

11-777 Spring 2021 Class Project

Andrew Singh* **Ankit Ramchandani*** **Vashisth Parekh***
{andrewsi, aramchan, vparekh}@andrew.cmu.edu

Abstract

Template for 11-777 Reports using the ACL
2021 Style File

1 Introduction and Problem Definition (1-1.25 pages)

**Thesis statement or Hypothesis we are aiming
to prove**

“Our approach is better is not a hypothesis”

*Everyone Contributed Equally – Alphabetical order

2 Related Work and Background

2.1 ALFRED

Though ALFRED is a relatively new task, a multitude of approaches have recently been proposed that demonstrate improved performance over the baseline introduced in (Shridhar et al., 2020a). The baseline model consists of a CNN to encode the visual input at each timestep, a bi-LSTM to encode the language directives, and a decoder LSTM to infer the action at each timestep while attending over the language encoding. (Corona et al., 2020) used the same architecture as the baseline, except they maintained separate modules for each *subgoal type* (e.g., GOTO, PICKUP). They then used a high-level controller to choose which module to execute at each step based on the language directives. (Singh et al., 2020) proposed a vision module for generating interaction masks and an action module for predicting actions, with the vision module first predicting the class of the object of interest and then generating the pixel-wise interaction mask given the predicted object class. (Storks et al., 2021) addressed ALFRED’s long action sequences by training the model to execute one subgoal at a time rather than all subgoals at once, and they address the agent’s poor navigation performance by augmenting the agent’s perception with additional viewing angles that are used for training an object detection module and for predicting the agent’s orientation angle relative to the goal.

Unlike methods that learn a direct mapping from observations to actions end-to-end, (Saha et al., 2021) proposed a truly modular framework that is able to learn from unaligned or weakly aligned data as opposed to requiring expert demonstrations. Their mapping module includes a novel mapping scheme based on graph convolutional networks (Kipf and Welling, 2016) for improved navigation, and their language module leverages a pre-trained model to perform joint intent detection and slot filling on the language directives.

While the previously mentioned works improve upon the modeling approach proposed in the original ALFRED paper, (Shridhar et al., 2020b) also proposed a new environment to address the challenge of generalizing to unseen tasks. They aligned tasks in ALFRED with a purely textual environment, TextWorld (Côté et al., 2018), allowing agents to first learn in an abstract setting in order to generalize better in the embodied setting. They additionally introduced a modular architecture to

demonstrate the effectiveness of their ALFWorld environment, consisting of a state estimator that translates visual observations to text, an abstract text agent pre-trained in TextWorld that generates high-level actions from textual observations and a goal, and a controller that translates high-level actions to sequences of low-level actions in the embodied environment.

To the best of our knowledge, the papers discussed above cover all of the approaches proposed thus far that attempt the full ALFRED task.

2.2 Related Tasks

2.2.1 Vision and Language Navigation

While ALFRED requires navigation and interaction with objects based on visual and language input, a related task is just vision and language based navigation (VLN). (Fried et al., 2018) proposed a policy consisting of two modules: an instruction follower model that produced a step-by-step action sequence from visual and textual input, and a speaker model that predicted the probability that a particular language instruction describes a given sequence. To predict the final trajectory, multiple trajectories were first generated by the follower model, and the one most likely to match with the natural language description (as assessed by speaker model) was chosen. (Wang et al., 2019) proposed an improvement over the previous method by learning a LSTM (Hochreiter and Schmidhuber, 1997) and attention-based policy using reinforcement learning (RL). They also used a “speaker model” which was used to generate an intrinsic reward for the RL algorithm based on the probability of the language description matching the predicted action sequence. (Wang et al., 2018) proposed a method to jointly perform imitation and reinforcement learning using a policy that consisted of an “action predictor” used to predict the final action based on inputs coming from model-free and model-based RL modules. The model-free module was an LSTM and attention-based network similar to other approaches (Shridhar et al., 2020a; Wang et al., 2019). The model-based module “imagined” multiple different trajectories in the future, and produced a combined representation to the action predictor. (Wani et al., 2020) performed several experiments on a long-horizon navigation task in a realistic 3D setting to empirically show that using a semantic map-like memory can significantly boost navigation performance. (Hao et al., 2020) pre-

trained their model on image-text-action triplets in a self-supervised manner. Their model was able to generalize better in unseen environments, improving the SOTA in the Room-to-Room task (similar to ALFRED). (Majumdar et al., 2020) improved VLN performance by using a visiolinguistic transformer based model that scores the compatibility between an instruction and a particular visual scene. Pretraining on the image-text pairs from the web improved the performance of the VLN.

2.2.2 Embodied Question Answering

Embodied Question Answering (Das et al., 2018a) (EmbodiedQA) is a related task in which an agent spawns at a random location in a 3D environment and is asked a question about an object. To correctly answer, the agent must navigate the environment and gather information through egocentric vision about the object and its surroundings. This challenging task requires many of the skills needed in the ALFRED benchmark, including active perception, commonsense reasoning, goal-driven navigation, and grounding language to vision and actions.

(Das et al., 2018a) proposed an approach with a two-step navigation module: a planner that selects actions and a controller that executes those actions a variable number of times. Their agent is initialized via imitation learning and then fine-tuned via reinforcement learning. (Das et al., 2018b) improved upon this approach by introducing a high-level policy that proposes compositional sub-goals to be executed by sub-policies. They train their model via imitation learning in a bottom-up fashion, first training the sub-policies before training the high-level policy. They then fine-tune their model via reinforcement learning in a similar bottom-up fashion, allowing the high-level policy to adapt to the behavior of the sub-policies.

(Yu et al., 2019) generalized the EmbodiedQA task to multiple targets; instead of a question asking only about a single object, it may ask about several objects and require comparative reasoning. They propose a novel architecture for the task consisting of four modules: a program generator that converts the question to executable sub-programs, a navigator that executes these sub-programs to guide the agent to relevant locations, a controller that selects relevant observations along the agent’s path, and a visual question answering module that uses the observations from the controller to predict the final answer.

2.3 Relevant ML Methods

2.3.1 Multimodal Alignment

In ALFRED, the agent receives all natural language instructions at the beginning of the episode, but receives visual observations at each time-step. It is imperative for the agent to align the natural language directives with its current visual observation so that it can spot objects of interest described in natural language in the current visual scene. In this section, we summarize some research in multimodal machine learning focused on this problem of learning such soft alignment (Baltrušaitis et al., 2018).

(Yu and Ballard, 2004) used a graphical model to align objects in (egocentric) images with spoken words. (Mei et al., 2015) uses a bi-LSTM with a multi-level aligner to map instructions with navigational actions. (Ma et al., 2019) proposed a visual textual co-grounding alignment mechanism and a corresponding progress monitor. They used the hidden state from the previous timestep of their LSTM to generate textual and visual grounding, which helps their agent decide which action to take next. Similarly, (Wang et al., 2019) used an LSTM to predict actions and included an attention mechanism on visual and textual input based on the current hidden state of the LSTM. (Ke et al., 2019) used attention mechanism over language to compute how the previous action aligned with the description. (Wang et al., 2018; Shridhar et al., 2020a) both used modules which perform attention over textual input using the hidden state of the LSTM, so that the agent knows which words in the input text to focus on.

2.3.2 Generalization in Multimodal Settings

The ALFRED dataset has unseen splits of validation and test data which measure generalization of the learned policy, but multimodal models are more prone to overfitting due to their increased capacity (Wang et al., 2020). To this end, (Wang et al., 2020) also proposed a gradient blending approach, which computes optimal blends of modalities based on overfitting behavior. This approach achieves SOTA results on egocentric action task similar to ALFRED. (Alet et al., 2019) presented a meta-learning strategy where they separately trained each modular component on related tasks and then combined them to create a more general model that scales across tasks. More specifically to ALFRED, (Nguyen and Okatani, 2018) proposed multi-task

learning approach that enables visual-language representations that can be generalized to other tasks. Their algorithm used representation encoders that learn hierarchical features by fusing visual and semantic representations and task specific decoders that decode those features however they see best fit for the given task.

2.3.3 Reinforcement and Imitation Learning

All known SOTA approaches (Singh et al., 2020; Corona et al., 2020; Storks et al., 2021) for AL-FRED use imitation learning (IL) (Hussein et al., 2017), despite IL having several known limitations because the standard i.i.d assumptions are not met (Ross and Bagnell, 2010). Methods like DAgger (Ross et al., 2011) that attempt to mitigate the limitations of IL cannot be applied directly because new data cannot be generated on the fly in AL-FRED (Shridhar et al., 2020a). For these reasons, in this section, we describe methods that use a combination of IL and reinforcement learning (RL) techniques in addition to the ones that were covered in Section 2.2.1 (Wang et al., 2019, 2018).

Many methods have been proposed to use RL methods when expert data is present. (Ho and Ermon, 2016) proposed a method to directly learn a policy from expert data that optimizes a reward function that would be obtained by running inverse RL (Abbeel and Ng, 2010) on expert data. Notably, their method directly outputs the policy and does not involve running inverse RL to extract the reward function first, which could be very costly. They experimentally show that their method outperforms other IL methods and often achieves expert level performance. (Reddy et al., 2019) proposed a much simpler alternative to (Ho and Ermon, 2016) which still achieves competitive performance. They simply give the agent a positive reward when it matches the expert action and no reward otherwise. This simple idea is theoretically motivated and forces the agent to return to states seen by the expert. (Salimans and Chen, 2018) proposed a RL-based method to solve the challenging Atari game, Montezuma’s Revenge, using a single demonstration. Their main contribution was to train the agent using a curriculum: they trained the RL agent to reach the goal by starting from states in the demonstration in reverse order. In other words, they first trained an RL agent to reach the goal state from second-to-last state in the demonstration, then from third-to-last, and so on. The main insight was that the RL agent had to learn only a

sub-task at each step, overcoming any hard exploration. (Hester et al., 2018) proposed a method to do Deep Q-Learning (Mnih et al., 2013) from demonstrations by adding a term to the loss function that forces the Q-value of the expert action to be at least a margin higher than other actions. This term adds a trade-off between following the expert action and the optimal action as predicted by the Q-values. (Rajeswaran et al., 2017) proposed a method to learn complex, non-trivial manipulation tasks using RL and IL. They use IL to warm start the policy, and then train it using RL with a modified gradient update which forces the policy to stay close to expert actions. (Garmulewicz et al., 2018) proposed a simple modification to the loss function used in actor-critic methods to account for expert data and showed that their simple modification can achieve satisfactory results on challenging tasks like Montezuma’s Revenge. (Nair et al., 2018) also proposed a method that involves a modification to the loss function to account for IL, but they only add this extra loss term when the learned critic believes that the expert actions are indeed better than the policy action. In other words, their modification accounts for cases when expert data may not be perfect.

3 Task Setup and Data

3.1 Task Definition

We plan to work with the ALFRED dataset (Shridhar et al., 2020a) with the goal of learning a set of actions in an indoor household setting which will help an agent complete a task described by natural language. The tasks require navigation and interaction with multiple objects in the scene. Each interaction action requires a pixel-wise interaction mask to specify the object of interest. The agent receives high-level and low-level natural language instructions at the beginning of the episode, and can use egocentric visual observation (i.e. access to current RGB image, depth map, and instance segmentation map) at each time step as input. The agent produces one or two outputs at each time step: the current action to take, and, if the action involves interaction, the interaction mask of an object of interest.

We intend to predict the interaction mask pixel-wise instead of using any other coarser representations like bounding boxes. We also intend to use inputs in their rawest representation (e.g. raw image data instead of extracted features) for maximum generality and flexibility of downstream methods. Furthermore, we plan to develop a method to solve the full task of navigation and interaction in the ALFRED dataset. We clarify this to convey that we are not working with a small sub-task or a sub-problem of the dataset. Since current methods (Corona et al., 2020; Singh et al., 2020; Shridhar et al., 2020a) struggle with generalization to novel objects and environments, we will attempt to primarily focus on improving generalization performance, which is measured by an “unseen” split of the test set which contains new environments and objects.

3.2 Dataset Statistics

In this section, we present a subset of the analysis we performed. **We encourage the reader to see the Jupyter notebook stored in the *Analysis* folder for full list of figures pertaining to the analysis since this report only includes a subset.**

3.2.1 Metadata Analysis

In this section, we analyze various metadata in ALFRED. Table 1 shows average values for the quantitative metrics we chose to measure on ALFRED. We can see that the averages are fairly consistent across splits. The navigation-interaction ratio indicates that for every interaction action in a

demonstration, there are roughly 9 navigation actions. The mask coverage indicates that on average, the ground-truth interaction mask covers a rather small (15-17%) proportion of the image. The step-object coverage of nearly 1 indicates that for almost all interactions, the name of the object of interest is mentioned in the corresponding language directive. By manually inspecting examples with low interaction step coverage, we find that the object’s name are usually substituted with a synonym (e.g. “rag” for “cloth” and “scoop” for “ladle”).

	Train	Valid (seen)	Valid (unseen)
Steps per directive	6.68	6.64	6.27
Tokens per step	12.39	12.18	12.63
Task desc. tokens	10.02	10.09	10.04
Images	286.75	287.24	277.72
Actions	49.78	50.12	46.98
Images per action	6.08	6.02	6.12
Actions per step	7.6	7.72	7.72
Nav-interact ratio	9.19	9.25	8.13
Total objects	33.2	32.84	38.44
Mask coverage	0.17	0.17	0.15
Step-object coverage	0.86	0.85	0.88

Table 1: Average values of various quantitative aspects of ALFRED by split. See appendix for definitions.

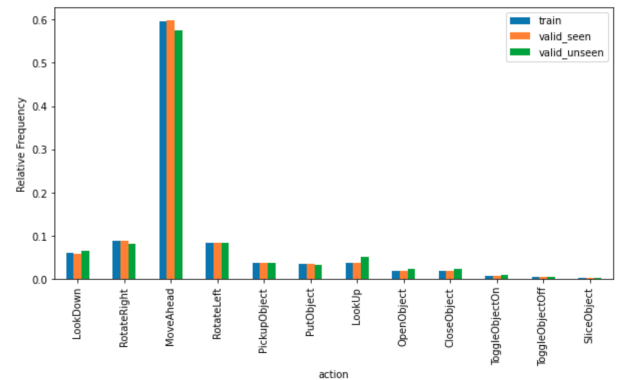


Figure 1: Relative frequency of each action type by split

Furthermore, Figure 1 shows the frequency of the 12 different actions (5 navigation actions + 7 interaction actions). Note that all splits have fairly equal frequency for all actions. Also, note that 60% of actions are “move ahead” actions which signifies the importance of a navigation module we may need in our model.

3.2.2 Textual Analysis

For textual analysis, we first identified out of vocabulary (OOV) words in the training and validation set using a vocabulary of 685k words defined by

spaCy. We found that less than 0.002% of all words were OOV in any split, indicating the dataset is already quite clean. Most of the OOV words were just misspelled (eg: "stovve"), indicating that it would be important to preprocess text using a simple spell checker before using it for downstream tasks.

We also found the top few synonyms used to describe objects in the dataset. This was performed by comparing the similarity of word vectors of all objects in the dataset with all common nouns identified in all task descriptions. The complete results are in the Jupyter notebook, but a few results are shown in Table 2. This reveals that our model will need to be robust enough to recognize synonyms of different words in order to be successful.

Furthermore, we analyzed how many objects present in the scene are directly referred to in the step-by-step instructions. The results are plotted in a histogram in Figure 2, which reveals that much less than 40% of objects in the scene are actually referred to in the instructions.

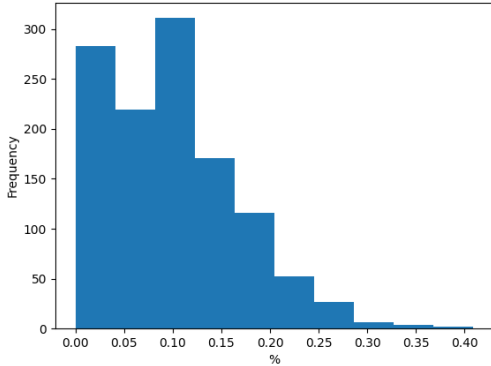


Figure 2: Percentage of objects referred to in instructions compared to objects in the scene

3.2.3 Visual Analysis

Due to compute constraints, most visual analysis was performed qualitatively by inspecting visual quality of different types of images. Figure 3 shows some sample RGB, depth and instance segmentation images. All images retrieved during simulation are of size 300 x 300.

Object Name	Synonyms used in task descriptions
Coffee Machine	Espresso Machine, Beverage Machine
Chair	Couch Chair, Sofa Chair
CD	DVD
Side Table	Corner Table
Butter Knife	Bread knife
Ottoman	Loveseat, Recliner
Fridge	Kitchen Fridge, Refrigerator
Poster	Wall Photo, Picture
Safe	Safety Box
Soap Bottle	Lotion Bottle

Table 2: Synonyms (i.e. closest words in embedding space) used in task descriptions of some objects in the dataset

3.2.4 Other Qualitative Analysis

In addition to the quantitative analysis, we also analyzed the solvability of the task. Our analysis in Figures 4 and 5 (in Appendix) shows that the unseen split of the validation set contains objects from the same classes as the training data, but could contain novel instances of those objects in novel environments. Since classes remain the same during training and testing times, the training data contains full information to solve the task, meaning a sufficiently intelligent agent should be able to solve the task, given training data.

3.3 Metrics

There are two primary metrics for evaluation. The first is “task success”, which is a binary value indicating if the object positions and state changes correspond correctly to the goal-conditions of the task at the end of the action sequence. The second is “goal-condition success”, which is the fraction of required goal-conditions that were completed at the end of the episode. Note that “task success” is true only if “goal-condition success” is 100%. Additionally, there exists a path-weighted version of these two metrics that considers the length of the episode, penalizing longer action sequences. For example, in the path-weighted version, an agent would receive half the score for taking twice as long as an expert to complete the task.

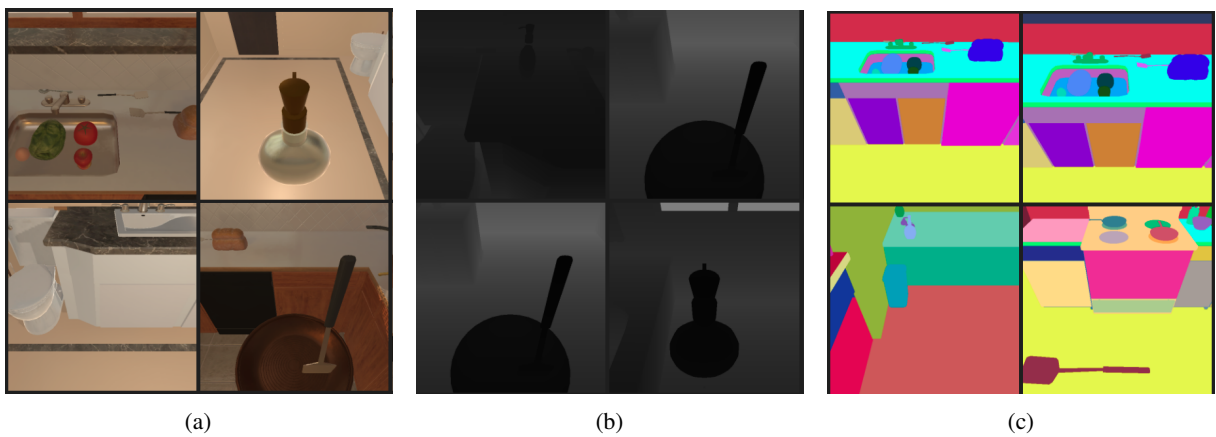


Figure 3: Sample RGB, depth, and instance segmentation images retrieved from AI2Thor simulator

4 Models (2 pages)

4.1 Baselines

Both existing baselines explained with citations and novel ones missing from the current literature

4.2 Proposed Approach

5 Results (1 page)

The columns above are just examples that should be expanded to include all metrics and baselines.

Methods	Dev		Test	
	Accuracy \uparrow	L_2 Error \downarrow	Accuracy \uparrow	L_2 Error \downarrow
Previous Approach 1 ()				
Previous Approach 2 ()				
Previous Approach 3 ()				
Proposed Method				

6 Analysis (2 pages)

This section should include at least two to three plots

6.1 Ablations and Their Implications

6.2 Qualitative Analysis and Examples

This section should likely contain a table of examples demonstrating how the current approach succeeds/fails.

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7 Appendix

7.1 Data Analysis Plots

Description of fields in Table 1:

1. Steps per directive: number of steps in each language directive
2. Tokens per step: number of words in each directive step
3. Task description tokens: number of words in directive task description
4. Images: number of images per demonstration
5. Actions: number of actions per demonstration
6. Images per action: number of images divided by number of actions per demonstration
7. Actions per step: number of actions divided by number of directive steps per demonstration
8. Nav-interact ratio: number of navigation actions divided by number of interaction actions per demonstration
9. Total objects: number of total objects in a scene per demonstration
10. Mask coverage: proportion of the image that is covered by the interaction mask per demonstration
11. Step-object coverage: proportion of interaction actions whose object of interest is mentioned in the step-by-step instructions, averaged over all interaction actions and language directives in the demonstration

In Figure 6, we see that ALFRED contains a roughly equal number of demonstrations for each type of task, and for the most part, a roughly equal proportion for each split. The validation data, especially the unseen portion, does have relatively less “Pick Two & Place” tasks than the training data. Additionally, the unseen portion has a significantly higher proportion of “Examine in Light” tasks than the other splits.

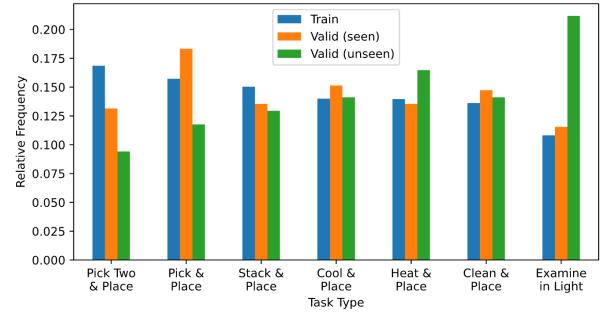


Figure 6: Relative frequency of each task type by split

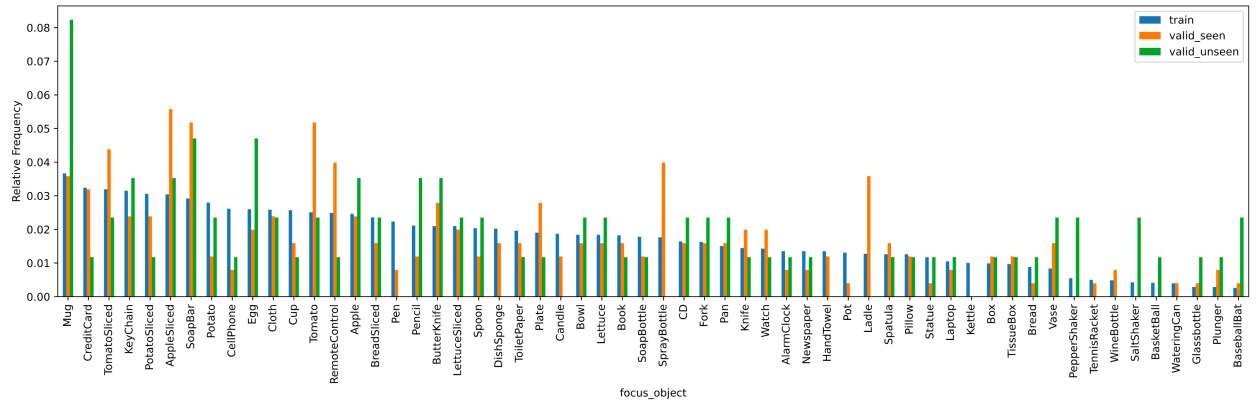


Figure 4: Relative frequency of focus objects used in different splits

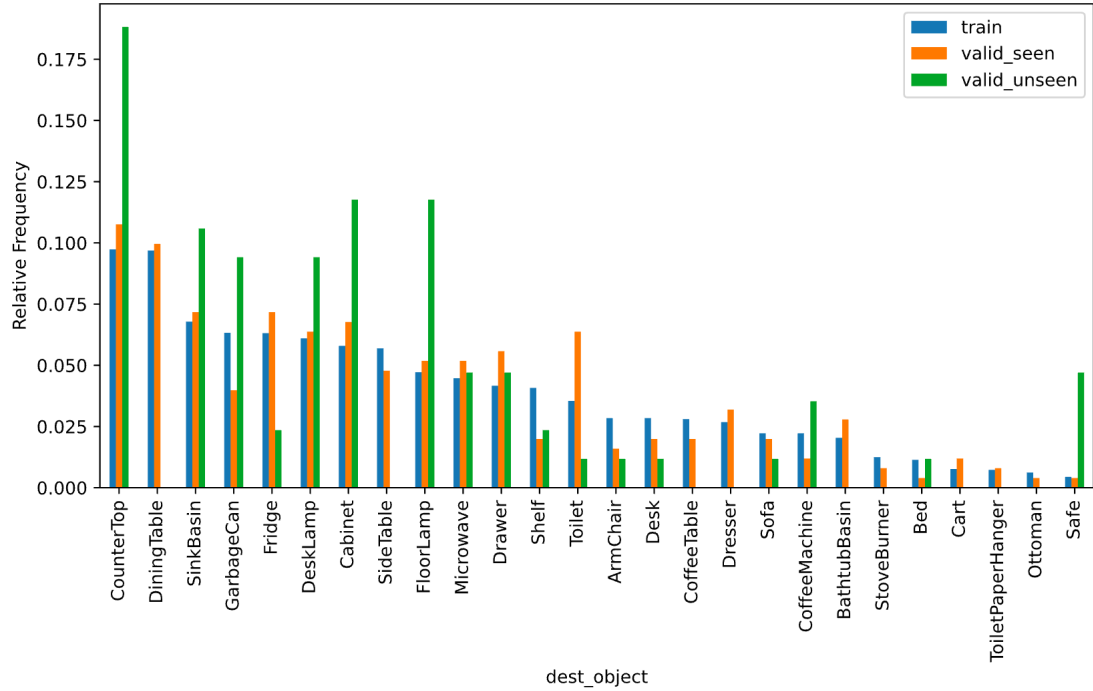


Figure 5: Relative frequency of destination objects used in different splits