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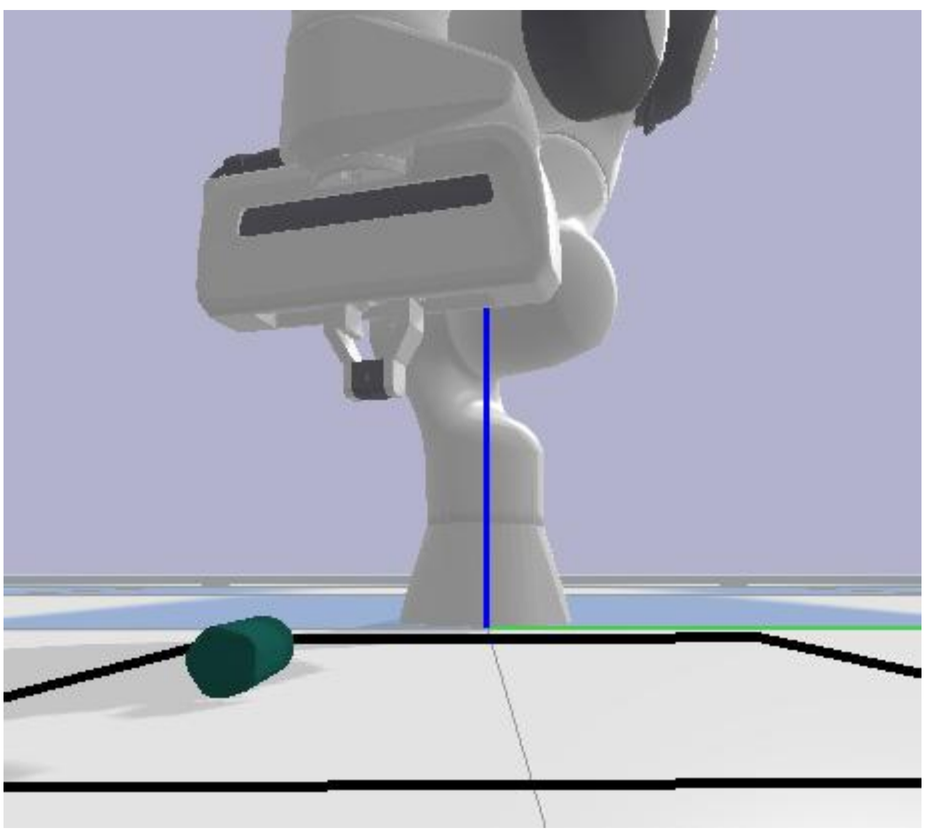
HW 6

Q1.(a) In terms of speed, the simulator can run a huge amount of iterations of different joint angles with no wear and tear to any actual robot arms. This can result in generating large datasets in a relatively shorter amount of time. Hence, a simulator can run at a much faster pace than physical experiments since it is not bound by physical limitations such as reaction time or mechanical wear and tear.

Relating to safety, a simulator can be trained on objects that may be unsafe to handle. Also, there would be configurations for a robot arm that may not be acheivable safely under environments where there are other humans present. Hence, a simulator eliminates the need for physical experimentation, thus reducing the risk of accidents and injuries.

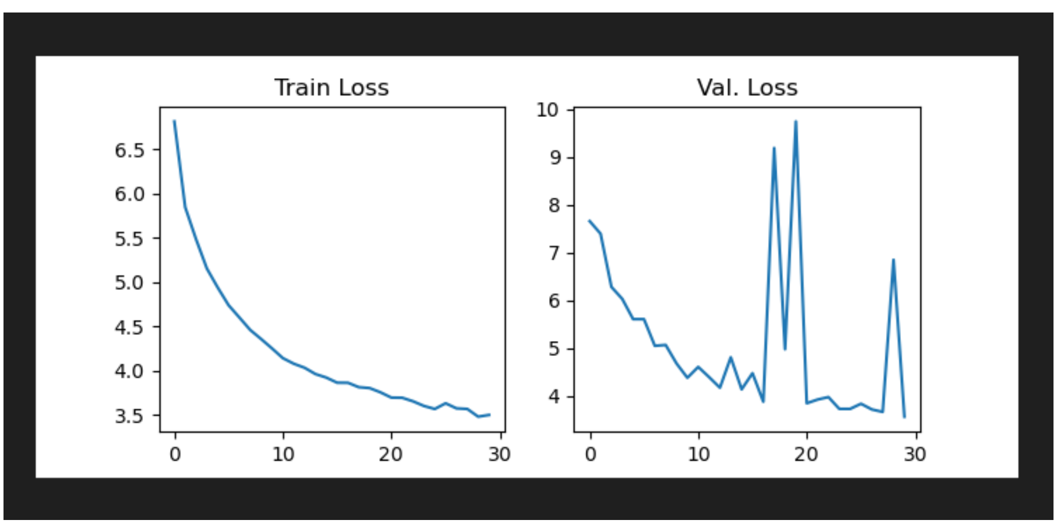
Q1.(b) Simulations would not accurately model the physical parameters of weight or surface friction which are all important in a grasping application. The camera sees only the top view of the object and does not view it at a plane parallel to the surface, which reveals significant gaps between the gripper and object. Hence, there are object grasping iterations, where from a parallel plane view, it would seem to slip out.

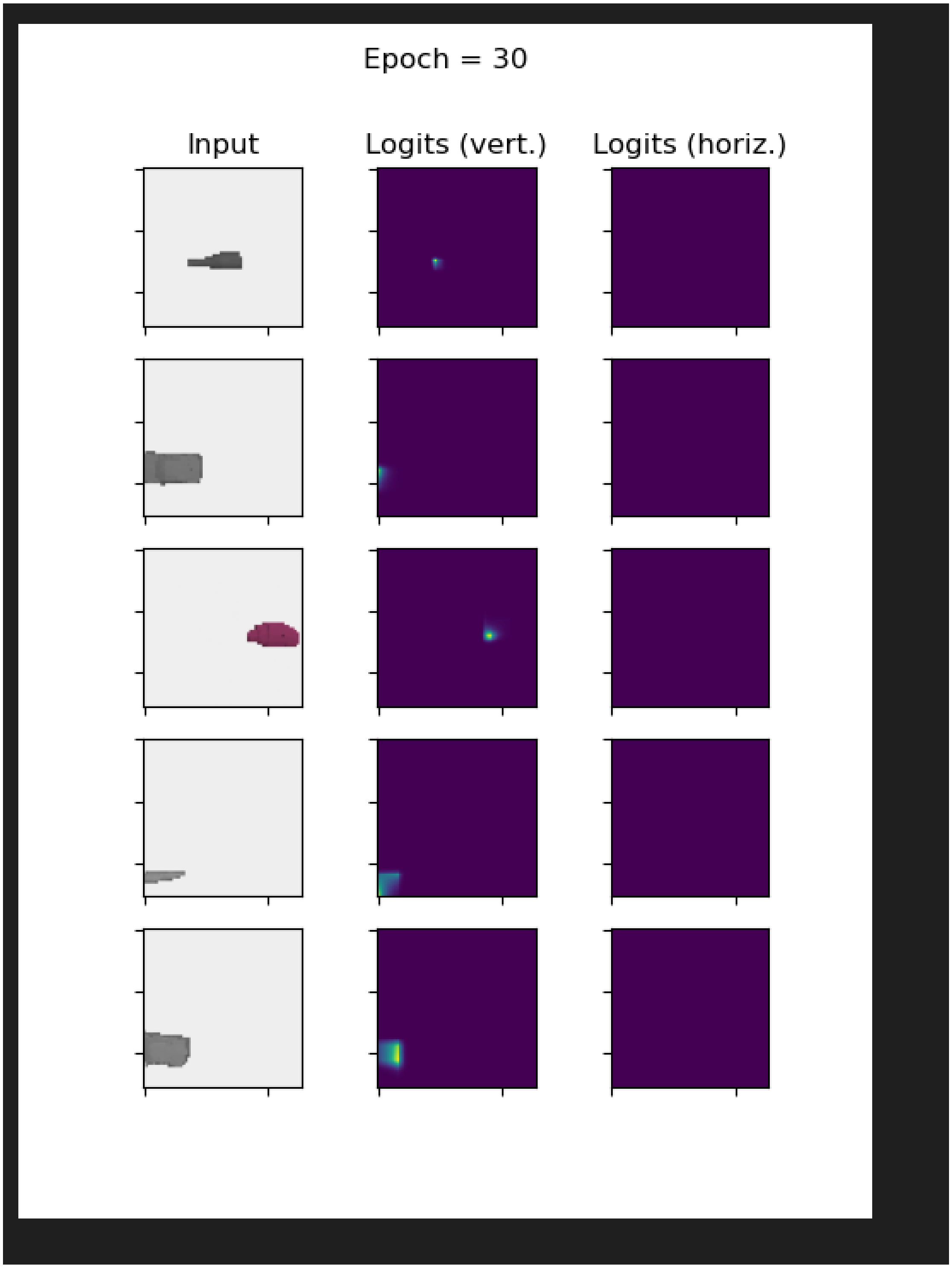


Q2)b) Some of the local information important to grasping include shape, size, and orientation of the object being grasped, the location of the object in the workspace, the geometry of the gripper and its alignment with the object, and the tactile feedback from the contact points between the object and the gripper. The local information such as the shape and orientation of the object, as well as the geometry of the gripper is captured by the high-resolution pathway of the network whereas the the low-resolution pathway of the network is intended to capture global contextual information such as the location of the object in the workspace and its relationship with other objects or obstacles in the environment.

Local information such as the shape, size, and orientation of the object being grasped, the geometry of the gripper, and tactile feedback from contact points is crucial for predicting grasp success. However, global information can also be important in some robotic grasping tasks. This includes information on the location and orientation of obstacles in the workspace, the overall layout of the environment, and the position of the robot relative to the workspace. For example, in cluttered environments, the robot may need to plan its grasp approach and trajectory while considering the surrounding objects or obstacles. Similarly, in scenarios where objects are out of reach, global information can be necessary to plan the robot's movements. Overall, while local information is critical, global information can play an important role in certain robotic grasping tasks.

Q3)Loss curves





Example predictions

a) During training, the validation loss curve is expected to be noisy due to several reasons. Firstly, the validation set is usually smaller than the training set, which can lead to higher variability in the validation loss curve. Secondly, the validation data may be less diverse than the training data, which can further increase the noise in the validation loss curve. The validation set may not cover the full range of variations in the data, which can also contribute to the variability in the validation loss curve. For instance, it may not contain all possible object shapes or sizes or all possible grasping scenarios. As a result, the performance of the model on different subsets of the validation data can vary considerably, leading to a noisy validation loss curve.

To summarize, the validation loss curve is expected to be noisy during training due to several factors, such as the smaller size of the validation set and the less diverse validation data, but it remains a critical metric to evaluate the model's generalization ability.

Q3)b) The network may still fail to predict some valid grasps or may predict false negative grasps, resulting in a higher failure rate during actual grasping experiments. Additionally, the validation loss may not fully account for certain factors that affect grasp success, such as lighting conditions or object texture. The validation loss is not a perfect indicator of how well the network can predict grasps. This is because the loss function used for training may not penalize false negative grasps, where the network fails to predict a successful grasp but a valid grasp location exists. These factors can make it more difficult for the network to generalize to unseen data, resulting in lower performance during actual grasping experiments.

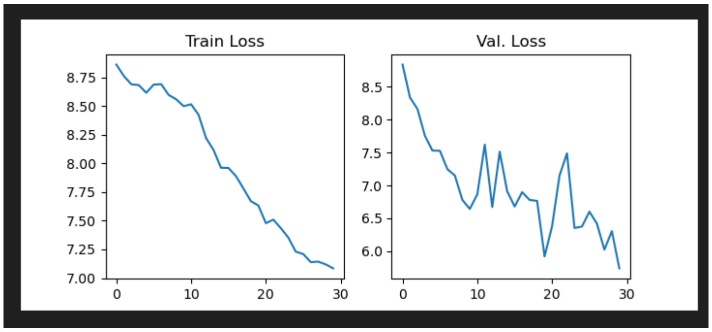
Q3)c) The success rate reported in terminal was 30%, averaged over all 50 attempts.

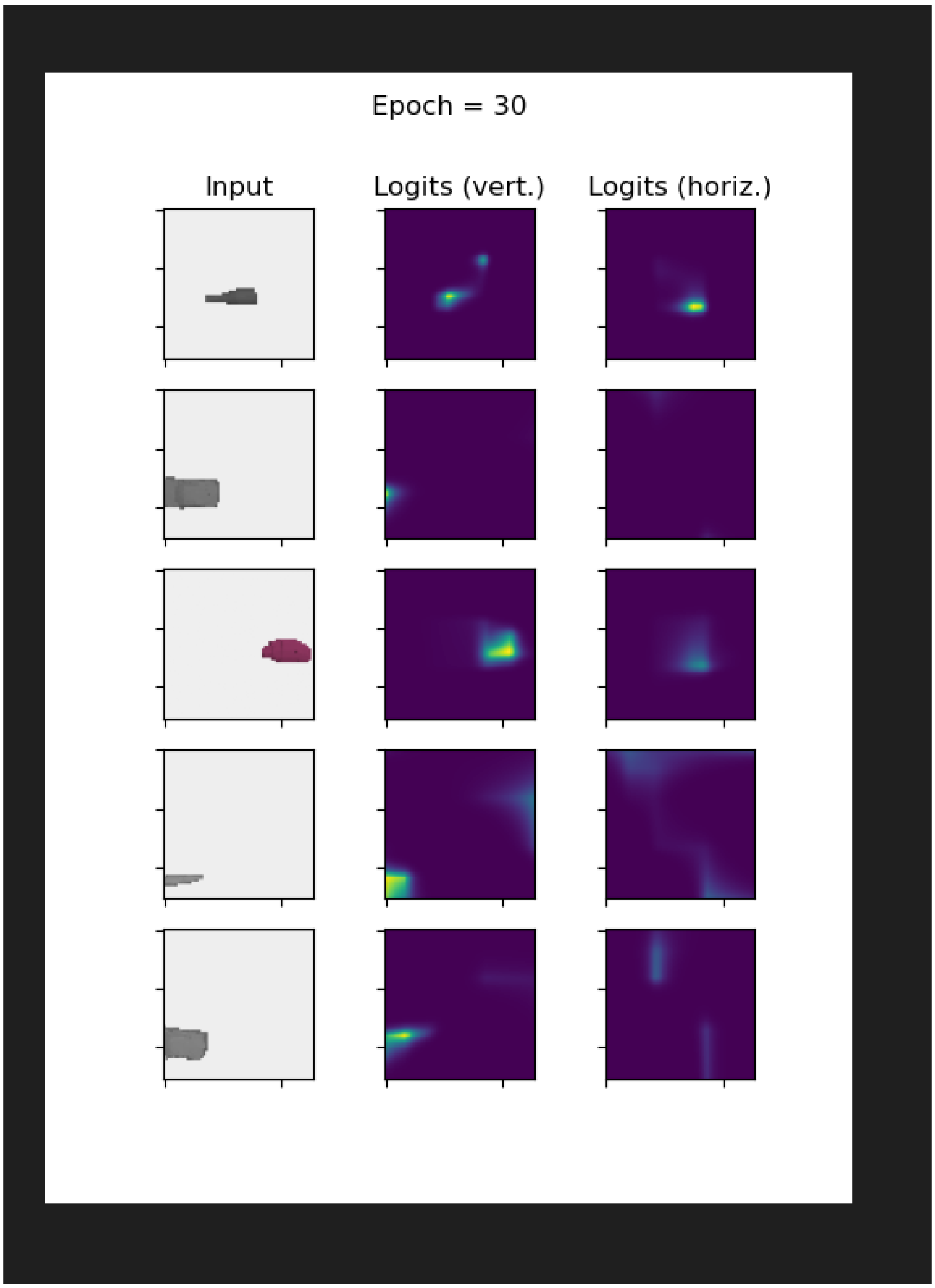
```
In [1]: runfile('C:/Users/josei/OneDrive/Documents/NEU/Assignments/
Assignments_Robotics Science and Systems CS5335/hw6/hw6-4/trainer.py',
wdir='C:/Users/josei/OneDrive/Documents/NEU/Assignments/Assignments_Robotics
Science and Systems CS5335/hw6/hw6-4')
loss=3.56: 100%|██████████| 30/30 [15:18<00:00, 30.62s/it]

In [2]: runfile('C:/Users/josei/OneDrive/Documents/NEU/Assignments/
Assignments_Robotics Science and Systems CS5335/hw6/hw6-4/evaluate_model.py',
wdir='C:/Users/josei/OneDrive/Documents/NEU/Assignments/Assignments_Robotics
Science and Systems CS5335/hw6/hw6-4')

pybullet build time: Apr  4 2023 15:52:30
Reloaded modules: dataset
Success rate = 30.0%: 100%|██████████| 50/50 [00:16<00:00,  3.12it/s]
```

Q4)b) the success rate reported in terminal after data augmentation was 44%.





Q4)c) The generalizations of translations of objects in the scene can be improved by various transformations such as random crops, flips, and rotations. Gripper rotation can also be randomly rotated around its z-axis to simulate different orientations during grasping. Pixel location can be perturbed to simulate translations by randomly shifting the pixel coordinates of the patch along the x and y axes. These transformations can increase diversity of training data and help the network generalize better.

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