure uses an objectifying idea.

All but the first approach employ different levels of abstraction, defined by Wing (2011) to be the “focusing on essential properties common to several instances, while hiding irrelevant distinctions”. When comparing the first drawing procedure to the latter three, it is easy to see that the different levels of abstraction support a more efficient and precise expression of the procedure than

1The reader is encouraged to perform this short exercise herself before reading further.
Table 2: Illustration of Levels of Abstractions. Providing natural language instructions for the task in Figure 1 with varying levels of abstraction.

1. In the leftmost column, paint from the top: white, red, red
2. In the second column from the left, paint from the top: red, yellow, red
3. In the third column from the left, paint from the top: white, red, red

1. Paint a red circle with a yellow center in the second tile from top in the second column from left.

3 The Proposed Methodology

The challenge of eliciting formal structures that naturally emerge in human language by non CS-trained speakers is genuine. Non CS-trained speakers are not familiar with the concepts of ‘control structures’ or ‘function application’ — at least not in their formal sense — so we cannot simply instruct them to include the three aforementioned levels of abstraction in their narratives.

Of course, one can explicitly train untrained workers, or even employ CS-trained experts, for eliciting such narratives. However, beyond the prohibitive cost, this also beats the initial purpose we set out to achieve. We want to elicit natural language that reflects authentic thinking, one that spontaneously emerges in day-to-day language of any speaker. Furthermore, we want the resulting trained models to be applicable to any native speaker who intuitively resorts to abstractions (cf. Table 2) when interacting with others. So, we cannot explicitly request to employ abstract structures from untrained workers, but explicitly training them will undermine the naturalness of expressions and applicability of our data. How can we break out of this loop?

Here we propose a solution inspired by the vast research in human learning and STEM education, on cultivating (and thus eliciting) higher-order computational thinking (CT) (Cuny et al., 2010; Shute et al., 2017). This is done through careful task design and the development of instruments that probe and assess humans’ CT skills (Ructtinger and Stevens, 2017; Basu et al., 2021; Relkin and Bers, 2019). Concretely, our elicitation methodology extends a recent trend in grounded semantic parsing, where players engage with a referential game (situated collaborative scenarios in terms of Jayannavar et al. (2020)) where an Instructor provides instructions that should be grounded and executed in a (simulated) world (Jayannavar et al., 2020; Bisk et al., 2016a; Kim et al., 2019; Long et al., 2016). Here, our task stimuli is carefully crafted to necessitate resorting to abstraction without actually requesting to do so.

The remainder of this Section elaborates on the virtual environment we design, the game we define, and the task stimuli designed for elicitation.

The Hexagons App In order to collect algorithmic descriptions which express diverse types of abstractions stated in Section 2, we design
an online visual drawing app that enables users to construct increasingly complex structures on a HEXAGONS board — a two-dimensional board paved with hexagonal tiles (Figure 2). The HEXAGONS board contains 18 columns and 10 rows,\(^2\) and the HEXAGONS app UI provides a drawing interface in which a user may paint tiles using a palette of eight colors (Figure 2). The HEXAGONS app implementation assumes a single primitive action that corresponds to the two-place predicate \(\text{paint}(\text{position}, \text{color})\), which specifies a color for each of the 180 hexagon tiles.

**The HEXAGONS Game** In order to elicit NL descriptions that contain abstract structures, we augmented the app with a so-called referential game, where a human agent is asked to describe the construction process of a given image (e.g., Figure 4) to a different user of the app, who has access to a similar but blank HEXAGONS board.

The game has two different modes. The first mode is called **Description** (Figure 3(a)), where a user is given an image from a pre-defined pool and has to provide instructions in natural language for how to construct the image. Every linebreak in the textual description initiates a new instruction. The second mode is called **Execution** (Figure 3(b)), where a user accepts a sequence of instructions and needs to execute them one by one to reconstruct the described image on the board.

We refer to each pair of instruction and its corresponding execution as a **drawing step**. We call the sequence of drawing steps composing the full image a **drawing procedure**.

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\(^2\)In determining the dimensions of the board we sought to find a trade-off between competing requirements: making the board large enough to enable images that stimulate abstract structures, but not too big so the data can be collected in reasonable time. We chose 18 as the long dimension as it has many divisors, which enables drawing repetitive patterns. For the shorter dimension, 12 is also divisible by many numbers but made the board too large, so we settled for 10.

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**The Image Gallery** To instantiate the game, we design images for the HEXAGONS board based on several principles: The images should be abstract rather than figurative; Their description should evoke diverse abstract structures; The images further compose different kinds of abstract structures; and the images are designed in increasing levels of complexity.

To design images that meet these criteria we first define categories of abstract structures and then design images that directly stimulate users to employ them when aiming for efficient and precise descriptions. Figure 4 illustrates representative images for the different categories, with Table 3 specifying the number of images for each category. In what follows we briefly elaborate how the design (the ‘form’) of the images evokes the abstract structure (the ‘function’) that we target.

- **Bounded Iterations.** To elicit bounded iterations (‘for’ loops) we design images that manifest replication of objects. To achieve a **bounded** iteration, we ensured that the replication is of identical objects. Figure 4(a) shows a replication of a flower 12 times.

- **Conditional Iterations.** To elicit conditional iterations (‘while’ loops), we again use a replication of objects. However, here the replicated objects are not identical, and meet a certain condition. In Figure 4(b) the lines differ in length and to replicate them one should use some condition, e.g., extend the lines out **up to the boundaries of the board**.

- **Conditional Statements.** To evoke conditional statements we design more than one variant of an object, so using a condition will enable users to capture all variants at once. (Particularly, we found randomization as a useful trait to evoke conditional statements which are not loops.) Figure 4(c) shows a replication of two variants of the same object (a line). Since the variants are not replicated periodically but randomly, simple repetition will not suffice. However, noticing that the red and blue ‘tops’ go with the green and yellow ‘tails’ respectively, enables a user to achieve an economic description using a condition on the ‘top’ tiles.
Figure 3: HEXAGONS’ Modes: (a) The **Description** Mode, and (b) The **Execution** Mode.

![Image](image1.png)

![Image](image2.png)

Figure 4: The HEXAGONS Image Gallery: Sample Images.

(a) ![Image](image3.png) (b) ![Image](image4.png) (c) ![Image](image5.png) (d) ![Image](image6.png) (e) ![Image](image7.png) (f) ![Image](image8.png)

| Category              | No. |
|-----------------------|-----|
| Simple                | 6   |
| Bounded Iteration     | 23  |
| Conditional Iteration | 23  |
| Conditional Statement | 12  |
| Objects               | 7   |
| Recursion             | 12  |
| Symmetry              | 12  |
| Other                 | 6   |
| **Total**             | **101** |

Table 3: Image Gallery Statistics.

- **Objects.** Objects are used throughout the images (see above), where *objectivizing* in our context generally means referring to a collection of elements, by means of the topographic form they make (line, circle, triangle, etc).

- **Functions.** To elicit functions and their application we replicate objects in different colors or on different positions, to encourage defining a ‘block’ and applying it to different parameters. In Figures 4(d,e) we illustrate a unique class of visual functions, of *symmetrical* operations, and particularly reflection and rotation, respectively.

- **Recursion.** Another type of functions relates to a computational aspect of the tasks (rather than a visual one such as symmetry) and it is a construct fundamental to algorithms — recursion. It is challenging to evoke this kind of abstraction and we tackled it in three ways: in describing images with growing patterns, spirals, and objects with self-similarity, e.g., fractals (Figure 4(f)).

Note that while the association between images and targeted abstract structures has been defined *apriori*, users can also use low-level (non-abstract) description or use a different set of abstractions to achieve the same result. Following Grice (1975) we assume that users will aim to be efficient (*economic*) in their descriptions, and are thus likely (but are not explicitly told) to employ these levels of abstraction.

4 The Hexagons Dataset

4.1 Data Collection

Using the methodology of controlled crowdsourcing (Roit et al., 2020), we employed English-speaking Amazon Mechanical Turk (MTurk) workers to collect drawing instructions for the images we designed. The collection is based on a two phased process of **Collection** and **Verification**, specified as follows:

(i) The **Collection** phase:

- First, an MTurk worker (henceforth, the **Instructor**) writes instructions for drawing a given image, step by step, via the **Description** mode of HEXAGONS. During this phase Instructors were encouraged to write their instructions **efficiently**, in order to avoid tiresome repetitions of the primitive action.
Then, the Instructor enters an alignment phase, executed through the Execution mode of HEXAGONS. For each specific instruction the Instructor illustrates its respective execution on the board. The alignment phase is used for revealing the intentions of the Instructor.

The result of this two-step process is a drawing procedure for each image.

(ii) The Verification phase. Each drawing procedure from the Collection phase is given to two other MTurk workers (henceforth, Executors) for verification. The Executors do not have access to the original images, and their task is to execute the instructions step by step via the HEXAGONS’ Execution mode. This phase is intended to reveal faulty instructions and to ensure the quality (and executability) of the collected procedures.

Having established the two fundamental phases of the data collection, the collection process itself consisted of four stages: Pilot, Recruitment, and two rounds of Data Collection. In the pilot we aimed to check the flow, clarity and feasibility of the data collection. Following the pilot we held two different recruitment rounds for recruiting Executors and Instructors. All in all, we recruited two (disjoint) sets of 24 Instructors and 15 Executors. Detailed explanations about the Pilot and Recruitment stages are given in Appendix A.

Data Collection In the collection stage we used all 101 images from our image gallery (Table 3). Each image is given to three Instructors to devise their drawing procedures, and each drawing procedure is given to two Executors for Verification.

Next, in order to extend the pool of images with interesting compositions, we offered Instructors with the opportunity to draw new images on a blank HEXAGONS board, keeping in mind the rationale of the task as they understood it. The pool of collected images reflect similar rationale to our own images set (Figure 5(a-c)) yet demonstrating more complex interactions between structures and patterns (Figure 5(d-f)), with both abstract and figurative images, (Figure 5(g-i)).

Drawing procedures in which Instructors did not reconstruct correctly the target image were either discarded or slightly fixed if possible, before moving on to the Verification phase. See Appendix B for further elaboration.

We repeated the data collection once more with the new image set, aiming that at least one of the three drawing procedures for each image will be written by that image’s maker, in order to purposefully elicit the kind of abstractions the maker intended when creating the image.

Annotation Costs We used Amazon Mechanical Turk (MTurk) to recruit English-speaking workers for this study. Participants in the Data Collection rounds were paid higher rates than the Pilot and Recruitment stages. The payments for both Data Collection rounds were $1.5 and $0.5 for Instructors and Executors HITs, respectively.

4.2 Quantitative Analysis

To empirically evaluate the dataset quality we first have to formally define appropriate evaluation metrics for comparing different executions of each drawing step (as it is defined in Section 3).

Board-Based Metrics Let us define a tile-state as a triplet \( t = (\text{column}, \text{row}, \text{color}) \). We define a drawing step as a pair, \( s_i = (u_i, b_i) \) where \( u_i \) is an instruction utterance and \( b_i = (t_{i1}, t_{i20}) \) is the state of the board resulting from executing \( u_i \). Now, let us define a function \( \text{painted}(b) \) which selects only the colored (non-white) tiles on a board \( b \). Then, for two states of the board \( b \) and \( b' \), where

\[ 1 \text{Drawing procedures in which Instructors did not reconstruct correctly the target image were either discarded or slightly fixed if possible, before moving on to the Verification phase. See Appendix B for further elaboration.} \]

\[ 2 \text{We never rejected results or blocked workers. Rather, we used carefully designed qualifications as part of our controlled data collection methodology (Section 4.1).} \]
$b$ and $b'$ are considered gold and hypothesis respectively, we define Precision, Recall as follows, with F1 their harmonic means as usual.

\[
\text{Precision}(b, b') = \frac{\text{painted}(b) \cap \text{painted}(b')}{\text{painted}(b')}
\]

\[
\text{Recall}(b, b') = \frac{\text{painted}(b) \cap \text{painted}(b')}{\text{painted}(b)}
\]

**Action-Based Metrics** Instead of evaluating the entire board state after each execution, we may want to evaluate only the specific tiles that were changed at a given drawing step. Formally, we wish to evaluate the instruction’s denotation. So, we can instead define a function $\text{action}(b)$ which selects only the tiles on the board state $b$ that were changed in that particular drawing step. Thus, for two states of the board $b$ and $b'$, (where $b, b'$ are again gold and hypothesis respectively) we define Precision and Recall, with F1 as usual.

\[
\text{Precision}(b, b') = \frac{\text{action}(b) \cap \text{action}(b')}{\text{action}(b')}
\]

\[
\text{Recall}(b, b') = \frac{\text{action}(b) \cap \text{action}(b')}{\text{action}(b)}
\]

The difference between Board-Based and Action-Based evaluation for a single state-transition of the board is illustrated in Figure 6.

**Aggregating Scores** For assessing the dataset quality, we compare for any utterance $u$ the board states (or actions) of the Instructor (gold) to that of an Executor (hypothesis). We report F1-Score and Exact Match (EM) (on either the complete board or the actions set) where EM is, naturally, a lot more restrictive.

We report the Macro-Average F1 and EM over the entire dataset, and also the Macro-Min/Macro-Max F1 and EM scores, by taking into account only the higher/lower scoring Executor (respectively) for each step in a drawing procedure.

Table 4 shows the evaluation of Executors compared against the Instructor of a given drawing procedure. For calculating these metrics, each Executor has its own datapoint compared against the drawing procedure.

To ensure the quality of the dataset we detected errors in the drawing procedures and manually fixed them. That quality assurance process results in a data wherein for each drawing procedure we have perfect gold execution. Appendix B provides a comprehensive description of error types and the data-cleaning process.

### 4.3 Qualitative Analysis

Our finalized dataset is then the collection of all drawing procedures, composed of instructions and their aligned executions collected in both rounds, after having passed our quality assurance process and error correction (as described in Appendix B). Tables 5 and 6 show the size of the dataset and its overall statistics.

Table 7 illustrates the types of abstract structures we were able to elicit in accordance with the categories we defined apriori (reflected in Table 3). Figures 7 and 8 are two detailed examples of drawing procedures that illustrate different levels of abstraction expressed with regard to a single target image.\(^5\)

To understand better the distribution of elicited structures, we sampled 24 drawing procedures, with a total of 194 drawing steps, while preserving the internal proportion between image categories (Table 3) and between both data collections rounds (Section 4.1). We manually categorized utterances according to abstract, linguistic and spatial phenomena observed in the NL utterances. Table 8 then summarizes the distribution of these phenomena in our sample.

\[^5\]See Appendix C for more examples illustrating the variety of abstractions for different images and categories.
Table 5: Dataset Volume.

| Collection | # Images | # Drawing Procedures |
|------------|----------|----------------------|
| Collection 1 | 101 | 304 |
| Collection 2 | 63 | 193 |
| **Total** | **164** | **497** |

| # Drawing steps | 3135 |
| # Tokens | 70,200 |
| Avg. length of drawing procedures (by number of drawing steps) | 6.31 |
| Avg. length of drawing procedures (by number of tokens) | 141.2 |
| Avg. length of drawing steps (by number of tokens) | 22.4 |

Table 6: Dataset Properties.

Noticably, abstract structures are found in about half of the steps (49%) and in most drawing procedures (92%). We will take this as an estimate of the occurrence of abstract structures in the entire dataset. The other linguistic and spatial phenomena we categorized are also found in abundance in this sample.

This sample shows that our dataset is rich in the desired phenomena: Instructors abundantly use objects, control structures and functions, such as those illustrated in Table 7 and in Appendix C. Instructors make use of spatial references, such as “Go diagonally down”, “going leftwards”, “leave the lower-left hex white”, and “Use the end of the green line just drawn”. We also noticed linguistic phenomena such as anaphora/coreference, e.g., “below the original”, “the spot above that”, ellipsis, e.g., “fill ... the next green”, “Paint the ... tiles below blue.” and superlatives / comparatives, e.g., “bottom-most tiles”, “lower-left”.

Interestingly, Instructors sometimes use a Goal or Result declaration, meant as an additional step with no action, to help for Executors orient themselves, e.g. “This will create a sort of flower look”, “Create a green circle by filling in the 5th and 6th spots ... [the rest of the instructions provide the details]”. Similar spatial and linguistic phenomena are found in datasets collected in the context of referential-games as in Long et al. (2016); Bisk et al. (2016a, 2018). Here we also provide an estimation of their quantity. To the best of our knowledge, the ‘Goal/Result declaration’ category was not reported for similar settings.6

6Though hinted in datasets reporting NL navigation tasks (e.g., ‘Verification’ in Paz-Argaman and Tsarfaty (2019)).

5 Experiments

5.1 Setting

Task Setup Given the HEXAGONS dataset we deliver, we aim to devise models that mimic the Executor’s role. We model that task as an instruction-to-execution task, that is, given a board state and an instruction, models learn to predict the resulting actions for that step. Concretely, this means predicting which tiles are painted in which colors in the executions of each drawing step.

Splits We created two types of train/dev/test splits with an 80/10/10 ratio of the drawing procedures: A random split and a hard split, where the latter does not contain any image overlap.
Abstract structure  | Examples
--- | ---
Bounded Iterations | “Make four more caterpillars below the original leaving an empty space between each caterpillar.”
Conditional Iterations | “Repeat this pattern until you run out of room on grid.”
Conditional Statements | “Directly beneath the painted tiles, paint green and yellow vertical columns of five touching tiles, using green below the red tiles and yellow below the blue tiles.”
Objects | “make a blue dog bone shape”
Symmetry | “Reflect the multi-colored triangle you made in the previous two steps symmetrically over the black diagonal.”
Recursion | “Form an X by ... At each corner, ... form 4 smaller X shapes”

Table 7: Abstract Structures Elicitation in The HEXAGONS Dataset.

| General Phenomenon | Type | Count | # Steps | # Drawing Procedures |
|--- | --- | --- | --- | --- |
| Abstraction | Object | 77 | 95 (48.97%) | 22 (91.67%) |
| Control Structures | 61 | 49 |
| Functions | |
| Goal/Result Declaration | Goal | 18 | 33 (17.01%) | 13 (54.17%) |
| Result | 17 |
| Linguistic | Anaphora | 63 | 88 (45.36%) | 15 (62.5%) |
| Ellipsis | 17 |
| Comparative/Superlative | 23 |
| Spatial | 225 | 132 (67.69%) | 23 (95.83%) |

Table 8: Qualitative Analysis. Distribution of the defined phenomena among sample of 24 drawing procedures containing 194 drawing steps.

Figure 8: Higher Level of Abstraction. This drawing procedure was produced to the same target image as Figure 7 but used two steps only. Here, the Instructor demonstrates a higher level of abstraction and actually states in informal way the control structure of iteration.

| Metrics | For evaluation we report the Macro F1 of the predicted actions, compared to the gold actions. Additionally, we report Exact Match, which measures whether the predicted actions for a given drawing procedure match the gold actions completely (see Section 4.2 for the Action-Based Metrics definitions and their aggregation).

5.2 Models

A Naïve Rule-Based Baseline The Naïve baseline model is a deterministic rule-based procedure that is able to detect the basic predicate paint using pattern matching. To do so we defined patterns that reflect paint(position, color) where the position assumes coordinates on a (top-down, left-right) grid, and search for these patterns in the instructions (e.g., Table 9). For example, given the sentence “In the first column, color the 2nd tile blue”, this model extracts the action Paint((2, 1), blue) by detecting the word “column”, the noun “tile”, the numbers (ordinal or cardinal) “first”, “2nd”, and the color name “blue”. In cases we detect column and row but no color, we retain the color used in the previous step. When the Naïve model fails to apply a pattern it predicts no action. This pattern-matching baseline is inline with previous work (Pišl and Mareček, 2017).
Classifier Models. Next, we model the instruction-to-execution task on our HEXAGON board as a classification task, where, given an input instruction, the model predicts 180 action labels, an action for each tile. The set of action labels consists of eight color labels (Section 3) and a “no-action” label. In practice, we decompose the task into 180 sub-tasks where, given a tile position and an instruction as input, we predict the action performed on this tile. We may of course augment the instruction with further context such as: the state of the tile, the state of the board, and previous instructions. In what follows, we elaborate the different modeling choices in our experiments. Figure 9 displays our model’s architecture with its various input variations.

M1: The basic model accepts as input a target tile and an instruction, in order to predict an action on this particular tile. The position of the target tile is represented as two coordinates: a number for the column (counting from the left) and a number for the row position, (counting from the top). The tile-position is concatenated with the instruction and passed through BERT (Devlin et al., 2019), and this is followed by a linear layer with softmax activation on the various possible actions.

M2: This model is the same as M1, but it also contain information about the state of the tile prior to execution. The tile-triplet (position+color) is concatenated with the instruction and passed through BERT (Devlin et al., 2019), followed by a linear layer with softmax activation as before.

M3: This variation is similar to M2 but uses more context in terms of the Board state. The board is represented by the colors of its tiles, with the target tile being marked with special delimiters to designate the position of the target token in the board. In the model, the tile and instruction are concatenated and encoded by BERT like before, and the previous board state is encoded with an MLP. Both the BERT and MLP vectors are fed into the classifier. In M3A we concatenate one previous instruction to the input encoded by BERT.

M4: Inspired by multi-modal studies which propose to encode an image and text in a single-stream transformer model (Li et al., 2019; Alberti et al., 2019; Chen et al., 2020), we implement a single-stream model which concatenates the previous board-state represented as a colors vector with the target-tile position and color, and with the current instruction. This concatenated input is then (contextually) encoded via BERT. Optionally, for M4A, we also concatenate one previous instruction to the single stream.

Sequence Tagging. Instead of predicting an action for each of the 180 tiles individually, we also experiment with a sequence tagging model, which tags a linearized representation of the board. The input to the sequence tagger is the current instruction and the previous board state. Both are encoded separately with a transformer layer and the CLS token of the encoded instruction is concatenated to each contextualized board tile representation. We then sequentially predict an action for each board tile, using CRF decoding.

Hyperparameters We train each model for 20 Epochs, using bert-base-uncased, a batch size of 16, a learning rate of $2 \times 10^{-5}$ and AdamW Optimizer. We report all our results on dev and then confirm on test a select set of the models.

5.3 Results

Table 10 shows the results on our instruction-to-execution task for all models. Note that when predicting an execution using either the previous board state or the previous tile color, we assume gold (oracle) previous state.

The Naïve rule-based model provides a baseline performance of Macro F1-score of 0.23 for the random split, and 0.15 for the hard split. It completely succeeds on just 8-9% of the steps, which means that those steps reflect simple predicate-argument structures of ‘paint’.

| Pattern | Predicate | Utterance | Assignment |
|---------|-----------|-----------|------------|
| Type 1  | NUM1–NOUN–NUM2–column | PAINT((NUM1,NUM2), COLOR) | “Paint the 4th hex from top of the 7th column orange from left.” | NUM1=4, NUM2=7 PAINT ((4,7), orange) |
| Type 2  | NUM1–column–NUM2 | PAINT((NUM2,NUM1), COLOR) | “In the first column, color the 2nd tile blue” | NUM1=1, NUM2=2 PAINT ((2, 1), blue) |
| Type 3  | column–NUM1–NOUN–NUM2 | PAINT((NUM2,NUM1), COLOR) | “In column 3 color tiles 4 and 6 red” | NUM1=3, NUM2=[4,6] PAINT ((4,3), red), PAINT ((6,3), red) |
Table 10: Results for Dev Set. Macro Average of Action-Based F1 and Exact Match scores of the Naïve model and the neural models, shown on the random and the hard splits, for dev.

|                     | Random Split | Hard Split |
|---------------------|--------------|------------|
|                     | F1  | EM  | F1  | EM  |
| Naïve model:        |     |     |     |     |
| Rule-Based          | 0.23| 0.08| 0.15| 0.09|
| Sequence Tagger:    |     |     |     |     |
| with CRF            | 0.29| 0.06| 0.12| 0.02|
| Model 1:            |     |     |     |     |
| No History          | 0.38| 0.27| 0.27| 0.19|
| Model 2:            |     |     |     |     |
| Local History       | 0.41| 0.17| 0.29| 0.17|
| Model 3:            |     |     |     |     |
| Board with MLP      | 0.41| 0.17| 0.28| 0.18|
| Model 3A            |     |     |     |     |
| Board with MLP + 1 Prev. Inst. | 0.41| 0.13| 0.29| 0.15|
| Model 4:            |     |     |     |     |
| Single Stream       | 0.49| 0.20| 0.34| 0.19|
| Model 4A            |     |     |     |     |
| Single Stream + 1 Prev. Inst. | 0.48| 0.17| 0.28| 0.12|

Table 11: Results for Test Set. Macro Average of Action-Based F1 and Exact Match scores of the Naïve model and some of the neural models, shown on the random and the hard splits, for test.

|                     | Random Split | Hard Split |
|---------------------|--------------|------------|
|                     | F1  | EM  | F1  | EM  |
| Naïve model:        |     |     |     |     |
| Rule-Based          | 0.14| 0.10| 0.11| 0.09|
| Model 1:            |     |     |     |     |
| No History          | 0.37| 0.21| 0.28| 0.16|
| Model 2:            |     |     |     |     |
| Local History       | 0.40| 0.21| 0.28| 0.17|
| Model 3:            |     |     |     |     |
| M3                  | 0.44| 0.21| 0.28| 0.19|

The neural baseline models generally outperform the Naïve model. The sequence tagger works worse for our task than the classification models. The results in Table 10 show that adding local (gold) history by including the color of the tile from the previous step helps to slightly improve F1 score, but does not help in creating a more accurate drawing on the board (Exact Match).

Some of the abstract structures and other linguistic phenomena we found in our qualitative analysis (Section 4.3) require additional context in order to properly parse an instruction. For example, in cases that refer to previous instructions, e.g., “Repeat the same pattern you just made...”, it is impossible to know what pattern should be repeated without knowing the previous instruction. Nevertheless, the results show that adding previous instructions does not improve performance and even harms Exact Match. Including more context in the form of previous instructions increases the complexity of the learning task and might require more sophisticated modeling.

The biggest effect on performance is obtained by adding previous context in form of the (gold) previous board state. Encoding the previous board state together with the instruction in a single stream works better than encoding it with an MLP.

In terms of the random versus hard split, we can see that it is harder for the model to generalize with the hard split, as it cannot ‘memorize’ drawing steps from previously seen images. The difference becomes more pronounced when increasing the complexity of the models.

We verify the models’ performance on the test set (Table 11), confirming the main trends on dev (Table 10): The Naïve model’s scores are the lowest, and single stream works best. While the board context helps classification, encoding a previous instruction does not.

We conclude that the classifiers work better than the sequence tagger for this task, and that jointly encoding board states and current instruction leads to the best performance. Yet, the models we present do not successfully interpret higher levels of abstraction. We probe further into this question next, in our error analysis.
5.4 Error Analysis

In this section we analyze the model that achieved the best results, M4. We wish to ask here: what is the level of abstraction M4 succeeds to ground? To answer this question, we first contrast its predictions with those of the Naïve model.

As a threshold for high-scoring drawing steps we choose a F1 score $\geq 0.66$. 12.7% of the Naïve model’s predicted steps are above the threshold, whereas for M4 it is 33.7%. Comparing those steps, M4 got comparable or higher results on 92.7% of the Naïve model’s steps, which indicates that this model succeeds in learning the basic predicate-argument structure of the instructions. This finding is in line with previous works that report on neural models that successfully unpacked the predicate-argument structure of utterances in similar settings (Bisk et al., 2016b).

We next wish to know whether the model succeeds in grounding higher-level abstractions. We manually checked the rest of the high-scoring steps beyond those in which the Naïve model succeeds. Aside from some anecdotal examples, the lion’s share of these steps express basic predicate-argument structures. However, for utterances dissimilar to those the Naïve model detects (Table 9), M4 succeeds to target more diverse compositional expressions of the basic predicate. An anecdotal example for such a higher order abstraction that the model succeeds to unpack is the execution in Figure 10(a), where the model is able to predict actions that form two diagonals starting and stopping at the right points. Also, in Figure 10(b), the model correctly predicts the alternating pattern.

However, in general we can conclude that the best model does not succeed in systematically grasping abstract structures. The execution in Figure 11 shows an example for a requested repetition of a pattern, that breaks when it is applied in a different position. Finally, Figure 12 illustrates the successes and failures of M4 to predict the correct actions in a single step of drawing a flower. Interestingly, while the first part describing the basic predicate is correctly executed, the loop (“all tiles touching it”) and the object (“look like flowers”) does not result in a correct prediction, which in turn means that the model, in actuality, did not manage to draw the aforementioned flower.

So, while our best model takes a step in the right direction, it does not succeed in systematically detecting higher-level abstractions, leaving ample space for advanced modeling for semantic parsing of complex instructions containing abstractions.

![Figure 10: Model M4’s Successful Predictions.](image1)

![Figure 11: Model M4’s Unsuccessful Execution.](image2)

6 Related Work

This work proposes to address the challenge of identifying and grounding abstract structures expressed in informal natural language. Previous studies on grounded semantic parsing are often situated in goal-driven collaborative scenarios between two players, where one gives instructions and the other follows them. The different studies in this space may be distinguished along (at least) three dimensions: the nature of the task assigned to the players, the nature of the communication, and the properties of the language used.

In terms of the task dimension, we distinguish between referential games (e.g., drawings or constructing tasks) (Jayannavar et al., 2020; Bisk et al., 2016b).
Figure 12: Model M4’s Successes and Failures in Predicting Actions. Figure (a) shows the prediction of M4 compared to the gold (b). The Action-Based F1-score is 0.46. The instructions: “On fifth row from right going leftward, vertically, color the second tile from the bottom Blue, all tiles touching it should be Green. This will result in 4 tiles that are circles but look like flowers.” The result of this execution is “a flower” which joins to a bouquet of three flowers constructed in drawing steps prior to that one. Note that while tile 158 is painted correctly, the rest of the "flower" is not. (See Figure 12 for explanations to the was the execution is illustrated here.)

et al., 2016a,b, 2018; Long et al., 2016; Kim et al., 2019; Wang et al., 2017) and navigation tasks (MacMahon et al., 2006; Chen et al., 2019; Suhr et al., 2019; Chevalier-Boisvert et al., 2018; Paz-Argaman and Tsarfaty, 2019; Anderson et al., 1991). In terms of communication dimension, we distinguish one-way communication (e.g., Jayannavar et al., 2020; Bisk et al., 2016a; Paz-Argaman and Tsarfaty, 2019) and two-way (dialogic) communication (e.g., Kim et al., 2019; Haber et al., 2019). Finally, in the terms of the language used, the data can be in natural language (e.g., Jayannavar et al., 2020; Bisk et al., 2016a) or in artificial synthetic languages (e.g., Wang et al., 2017; Chevalier-Boisvert et al., 2018). In this space, our work defines a referential game between two players, with one-way communication, collecting utterances in free and unrestricted natural language.

In navigation tasks, an instruction needs to be executed on a map or image that functions as a world representation (Anderson et al., 1991; Chevalier-Boisvert et al., 2018; Chen et al., 2019; Paz-Argaman and Tsarfaty, 2019; Suhr et al., 2019). The setup of navigation tasks can either resemble a real-world navigation setting (Paz-Argaman and Tsarfaty, 2019; Chen et al., 2019; MacMahon et al., 2006), or it is structured in an interactive setting with participants instructing each other (Anderson et al., 1991; Suhr et al., 2019).

Some navigation tasks use synthetic rather than natural language (Chevalier-Boisvert et al., 2018). Navigation tasks are similar to our setup in that they involve instructions to be grounded in a simulated world, however, abstractions of the kind we target here (iterations, reflections, recursion, etc.) do not typically characterize navigation data.

The instruction-following dataset of SCONE (Long et al., 2016; Guu et al., 2017) uses a setting similar to ours, where instructions map to execution, but rely on controlled single step descriptions, and thus cannot satisfy our desiderata of eliciting abstract structures in NL that reflecting authentic thinking of non CS-trained speakers. CoDraw (Kim et al., 2019), another dataset stemming from a referential-game, does contain natural language, and it is similar to ours in the sense that one is required to draw scenes on an empty canvas. However, the interaction in CoDraw always refers to concrete objects (clip-art objects such as beach ball, table and sun) and barely resorts to abstractions of the kind we are interested in.

The closest studies to ours in this space we defined are Minecraft’s Builder (Jayannavar et al., 2020) and the 2-D and 3-D Blocks Worlds of Bisk et al. (2016a,b) and Bisk et al. (2018). In these studies, the model mimics the Executor’s actions based on natural language, in a settings of referential games that use collaborative construction tasks. Even though instances of abstract structures are occasionally found in these datasets, eliciting them was not the primary goal when creating these datasets. Accordingly, it is not possible to track and systematically study the abstraction detection and the grounding of abstraction by these models. In contrast, our main goal is to address the grounding of abstract structures and we define this challenge methodologically and systematically. We hence employ a simpler setting compared to those used in Minecraft’s Builder and the 3-D Blocks World, one that implements 2-D world with a single primitive predicate, allowing us to focus on the variety of abstractions and control interfering lexical and spatial complexity.

While the 2-D Blocks World (Bisk et al., 2016a,b) also uses a 2-D world it profoundly differs from our work in the methodology and task stimuli designed for elicitation. The images given to users to describe in the 2-D Blocks World are randomly created and the models in Bisk et al. (2016b); Pišl and Mareček (2017) are
designed to unpack the basic predicate-argument structures of the elicited utterances. In contrast, the HEXAGONS dataset relies on a careful image design that elicit the desired structures (Section 3), and indeed, the dataset reflects an abundance and a variety of abstractions (cf. Section 4.3).

Finally, we highlight two previous studies that are particularly related to our work. In the VoxeLurn study (Wang et al., 2017) a community of users is interacting with a computerized executor in order to accomplish constructions in a 3-D blocks world. The community gradually and collaboratively builds increasingly complex and more abstract language from a core programming language via a process called "naturalization". SHRDLURN (Wang et al., 2016) exhibits similar constructions but on an individual effort rather than a community effort. Both of these studies indeed aim to address abstraction, but from an opposite direction to ours; while both of these works assume a strict narrow and synthetic language and build abstractions bottom-up, our work aims to tackle the opposite direction, uncovering abstractions expressed in unrestricted NL and grounding them in an executable formal language in the ‘backend’. Thus, these studies and ours exhibit two orthogonal and complementary ways to address the challenge of processing abstractions in NL, while, to the best of our knowledge, this work is the first to do so in a free-form language.

7 Conclusion and Future Work

The HEXAGONS dataset brings to the fore a new aspect of semantic parsing, namely, the ability to detect and ground abstractions expressed in NL. Firstly, we propose here a novel referential game and a methodology to elicit abstract structures in informal natural language. Disseminating this protocol we hope to encourage further research efforts on purposefully eliciting and detecting abstract structures in other domains, such as navigation tasks and virtual assistants.

Secondly, using the HEXAGONS game and our methodology we collected 497 drawing procedures with over 3000 steps which exhibit a variety of abstract structures (objects, control structures, functions) embedded throughout the instructions. To the best of our knowledge, this is the first dataset to explicitly tackle the abstraction elicitation challenge in a broad context, with a variety of formal structures expressed in NL by non-experts.

Finally, we present strong baselines to tackle the challenge of grounding formal abstract structures stated in informal natural language. Our results on simple BERT-based classification models show that these models succeed in unpacking the transparent predicate-argument structures, but showed only limited evidence of successfully interpreting and executing abstractions. These results support the conjecture that grounding abstract structures is novel, hard, and fundamentally different from the core of semantic parsing nowadays, targeting a higher-level of understanding of the flow of executable scenarios. In future work, we aim to focus on more advanced models for this task.

Our dataset shows that when Instructors engage in HEXAGON they naturally tend to evoke abstract structures in order to communicate more precisely and effectively. Putting it in Dijkstra’s words: “The purpose of abstraction is not to be vague, but to create a new semantic level in which one can be absolutely precise.” Therefore, understanding and interpreting human-generated abstractions is an essential necessity for systems that attempt to follow non-trivial human instructions. However, current NLP applications such as virtual assistants or conversational systems (‘bots’) are less concerned with this higher semantic level and are mainly focused on extracting and executing predicate-argument structures (e.g., "book a flight", "send an email"). The performances of our neural models show that the means used to successfully process the predicate-argument level are not sufficient to tackle this new challenge.

To further develop capable applications for human-computer interaction it is high time for NLP research to invest in this direction. We propose the HEXAGONS dataset as a new benchmark for this endeavor. Moreover, as abstraction is a core concept of formal programming languages, we envision future work in this direction making a significant leap towards programming in NL.

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A Data Collection: Pilot and Recruitment

The collection process itself consisted of four stages: Pilot, Recruitment, and two rounds of Data Collection. Here we provide more details on the two first stages:

Pilot In the pilot we aimed to check the flow, clarity and feasibility of the data collection. That is, to verify that we indeed elicit diverse instructions at different levels of abstraction, and to examine the quality of the results, particularly in terms of the agreement between the Instructors and Executors. For the Pilot we sampled 13 images representing all categories (see Table 3) and used each image twice. The pilot results were encouraging in terms of feasibility and data quality and yielded diverse levels of abstractions.

Recruitment We held two different recruitment rounds for recruiting Executors and Instructors:

- The main requirement from Executors is to be precise in executing instructions. Therefore, to recruit such workers, candidates had to execute challenging drawing procedures. We used two tests. The first contained simple drawing procedures consisting of a single or a pair of drawing steps, scored automatically by the similarity of the resulting image to the target image. The second test included three, more demanding drawing procedures, selected from the pilot study. The score was based on the similarity of the executions of the drawing steps to the original ones. The final decision to recruit workers was based on this score as well as a manual review of the executions by the first author.

- A major goal in recruiting Instructors was to assemble a group of workers that together exhibit diverse descriptions and different levels of abstraction. For that, we employed a three-phased process. First, candidates had to describe simple shapes and were scored automatically by the similarity of their alignment phase (see previous Section) to the target image. Next, three images randomly selected from a pool of 10 pilot images were given to the candidate to write the instructions and then execute them (i.e., work through the Collection phase). Those Instructions were given to qualified Executors and were scored by the success of the Executors to execute the drawing procedure. Further, candidates were trained to stretch their level of abstractions by working on a kind of task we developed called triggers. A trigger is a partial drawing procedure augmented with a challenge (See Figure 13). Recruitment decisions were made based on the automatic scores as well as a qualitative review of the drawing procedure and four triggers. To diversify the pool of Instructors, we retained 10% of Instructors exhibiting low-level descriptions.

All in all, we recruited two (disjoint) sets of 24 Instructors and 15 Executors.

B Quality Assurance of the Hexagons dataset

To ensure the quality of the dataset we went through a careful quality assurance process elaborated here.

When we consider the procedures themselves, 57.3% of the drawing procedures have a complete agreement with at least one Executor, in all the drawing steps (EM=1). We assume that those drawing procedures do not contain Instructor errors, and that they suit our purposes.

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7 We contrasted the task implementation using a numbered vs. unnumbered HEXAGONS board. The unnumbered board elicited more interesting procedures with higher-level abstractions compared with the numbered board. This is consistent with previous work (as in Long et al. (2016)).
In the rest 42.7% of the drawing procedures (i.e., 212 drawing procedures) there is at least one disagreement between the Instructor and each of the Executors. All in all there are 1100 drawing steps containing Instructor-Executors disagreements. For those instructions we went through yet another labeling process. We manually reviewed the Instructor’s drawing procedures and respective executions in order to (i) detect Instructor errors (ii) categorize them, and (iii) correct the Instructor executions to match the instructions.

The types of Instructor errors we identify are:

- **Over-execution**: The Instructor executes more than s/he writes per an instruction;
- **Under-execution**: The Instructor executes less than s/he writes per an instruction.
- **Miscounting**: The Instructor counts incorrectly the number of columns, rows, tiles, etc.
- **Error Propagation**: An error is conducted in a previous step and is propagated to the current step.
- **Other**: Other mistakes, such as painting unrelated tiles or using wrong colors. We aimed to keep this category to the minimum.

We validated the labeling scheme by calculating Inter-annotator agreement on samples of 30 drawing procedures, in two (iterative) sessions.

Table 12 shows the Inter-annotator agreement for these sessions. The high scores validate the quality of the scheme, the validity of the categories, and the consistent labeling by the annotators. All types of errors detected above in instructions where manually corrected by the authors, resulting in a data wherein for each drawing procedure we have a 100% correct gold execution.

| Tasks (dis-agreed steps) | Is Error? | Type of Error | Error Correction |
|--------------------------|-----------|---------------|------------------|
| session 1                | 30        | 0.96          | 1.0              | 100%             |
| session 2                | 30        | 0.94          | 0.96             | 90%              |

Table 12: Rater Agreement. Cohen’s Kappa is used in “Is Error?” and “Type of Error” columns to measure rater agreement on detecting errors in instructions and identifying the type of error. Average Exact Match is used in “Error Correction” column to measure rater agreement on error correction, that is, raters’ corrections of the Instructors’ executions.

### C The Hexagons Dataset: Additional Examples

We illustrate here examples of different types of abstractions obtained in our elicited data, additionally to those provided in Section 4.3. The next figures illustrate drawing procedures that express abstract structures following our image categorization (see Table 3): Figure 15 illustrates the abstract structure of bounded iteration; Figure 16 illustrates a conditional iteration; Figures 14 and 17 illustrate conditional statements; Figures 18 and 19 illustrate symmetry - reflection and rotation respectively. The next three figures illustrate types of recursion: Figure 20 (growing patterns), Figure 21 (spiral) and Figure 22 (fractal). Finally, Figure 23 taken from the second round whose target image was made by a trained MTurk worker (see Section 3) illustrates a composition of abstract structures.
Figure 14: Abstract Structure Elicitation: Conditional Statement.

Figure 15: Abstract Structure Elicitation: Bounded Iteration.

Figure 16: Abstract Structure Elicitation: Conditional Iteration.

Figure 17: Abstract Structure Elicitation: Conditional Statement.
Figure 18: Abstract Structure Elicitation: Symmetry (Reflection).

3. Connect a diagonal (BLACK) between the two tiles you filled in the previous steps.

4. Color (BLUE) all tiles adjacent to at least TWO black squares on the upper right edge of the diagonal you made above.

5. Repeat the above step four more times, thinking of the black diagonal as the base of a pyramid. From "bottom to top", the colors should be: GREEN, RED, YELLOW, PURPLE. There should only be one purple tile.

6. Reflect the multi-colored triangle you made in the previous two steps symmetrically over the black diagonal.

Figure 19: Abstract Structure Elicitation: Symmetry (Rotation).

1. In the 10th column from the left, color the 5th hex from the bottom red.

2. The three red hexes are the points of triangle pointing to the left. Fill the 5 squares behind each so the 3 hex base of the triangle is to the right of each.

3. The hex in the middle that can touch all 3 triangles should be black.

4. The two points of the red triangles not touching black have lines extending out by two hexes in each direction, continuing in the direction of each edge of the triangle. The hexes which are counter-clockwise to the outermost corners are green, the hexes clockwise to the outermost corner of the red triangle are purple.

5. Make the green and purple lines into triangles by filling in a single hex, opposite each other so that the triangles attached to each red triangle point only share one free edge; and there is a full empty hex between them.

Figure 20: Abstract Structure Elicitation: Recursion (Growing Patterns).

1. At the top of the board, count over to the 5th cell that extends up from the body of the board.

2. Going straight down from the cell in the previous step, skip the next 3 cells and color the 4th cell blue.

3. Create concentric circles by first coloring all cells touching the blue cell red. Then color all cells touching those yellow; the next circle green and finally an orange circle.
Figure 21: Abstract Structure Elicitation: Recursion (Spiral).

Figure 22: Abstract Structure Elicitation: Recursion (Fractal)

Figure 23: Abstract Structure Elicitation: Composed Structures.