SPATIAL REASONING AS OBJECT GRAPH ENERGY MINIMIZATION

Anonymous authors
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ABSTRACT

We propose a model that maps spatial rearrangement instructions to goal scene configurations via gradient descent on a set of relational energy functions over object 2D overhead locations, one per spatial predicate in the instruction. Energy based models over object locations are trained from a handful of examples of object arrangements annotated with the corresponding spatial predicates. Predicates can be binary (e.g., left of, right of, etc.) or multi-ary (e.g., circles, lines, etc.). A language parser maps language instructions to the corresponding set of EBMs, and a visual-language model grounds their arguments on relevant objects in the visual scene. Energy minimization on the joint set of energies iteratively updates the object locations till their final configuration. Then, low-level local policies re-locate objects to the inferred goal locations. Our framework shows many forms of strong generalization: (i)joint energy minimization handles zero-shot complex predicate compositions while each EBM is trained only from single predicate instructions, (ii) the model can execute instructions zero-shot, without a need for paired instruction-action training, (iii) instructions can mention novel objects and attributes at test time thanks to the pre-training of the visual language grounding model from large scale passive captioned datasets. We test the model in established instruction-guided manipulation benchmarks, as well as a benchmark of compositional instructions we introduce in this work. We show large improvements over state-of-the-art end-to-end language to action policies and planning in large language models, especially for long instructions and multi-ary spatial concepts.

1 INTRODUCTION

Rearranging objects to semantically meaningful configurations has many practical applications for domestic and warehouse robots (Cakmak & Takayama, 2013). In this work, we focus on the problem of semantic rearrangement depicted in Figure 1. The input is a visual scene and a language instruction. The robot is tasked with rearranging the objects to their instructed configurations.

End-to-end language to action mapping Many works in semantic scene rearrangement have made progress by mapping language instructions directly to actions (Shridhar et al., 2021; Liu et al., 2021c; Janner et al., 2018; Bisk et al., 2017) or object locations (Mees et al., 2020; Gubbi et al., 2020; Stengel-Eskin et al., 2022). Many recent end-to-end language to action or language to object locations approaches use transformer architectures to fuse visual, language and action streams (Shridhar et al., 2022; Liu et al., 2021c; Pashevich et al., 2021). Despite their generality and their impressive results within the training distribution, these methods typically do not show generalization to different task configurations, for example, longer instructions, new objects present in the scene, novel backgrounds, or combinations of the above (Liu et al., 2021c; Shridhar et al., 2021). Furthermore, these methods cannot easily determine when the task has been completed and they should terminate (Shridhar et al., 2021; Liang et al., 2022) since they do not model explicitly the goal scene configuration to be achieved.

Symbolic planners and learning to plan To handle the challenges of reactive mapping of language to actions, some methods use look-ahead search to infer a sequence of actions or object rearrangements that eventually achieves the goal scene implied by the instruction (Prabhudesai et al.,

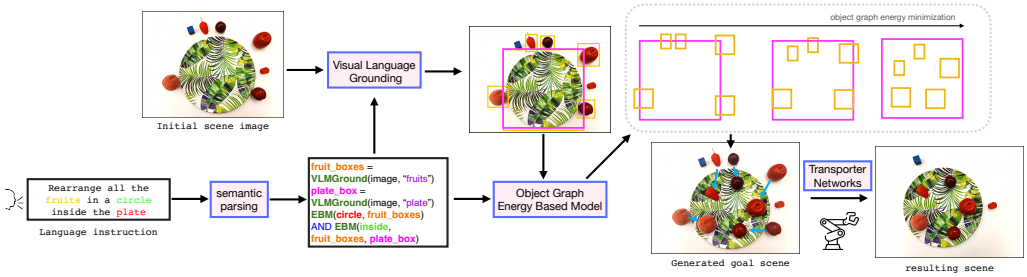


Figure 1: **Scene rearrangement as object graph energy minimization.**

2019). Look-ahead search for scene re-arrangement requires dynamics models that can handle complex multi-object scenes and generalize across varying number of objects and their configurations, which is an open area of research (Yann Lecun). Latest learning-based planners (Hafner et al., 2019; 2020; Schrittwieser et al., 2019; Micheli et al., 2022) have not shown so far such generalization abilities (Goyal et al., 2021; Hamrick et al., 2020). As a result, planning for scene re-arrangement is dominated by symbolic planners, such as, PDDL (Planning Domain Definition Language) planners (Migimatsu & Bohg, 2019; Kaelbling & Lozano-Pérez, 2011; Toussaint, 2015; Lyu et al., 2018). Symbolic planners assume that each state of the world, scene final goal states, and intermediate subgoal states can be sufficiently represented in a logical form, using language predicates that describe object spatial relations. These methods predominantly rely on manually specified symbolic transition rules and planning domains. They use out-of-the box object detectors for state estimation (Kase et al., 2020) and interface with low level controllers for object manipulation. Many recent methods use learning to guide the combinatorial symbolic search by predicting directly semantic subgoals, conditioned on the instruction and the visual scene (Xu et al., 2019; Zhu et al., 2020; Drieß et al., 2020). Symbolic state bottlenecks used in these methods usually limits them to modelling pairwise spatial predicates. Spatial configurations that involve multi-ari relations between objects, such as circles, lines, squares, etc., are not easy to achieve because the long sequence of actions needed to put together such a shape configuration is outsourced to the low-level policy since intermediate states cannot be easily described in symbolic form (Figure 1). Under such long action horizon, the low-level policy often fails.

Large language models for spatial planning Recent methods wish to capitalize on knowledge of large language models (LLMs) (Brown et al., 2020; Liu et al., 2021b) for spatial planning (Huang et al., 2022a) and instruction following (Huang et al., 2022b; Ahn et al., 2022). Works of (Huang et al., 2022a) showed that LLMs can predict relevant language subgoals directly from the instruction and a symbolic scene description when conditioned on appropriate plan-like prompts, without any additional training (Huang et al., 2022b; Ahn et al., 2022; Huang et al., 2022a). The scene description is provided by an oracle (Huang et al., 2022b) or by object detectors (Huang et al., 2022b; Chen et al., 2022) as a list of objects. Predicted language subgoals, e.g., *"pick up the can"* are directly fed to low-level visual conditioned policies, or engineered controllers (Huang et al., 2022b). Work of (Liang et al., 2022) builds upon LLMs for code generation and predicts actions in the form of policy programs. It capitalizes on knowledge of LLMs for code generation regarding various functions necessary for semantic parsing of diverse language instructions. For the input programmatic scene description it uses lists of objects alongside their spatial box coordinates, missing from previous works. The language model predicts the actions in terms of low level program functions that interfaces with low level manipulation skills and object detection routines. The hope is that with appropriate prompting the LLM will draw from its vast implicit knowledge of code functions associated with natural language, provided in the comments of programs it has seen, to generate programmatic code that solves novel task instances of scene rearrangement. As highlighted in both (Liang et al., 2022; Huang et al., 2022b), prompting dramatically affects the model's performance and its ability to predict reasonable subgoals, and programmatic code, respectively. In this paper, we question whether the language space is the most efficient means to reason about objects and their spatial arrangements.

Spatial reasoning as graph energy minimization In this paper, we introduce Spatial Planning as multi Graph Energy Minimization (SPGEM), a framework for spatial reasoning for instruction following via compositional energy minimization over sub-graphs of object entities, one per spatial predicate in the instruction, as shown in Figure 1. We represent each spatial "predicate" as a binary or multi-ari energy based model (EBM) over a graph of object spatial coordinates (LeCun et al., 2006). Predicates and corresponding EBMs can be binary (for concepts such as left, right, front, behind) or multi-ari (for circles, lines etc.). We train EBMs from examples of visual scenes paired with language descriptions of spatial relations, to predict gradients for object locations updates starting from randomly sampled object arrangements through Langevin dynamics minimization (Du et al., 2020b). Given a language instruction, e.g., *"put all the red objects in a circle inside the plate"*, a neural semantic parser maps the instruction to the set of predicates and corresponding EBMs, and grounds the object arguments for each EBM using visual language grounding models (Kamath et al., 2021; Jain et al., 2022). Gradient descent on the sum of energies with respect to the object argument coordinates in 3D or in 2D overhead space, provides the final object configurations that best satisfies the set of spatial constraints expressed in the predicates. Given the predicted locations of objects, we use pick and place visually grounded short term polices (Zeng et al., 2020; Shridhar et al., 2021) to move the objects to their inferred locations.

We show SPGEM generalizes zero shot to complex predicate compositions, e.g., "put all red blocks in a circle in the plate" when trained from single relation predicate examples, e.g., " A inside B" or "a circle of A", as shown in Figure 1. Contrary to LLMs, SPGEM has been trained with a handful of visually grounded examples of spatial predicates. Contrary to symbolic planners, energy minimization "searches over" object placements while traversing non symbolically meaningful scene configurations, and without manual engineering of the transition operators. Contrary to end-to-end language to action models, SPGEM infers a spatial abstraction of the goal scene that helps it to better evaluate whether the task has been completed. By representing EBMs over object locations as opposed to object visual pixel appearances (Du et al., 2020a; Liu et al., 2021a) the model can generalize zero-shot spatial concepts to novel objects. We build upon recent advances on training energy based models (Mordatch, 2018; Du et al., 2020b). To the best of our knowledge, this is the first work that uses EBMs for scene re-arrangement of complex language instructions.

We test SPGEM in scene re-arrangement of table top environments in simulation benchmarks of previous works (Shridhar et al., 2021; Liu et al., 2021c) as well as in a new simulation benchmark we contribute with more compositional instructions. We curate multiple train and test splits with varying amount of OOD for the test set with respect to i) longer instructions with more predicates, ii) novel objects. We compare our method with SOTA language to action models (Shridhar et al., 2021; Liu et al., 2021c) as well as Large Language Model planners (Huang et al., 2022b). We ablate each component of our model in an effort to isolate contributions of perception, goal parsing, goal generation and low-level policy execution modules. Our model outperforms the baselines, especially in complicated instructions.

In summary, out contributions are: **(i)** An energy-based object-centric framework for language-guided goal scene generation. **(ii)** A modular system for language-guided scene re-arrangement, that uses semantic parsers, referential language grounding models, EBMs for scene generation and low-level vision-based policies for zero-shot task instruction following. **(iii)** Contribution of an extensive scene re-arrangement benchmark in simulation with compositional language instructions and shapes. **(iv)** Comparisons against SOTA end-to-end language to action models and LLMs, and extensive discussions of the pros and cons of each. We have included our code in the supplementary file. We will make our code and datasets publicly available upon publication.

2 Related Work

2.1 Instructing robots through language

Language robot instruction has a long history (Shridhar & Hsu, 2018; Matuszek et al., 2014; Bollini et al., 2013; Misra et al., 2016; Chen et al., 2021; Blukis et al., 2020; Paxton et al., 2019; Tellex et al., 2011; Lynch & Sermanet, 2020; Simonyan & Zisserman, 2014; Feichtenhofer et al., 2016). Here, we focus our literature review on the task of spatial scene re-arrangement, and we refer the reader to the recent reviews of (Tellex et al., 2020; Luketina et al., 2019) for coverage of broader background work. Language is a natural means for communicating goals and can easily describe compositions

of actions and arrangements seen at training time (Akakzia et al., 2021; Colas et al., 2020; 2022). Language is a much-preferred means of communicating a task than supplying goal images (Nair et al., 2018; Pong et al., 2019; Seita et al., 2021; Wu et al., 2022).We distinguish the following categories in the literature for robot instruction for scene re-arrangement: (i) End-to-end mapping of language to actions or language to object locations (Lynch & Sermanet, 2020; Shridhar et al., 2021; Liu et al., 2021c; Stengel-Eskin et al., 2022). (ii) Semantic parsers that map a language command and a visual scene description to programs over perceptual and control primitive functions (Karamcheti et al., 2020; Andreas et al., 2015; Walker et al., 2019; Matuszek et al., 2012; Wang et al., 2020; Srinet et al., 2020). These parsers require annotations of instructions with corresponding programs, which are typically hard to collect at scale, despite recent progress on this topic through paraphrasing of instructions (Wang et al., 2015; Berant & Liang, 2014; Wu et al., 2021). Our work proposes a semantic parsing framework that instead of predicting action directly predicts EBMs constraints. We show such representation's ability to adapt few shots to complex spatial compositions. (iii) Symbolic planners that rely on predefined symbolic rules and known dynamic models, and infer discrete task plans given an instruction with logic search (Kaelbling & Lozano-Pérez, 2011; Garrett et al., 2018). These methods can generalize to arbitrary goals defined in a problem domain but necessitate manual design of the planning domain, its predicates, symbolic rules and transition operators. (iii) Large language models that map instructions to language subgoals (Zhu et al., 2020; Xu et al., 2019; Huang et al., 2022a;b) or program policies (Liang et al., 2022). Subgoals predicted interface with low level short-term policies or skill controllers. We detail the last category of work right below.

Large language models LLMs trained from Internet-scale text have showed impressive zero-shot reasoning capabilities for a variety of downstream language tasks (Brown et al., 2020) when prompted appropriately, without any weight finetuning (Wei et al., 2022; Liu et al., 2021b). Researchers in robot learning have repurposed language models for the task of the instruction following (Chen et al., 2022; Lin et al., 2022). Works of (Huang et al., 2022a;b) have shown that LLMs can map instructions to a reasonable sequence of subgoals when prompted with analogous text action plans open loop or closed loop during instruction execution. The scene description is usually provided in a symbolic form as a list of objects present and their relations, predicted from open vocabulary detectors (Kamath et al., 2021). Recent works of (Liang et al., 2022; Lin et al., 2022) have also fed as input overhead pixel coordinated of objects to inform the LLM's predictions. The prompts for these methods need to be engineered per family of tasks. It is yet to be shown how the composition of spatial concept functions can emerge in this way.

2.2 Language Conditioned Scene Generation.

A large body of work has explored scene generation conditioned on text descriptions (Johnson et al., 2018; Ramesh et al., 2021; Saharia et al., 2022; Yu et al., 2022; Mansimov et al., 2015). In this work, we seek to make scene generation useful as scene goal imagination for robot spatial reasoning and instruction following. Instead of generating pixel accurate images, we generate object configurations by abstracting the appearance of object entities. We show this abstraction suffices for a great number of diverse scene rearrangement tasks.

2.3 Energy based models

Our work is related to existing work on energy-based models (Grathwohl et al., 2019; Mordatch, 2018; Liu et al., 2021a; Du et al., 2020a;b; 2019). Most similar to our work is that of (Mordatch, 2018) which proposes a framework for learning to generate and detect spatial concepts with EBMs on images with dots, and (Du et al., 2020a; Liu et al., 2021a) which demonstrated composability of image-centric EBMs for RGB face and ClEVR image generation. Here we demonstrate zero-shot composability of graph-centric EBMs, their applicability on spatial reasoning, and their utility for vision-based instruction following for scene re-arrangement.

3 Method

The architecture of SPGEM is shown in Figure 1. The model takes as input an RGB-D image of the scene and a language instruction. A semantic parser maps the instruction to a set of predicate EBMs and their referential expression arguments. A visual grounding model grounds the arguments of each

EBM to object entities in the scene. Then, the goal configuration is predicted in a symbolic space of bounding boxes by minimizing the total energy over the object locations to satisfy the desired object arrangements. Lastly, short-term vision-based pick n' place policies move the objects to their goal locations. Below, we describe each component in greater detail.

A library of graph energy-based models for spatial concepts In our work, a spatial predicate is represented by an EBM that takes as input x the set of objects that participate in the spatial predicate and maps them to a scalar energy value $E_\theta(x)$. An EBM defines a distribution over configurations x that satisfy its concept through the Boltzmann distribution $p_\theta(x) \propto e^{-E_\theta(x)}$. Low-energy graph entity configurations imply that the entities satisfy the language concept and have high probability. An example of the spatial concept can be generated by optimizing for a low-energy configuration through gradient descent on (part of) the input x. We represent each object entity by its 2D overhead centroid coordinates and its 2D overhead box size. During gradient descent, we only update the object coordinates and leave box sizes fixed. We consider both binary spatial concepts (*in*, *left of*, *right of*, *in front of*, *behind of*) as well as multi-entity spatial concepts (*circle*, *line*).

During training, we sample configurations from p_θ, by starting from an initial configuration x^0 and refine it using Langevin Dynamics (Welling & Teh, 2011):

$$x^{k+1} = x^k - \lambda \nabla_x E_\theta(x^k) + \epsilon^k z^k, \tag{1}$$

where z^k is random noise, λ is an update rate hyperparameter and ϵ^k is a time-dependent hyperparameter that monotonically decreases as k increases. After K iterations, we obtain $x^- = x^K$. During training, we learn the parameter θ of our EBM by minimizing a loss that penalizes energies of examples sampled by the model being lower than energies of ground-truth configuration:

$$\mathcal{L} = \mathbb{E}_{x^+ \sim p_D} E_\theta(x^+) - \mathbb{E}_{x^- \sim p_\theta} E_\theta(x^-),$$

where x^+ a sample for the data distribution p_D and x^- a sample drawn from the learned distribution p_θ. Compositions of concepts can be created by simply summing energies of constituent concepts, e.g., *"a circle of cubes inside the plate"*, as shown in Figure 1. For detailed implementation and architectural figures of our energy-based models, please see our supplementary file.

Semantic parsing of instructions into spatial concepts graphs and their arguments Our parser maps language instructions to instantiations of energy-based models and their arguments. Examples of instructions and paired programs are shown in Figure 1. Our parser is a Sequence-to-Tree model (Dong & Lapata, 2016) with a copying mechanism (Gu et al., 2016) which allows it to handle a larger vocabulary than the one seen during training. Specifically, the input utterance is first encoded using a pre-trained RoBERTa encoder (Liu et al., 2019), giving a sequence of contextualized word embeddings and a global representation of the full utterance. Then, a decoder is iteratively employed to i) decode an operation (`EBM` or `VLMGround`), ii) condition on this operation to decode or copy the arguments for this operation, iii) add one (or more) child node(s).

We train our semantic parser with synthetic data of synthesized instructions paired with programs, each 1-7 predicates long, that we generate by sampling from a grammar, similar to previous works (Mao et al., 2019; Wang et al., 2015).

Referential visual language grounding We ground referential noun phrases predicted by our parser with an off-the-shelf language vision grounding model (Jain et al., 2022). The input is the noun phrase, e.g., "the blue cube" and the image, and the output is the boxes of all object instances that satisfy the noun phrase. We finetune the publicly available code of (Jain et al., 2022) to our training data.

Short-term vision-based manipulation skills Our short-term manipulation skills build upon transporter networks (Zeng et al., 2020). Transporter Networks take as input an overhead RGB-D image registered at the overhead bird view and predict two robot gripper poses: i) a pick pose and ii) a pick-conditioned placement pose. Transporters can model any behaviour that can be effectively represented as two consecutive poses for the robot gripper, such as pushing, sweeping, rearranging ropes, folding, and so on. For more details and visualizations of the basic transporter framework, please see (Zeng et al., 2020).

We modify Transporter Networks to be locally conditioned. Specifically, we take as input an image patch around the object pick and object placement locations predicted by our visual grounding and energy-based minimization modules, respectively, instead of the whole image. In this way, the low-level policies know roughly what to pick and where to place it, and only locally optimize over the best pick location (within an object of interest) or placement location, at a particular part of the scene, respectively.

4 EXPERIMENTS

We test SPGEM in its ability to follow instructions for re-arranging tabletop scenes in simulation. We compare our model against large language model planners (LLM) (Huang et al., 2022b) and end-to-end language to action models (Shridhar et al., 2021; Liu et al., 2021c).

Our experiments aim to answer the following questions: **1)** How does the proposed set energy minimization over object configurations compare with LLM planners in predicting object arrangements from spatial instructions? How much this ability scales with the length of the instruction? **2)** How does SPGEM compare with state-of-the-art end-to-end instruction to action models across varying instruction lengths? **3)** How do different modules of our framework contribute to performance?

Baselines We compare SPGEM against the following baselines:

(i) CLIPort (Shridhar et al., 2021), a model that takes as input an overhead RGB-D image and an instruction and uses pretrained CLIP language and image encoders to featurize the instruction and RGB image, respectively, then fuses with depth features to predict pick and place actions using the parametrization of Transporter Networks (Zeng et al., 2020). Its aim is to capitalize on language vision associations already learnt by the CLIP encoders. We use the publicly available code of (Shridhar et al., 2021).

(ii) LLMplanner (Huang et al., 2022b) is an instruction following scene rearrangement model that uses Instruct-GPT to predict sequential low-level subgoals in language form, e.g., *"pick the red cube and place it to the right of the blue bowl"*. These predictions interface with vision and language-conditioned short-term policies, such as CLIPort. Scene state description is provided as a list of objects in the scene. LLMplanner does not finetune the LLM but instead uses appropriate prompts.

Benchmarks We test our models and baselines for scene re-arrangement in the following benchmarks: (i) The four tasks of put-block-in-bowls, pack-google objects-seq, pack-google objects-group, and assemble-kits-seq from the manipulation benchmark introduced in (Shridhar et al., 2021). The environments support changing of the colors of the objects and the background of the background. (ii) Scene rearrangement benchmarks we introduce which are the following: a) SpatialRelations benchmark, which contains single pick 'n' place instructions with referential expressions in cluttered scenes with distractors, e.g., *"Put the cyan cube above the red cylinder"* b) Compositional-one step scene rearrange benchmark, which contains compositional instructions with referential expressions in cluttered scenes with distractors that require one object to be re-located to a particular placement location, e.g., *"put the red bowl to the right of the yellow cube and put the red bowl to the left of the red cylinder and put the red bowl above blue cylinder"*. c) Compositional-group scene rearrange benchmark, which contains compositional instructions with referential expressions in cluttered scenes with distractors that require multiple objects to be re-located, e.g., *"put the grey bowl above the brown cylinder and put the yellow cube to the right of the blue ring and put the red bowl above the blue ring and put the blue ring below the grey bowl and put the brown cylinder to the left of the blue ring."*. d) Shapes benchmarks, which contain instructions for making multi-entity shapes, such as circles and lines, e.g., *"rearrange all red cubes in a circle"*

Evaluation Metrics We adopt 0 (failure) to 100 (success) scores proposed in the Ravens benchmark (Zeng et al., 2020) for evaluation. For packing-style tasks, the evaluation metric represents the percentage of referred objects placed in the goal location. (e.g. 4/5 - 80.0% for packing 4 out of 5 objects specified from language instructions). For the introduced benchmarks we have oracle reward functions that evaluate whether the task constraints are satisfied. Partial rewards are supported, reflecting the percentage of satisfied constraints. Please see the supplementary file for a detailed description of evaluation metrics for the newly introduced tasks of circle and line arrangement.

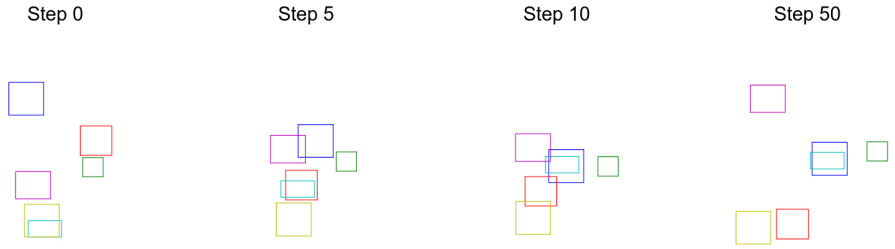
4.1 SPATIAL SCENE RE-ARRANGEMENT UNDER ORACLE PERCEPTION AND LOW-LEVEL CONTROL

Our goal is to evaluate spatial reasoning in a language space and in an abstract visual space for predicting instruction-guided subgoals. We compare our model with LLMplanner. In this section, we assume oracle perception, that is, oracle object detection and referential grounding for both LLMplanner and SPGEM, as well as oracle low-level control policies. We carry out inferred instructions from LLMplanner using oracle controllers that relocate the right objects to locations in the scene that satisfy the predicted instruction while not occupying other objects. Note however though that SPGEM relies on simple pick and place policies that are not language conditioned, while the LLMplanner relies on language conditioned policies, thus, the oracle control assumption may be more unrealistic in the latter case. We forego this difference for the sake of comparison.

We show quantitative results of SPGEM and LLMplanner on compositional-one-step and group benchmarks in Table 1. Our model outperforms LLMplanner, and the performance gap is larger in more complex instructions. To elucidate why an abstract visual space may be preferable for spatial planning, we visualize steps of energy minimization for different instructions in Figure 2 and we visualize steps of the execution of the InstructGPT prompted by us to the best of our capability in Figure 3. As you can see, SPGEM trained on single predicate scenes shows remarkable composability to much more predicates. Language planning on the other hand suffers from the ambiguity of translating geometric concepts to language and vice versa: step-by-step execution of language subgoals does not suffice for the composition of the two subgoals to emerge. (Figure 3).

	Composition-one-step		**Composition-group**	
Method	Task Progress	Task Completion	Task Progress	Task Completion
LLMplanner oracle	82.0	59.0	75.3	29.0
SPGEM oracle	**90.8**	**76.0**	**88.7**	**62.0**

Table 1: **Evaluation of SPGEM and LLMplanner with oracle perception and oracle low-level execution policies** on compositional spatial arrangement tasks.



"Place the blue box left of the green, right of the red box and above the yellow box. Put the cyan box inside the blue box. Move the red box below the magenta box."

Figure 2: **Spatial planning via composable concept graph energy minimization.** The EBMs handle complex instructions as multiple steps of joint energy minimization. Step 0 indicates the starting point and step 50 the result after 50 gradient steps. Our model "imagines" the goal scene in a pixel-abstract but spatially-aware manner. Note that the optimization is not aware of physical constraints: in intermediate time steps the objects can overlap, e.g. steps 5 and 10. However, this is a planning procedure and the intermediate steps, where the energy is high, are not executed.

4.2 SPATIAL SCENE RE-ARRANGEMENT

In this section, we compare our model and baselines in the task of instruction-guided scene rearrangement. We show quantitative results in Table 2 for the benchmarks of Composition-one-step and Composition-group. We compare our model with CLIPort model trained on atomic spatial relations and zero-shot evaluated on compositional benchmarks. We further fine-tune the CLIPort on demos from the compositional benchmark. Under all different setting, we vastly outperform all

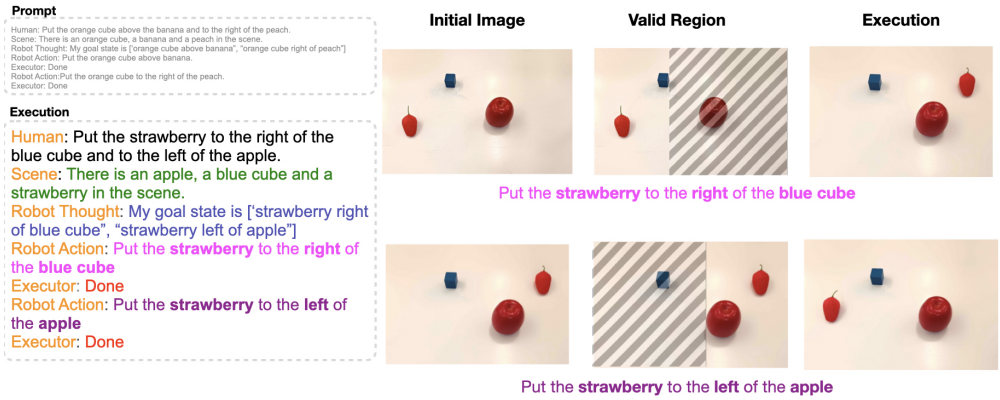


Figure 3: **Spatial planning via Large Language Models (LLMs).** Typical LLM Planners need to describe their plans in words using shared action space with the executor policy. However, this can be limiting. Here, the policy understands four atomic relations i.e. left, right, above and below. LLM instructs the executor to put the strawberry to the right of the cube which the executor can place anywhere in the shaded area. However, in the next instruction of putting the strawberry to the left, the executor violated the first constraint and ended up in a similar initial configuration. Note that while "middle" is a valid English relation that can convey both constraints jointly, however, a) it is outside the vocabulary of the executor and b) words do not exist for every configuration especially when the joint constraint increases.

	Composition-one-step seen-colors		**Composition-one-step unseen-colors**		**Composition-group seen-colors**		**Composition-group unseen-colors**	
Method	10	100	10	100	10	100	10	100
Initial (no movement)	0.0	0.0	0.0	0.0	31.7	31.7	31.8	31.8
CLIPort (zero-shot)	9.0	12.0	7.0	12.0	37.4	37.5	32.6	38.4
CLIPort	13.0	15.0	14.0	9.0	38.2	38.5	34.7	40.9
LLMplanner	51.2	53.2	49.4	53.5	38.6	39.0	37.1	39.0
Ours (zero-shot)	**90.0**	**91.0**	**92.7**	**90.3**	**77.2**	**77.4**	**77.7**	**78.4**

Table 2: **Evaluation of SPGEM and CLIPort on compositional tasks** SPGEM is trained only on atomic relations and tested zero-shot on tasks with compositions of spatial relations. Composition-one-step involves moving only one object to satisfy all constraints specified by the language. Compositional group task involves moving all objects to satisfy the task constraints. Some language constraints are satisfied already in the initial configuration, and the Initial model captures that.

variants of CLIPort and LLMplanner. Specifically for compositional tasks, our model does not need any re-training because the energy functions are composable, meaning that we can jointly optimize over an arbitrary number of constraints by simply summing the different energy terms, however, we need few synthetic labels from our grammar for the language parser. We also show results on SpatialRelations and shapes benchmark in Table 3 where we vastly outperform all our baselines. We also show results for cliport benchmark in the supplementary.

4.3 Ablations

We do ablations and error analysis of our model in Table-4. First, we remove the goal generation from SPGEMby conditioning the place network on the language input instead of the EBM-generated goal image while keeping the pick network and object grounders identical. We observe a drop of 35.1% in

Model	Accuracy
SPGEM	77.2
SPGEM without goal generation	42.1
SPGEM w/o learnable policies	61.2
SPGEM with oracle language visual grounding	82.3
SPGEM with everything oracle except goal	88.3

Table 4: **Ablative versions of SPGEM with oracle sub-components in the benchmark compositions-group-seen-colors.**

Method	left-seen-colors		left-unseen-colors		right-seen-colors		right-unseen-colors	
	10 demos	100 demos	10 demos	100 demos	10 demos	100 demos	10 demos	100 demos
CLIPort-multi	13.0	44.0	9.0	33.0	29.0	43.0	28.0	44.0
Ours	**95.0**	**95.0**	**93.0**	**94.0**	**89.0**	**92.0**	**93.0**	**96.0**

Method	above-seen-colors		above-unseen-colors		below-seen-colors		below-unseen-colors	
	10	100	10	100	10	100	10	100
CLIPort-multi	24.0	45.0	22.0	51.0	23.0	55.0	13.0	40.0
Ours	**87.0**	**87.0**	**89.0**	**90.0**	**89.0**	**90.0**	**88.0**	**89.0**
	circle-seen-colors		**circle-unseen-colors**		**line-seen-colors**		**line-unseen-colors**	
Method	10 demos	100 demos	10 demos	100 demos	10 demos	100 demos	10 demos	100 demos
CLIPort-multi	34.1	61.5	31.2	55.6	36.2	67.6	33.2	62.1
Ours	**91.3**	**91.5**	**90.2**	**91.2**	**78.9**	**79.1**	**76.8**	**77.5**

Table 3: **Evaluation of SPGEM and CLIPort on spatial relations in simulation.**

accuracy underscoring the importance of goal generation. We then remove our executor policy and instead randomly select pick and place locations inside the bounding box of the relevant object. This results in a drop of 16% showing the importance of robust low-level policies. We do not remove the grounder and parser since they are necessary for goal generation. We then experiment with oracle visual language grounder that perfectly detects the objects mentioned in the sentence and we observe a gain of 5.1%. We posit that this difference would be even higher with real-world scenes. We observe that language parsing in our domain is close to perfect, hence we skip that. We finally evaluate with perfect grounding, language parsing and low-level execution to test the error rate of our goal generator. We obtain 88.3% accuracy thus concluding that our goal generator fails in 11.7% cases.

4.4 Limitations

Our model presently has two important limitations. First, it predicts the goal object scene configuration but does not have any knowledge regarding temporal ordering constraints implied by physics. For example, our model can predict a stack of multiple objects on top of one another but cannot suggest which object needs to be moved first. Adding such temporal energy priors is a direct avenue for future work. Second, our EBMs are currently parametrized by object locations but many tasks, e.g, manipulation of articulated objects, fluids, deformable objects or granular materials, would require finer grain parametrization in both space and time. Furthermore, even for rigid objects, many tasks would require finer in-space parametrization, e.g., it would be useful to know a set of points in the perimeter of a plate as opposed to solely representing its centroid and box for accurately placing things inside it.

5 Conclusion

We introduced SPGEM, a modular framework for instruction-guided scene re-arrangement that maps spatial language to object scene configurations via compositional energy minimization over detected object graphs, one per spatial concept. We showed strong generalizations of our framework to predicate concept compositions, novel object combinations, and object scene arrangements never seen at training time. We test our model in diverse table top manipulation tasks in simulation and show improvements both in and out-of-distribution settings, as well as in low training data regimes, against state-of-the-art end-to-end language to action mapping models, and LLM-based instruction following methods. We contributed a new scene rearrangement benchmark for more compositional language instructions, which we will make publicly available to the community, alongside our code, upon publication. Our work questions the sample efficiency of spatial reasoning in language space, and shows a handful of examples suffice to learn EBM concepts, and compose them over novel arrangements.

REPRODUCIBILITY STATEMENT

To ensure the reproducibility of the empirical results, we submit a zip file with an anonymized version of our code as part of the supplementary file. Upon publication, we will make our full code, data and benchmark publicly available on GitHub.

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6 MODEL DETAILS

6.1 TRAINING A SEMANTIC PARSER WITH SYNTHETICALLY GENERATED UTTERANCE-PROGRAM PAIRS

Domain Specific Language for grounding and Generation We design a Domain-Specific Language (DSL) which extends the DSL of NS-CL (Mao et al., 2019) (designed for visual question answering in CLEVR (Johnson et al., 2017)) to further predict scene generations, e.g. *"put all brown shoes in the green box"*. Inspired by StructFormer (Liu et al., 2021c), we extend our DSL for rearrangement tasks, which includes action types, target object's property, shape information and location relative to the table. Detailed description of our DSL can be found in Table 5.

Grammar We sample re-arrangement instructions paired with ground-truth programs over our modules from the grammar shown in Table **??**. The *START* token represents the production rule from which grammar-to-language decoding starts. Each capitalised word (like TARGET_OBJECTS, SIZE etc.) represents a variable which gets expanded into a production rule. The lowercase words (like 'rearrange', 'into', etc.) represents the constants of the grammar which do not decode into anything further. We decode the variables into their rules until only constants remain and finally form a language utterance. We also keep a record of each rule expansion which is later used to produce the program annotations.

6.2 EBMs

We implement two EBMs, namely a BinaryEBM and a MultiAryEBM, for binary (e.g. "on top") and multi-ary (e.g. "circle") concepts respectively. The BinaryEBM is used for all tasks that ask for moving objects with respect to some object of reference, e.g. as in the "Put" and "Pack" tasks. We train a separate EBM for each basic concept, i.e. "left", "right", "on top", "in front", "behind", etc. It takes as input two objects and learns to move the first object with respect to the second one. The MultiAryEBM receives a set of objects, an approximate location of the center and an approximate size of the shape. It generates a shape conditioned on those parameters. Again we build a separate EBM for each shape concept, e.g. "circle" and "line". At execution time, the parser also predicts the concept, i.e. which EBM to call.

We implement the BinaryEBM as a relational network that operates on the relative locations between the objects (Figure 4). Then, a multi-layer perceptron (MLP) is used to map the featurized pair to a scalar value, which is the energy.

6.3 TRANSPORTER NETWORKS

A detailed description of Transporter can be found in Section 3.2 of the Transporter paper (Zeng et al., 2020). The Transporter decomposes a given task as a sequence of pick and place tasks. It takes a pick location, a place location and an overhead image as its input. Then it crops a small region around the pick location and rotates it with 360/k angle to form k queries. Next, it independently featurizes the k queries and the overhead image through a ResNet, and take the argmax of the cross-correlations between the overhead image and the k queries to arrive at the final place location. We closely follow the original transporter network, except that we do a pixel-wise multiplication of the EBM generated goal heatmap with the featurized overhead image before performing the cross-correlations with the queries. Please see our supplementary video for more qualitative results.

7 EXPERIMENTS

7.1 EVALUATION METRICS FOR REARRANGEMENT TASKS

For evaluating making-a-circle task, we fit a best-fit circle for the final configuration predicted by SPGEM. To do this, we consider the centers of the bounding boxes as points. Then, we compute the centroid of those points and the distance of each point from the centroid. This is an estimate of "radius". We compute the standard deviation of all this quantity. If this is lower than 0.03, then we assign a perfect reward. The reward linearly decreases when the std increases from 0.03 to

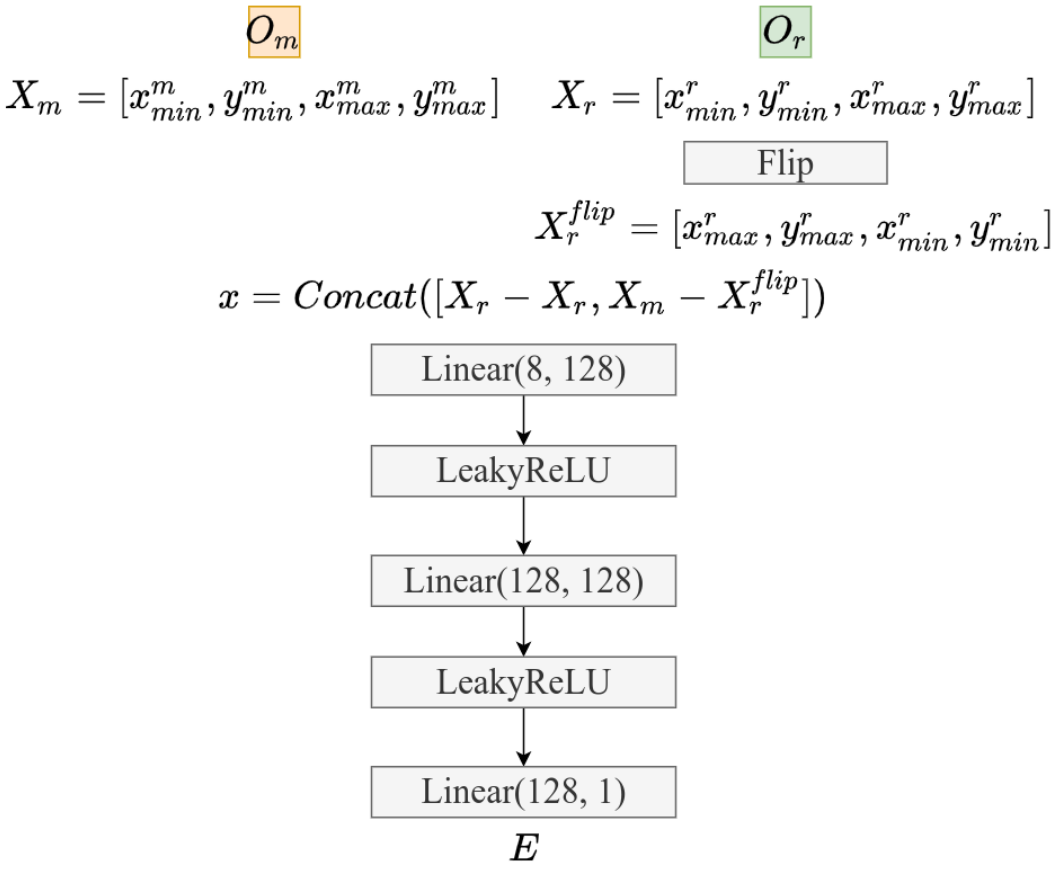


Figure 4: Architecture of the EBM used for binary concepts such as "right of". The inputs are a "moving" point O_m and a "reference point" O_r and the output is the energy of their relative placement.

0.06. Beyond that, we give zero reward. We tuned these thresholds empirically by generating and distorting circle configuration.

We follow similar evaluation strategy for make-a-line. Here we compute the average slope and fit a line to our data. Then we measure the standard deviation of the distance of each point from the line. We found that the same thresholds we used for circles work well for lines as well.

8 Ethical Statement

Mapping language instructions to goals for robot coaching would contribute to the development of intelligent agents that are programmable using natural language, as opposed to being programmed explicitly or through positive and negative examples. This will facilitate human-robot interaction. Robots will then be able to acquire new concepts and commands on-the-fly, adapting to every user's needs and desires, as opposed to maintaining a fixed set of functionalities.

With the potential benefits of easier communication with artificial agents, however, come some drawbacks. An increased ability to program robots would also be followed by more automation and less demand for employees, even for jobs that are now considered "safe". While in the long term, automation would probably be beneficial to society by increasing productivity, in the short term, the process of automation could have a negative impact on many people.

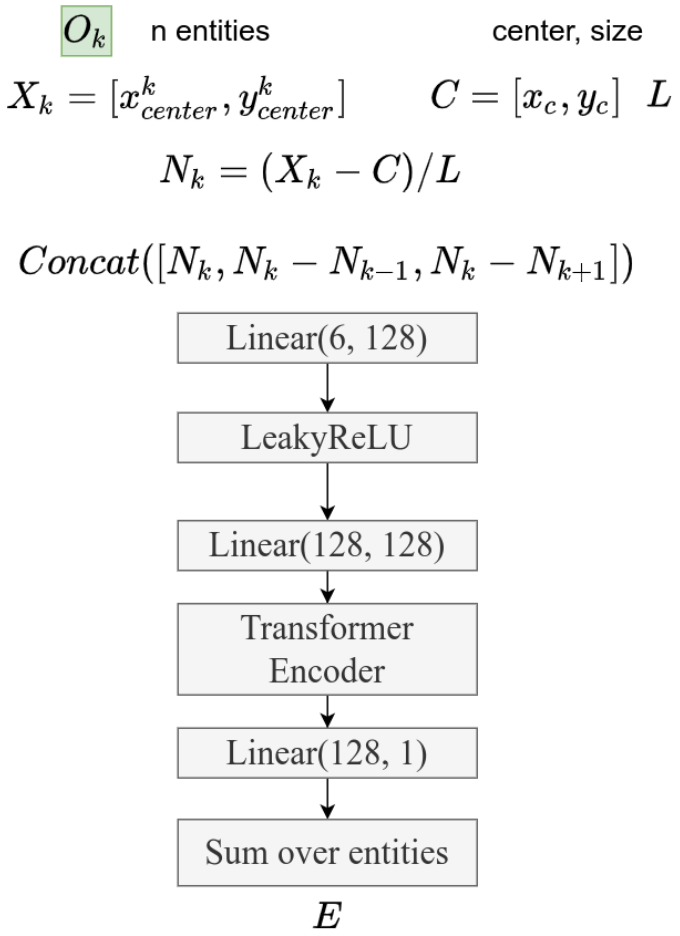
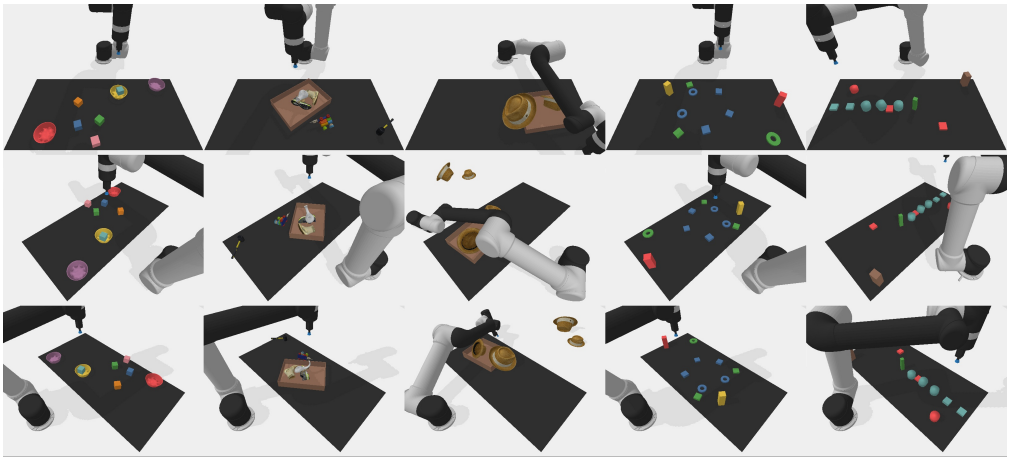


Figure 5: Architecture of the EBM used for multi-ary concepts such as "circle". The input is a set of n entities $O_k, k = 1, \ldots, n$, along with an estimated center and size of the shape. The output is the energy of this set of entities.

Lastly, while we aim to ease the programming of a robot, we cannot have control over the purposes this technology will be used, e.g. whether a robot is tasked for beneficial or catastrophic purposes. Our aim is to enable the technology's potential for social good, such the potential of non-expert users, e.g. elderly people, to instruct a robotic assistant.

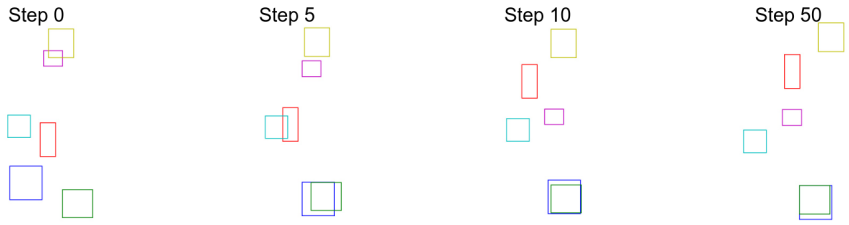


put-blocks-in-bowls | packing-unseen-google objects-seq | packing-unseen-google objects-group | make-a-circle | make-a-line

Figure 6: **Manipulation tasks in simulation.**

Operation	**Signature**	**Semantics**
Scene	() → ObjectSet	Returns all objects in the scene using class-agnostic detector
Filter	(ObjectSet, ObjectConcept) → ObjectSet	Filter out set of objects based on some *Object Concept* like object name (eg. cube) or property (color, material)
BinaryEBM	(Object A, Object B, Relation) → (Pick locations, Place locations)	Executes *BinaryEBMs* for rearranging Object A and Object B to satisfy the given binary *relation* (like left of/right of/inside etc.)
MultiAryEBM	(ObjectSet, Shape Type, Property) → (Pick locations, Place locations)	Executes *MultiAryEBMs* for the given *Shape Type* (circle, line, etc.) with specified *Properties* (like size, position etc.) on a set of given objects and generates pick and place locations to complete the shape.

Table 5: All operations in the domain-specific language for SPGEM



"Place the blue box right of the red box and below the yellow box. Put the cyan box left of the blue box. Move the red box above the magenta box. Place the green box inside the blue box."

Figure 7: **Spatial planning via composable concept graph energy minimization.**