<u>CS5335:Robotics Science and Systems</u>
HW6 : Grasping

Q1- a)

Speed: Compared to a physical robot, a simulator has the advantage of being able to perform grasp attempts at a much faster pace. This is because the simulator can simulate without any constraints by the physical limitations of a robot's hardware. As a result, a simulator can quickly generate large data on grasp attempts. Also having a significant amount of data will be helpful to train the models.

Safety: When performing grasp attempts with a physical robot, there is a risk of causing harm to the surrounding objects/ person or sometimes it can harm itself. Since, there is lower risk of injury and reduced damages to nearby objects/ to the equipment, we also get greater flexibility. We can perform a wide range of experiments without which might be dangerous / difficult to create in the real world. Also we can do extensive testing and training of grasp attempts than would be feasible with a physical robot.

b)

Here is the list of unrealistic physics that might occurs on some grasps -

(I was able to observe these changes after closing looking at the gripper trying to pick the objects)

1.If the simulator's physics engine is not accurately modeling the friction between the object and the robot's grasp, the object may slip out of the robot's grip too easily.

2. Sometimes the engine is trying to pick the objects from edges which might not be possible to grab in real-time cases.

3. If the simulator's iis not correctly modeling the object's weight, friction or any other physical properties, it may bounce excessively or spin out of control. It might also damage the objects.

4. Sometimes the grasp simulator doesn't work properly because it doesn't accurately calculate what happens when objects touch each other. It might make a guess about what happens or not do anything at all, which can cause things to move in ways that don't make sense.

Q2 b)
Important local information includes:

1. Object edges plus corners: To identify the object's edges and corners to understand where a gripper can make stable contact points and avoid slipping.
2. Object texture: it provides valuable information about the friction and surface properties, and might make the grasp stable.
3. Object shape plus curvature: This information can make sure that the gripper can pick the objects correctly, leading the successful grasp.
4. Object material properties: material properties such as - stiffness or softness can affect the gripping force required for a successful grasp.

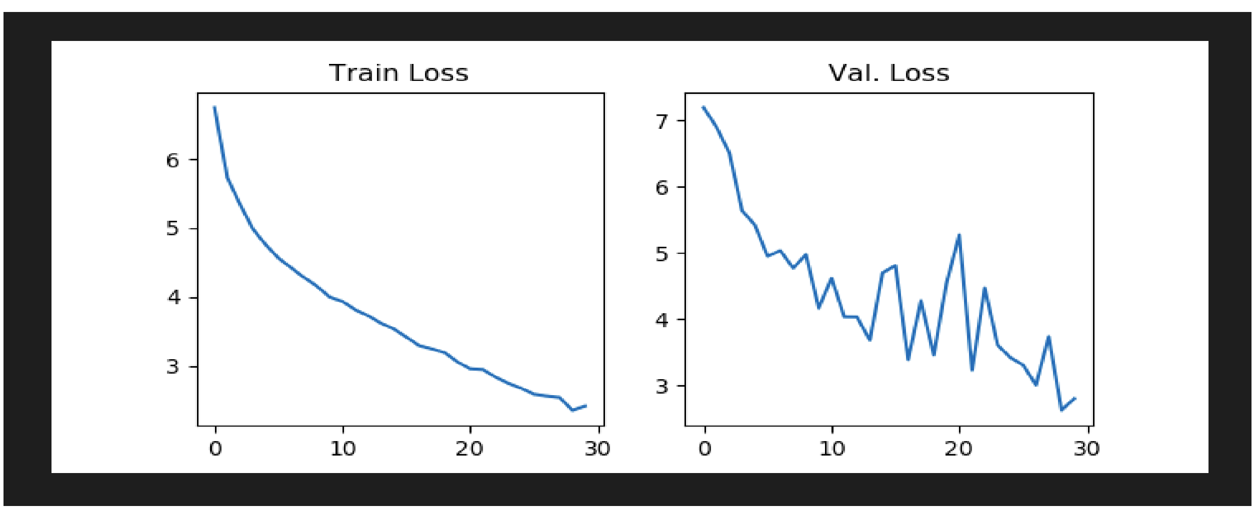
Considering the grasp prediction is based on local geometry and the shape of the object, I think global information is generally less important. It includes the layout of the scene, environmental information, or the relative positions of other objects.

We can use this info for ->

1. Navigation and path planning: For mobile robots or autonomous vehicles, global information about the environment, such as the location of obstacles. It will plan out safe and optimal routes.
2. Object detection: To know the relationships between objects and their positions within the scene is the major factor for accurate prediction.

Loss without data augmentation - 2.77

Q3



<u>Extra Credit</u> -
Why the validation loss curve will be very noisy ->
I think following factors might be responsible for the fluctuations in the validation loss -

1. Overfitting - We can see that initially the validation loss decreases and then it increases. This behavior tells us about the model overfitting. This is what came to mind when I saw the validation curve. I think the model becomes too complex and starts to fit the training data too closely. To avoid this, we can use regularization, early stopping.
2. Impact of learning rate on validation loss -
   1. if the learning rate is too low, the model may take longer to converge, and the validation loss may fluctuate more
   2. If the learning rate is too high, the model may converge quickly but may not reach the optimal solution, resulting in a high validation loss.
   3. a high learning rate can lead to overfitting.
3. If the data quality is poor like noisy data, then this will lead to fluctuations in the loss.
4. Fluctuations in the validation loss may indicate that the model is struggling to find the right balance between complexity and generalization, as too complex models can cause overfitting.

a)
The validation loss is not a perfect indicator of how well the network can predict grasps because the network could predict a valid grasp location that results in a large loss term. For example, the network could predict a grasp location that is valid but not optimal, resulting in a large loss term. The network could predict a grasp location that is valid for some objects but not for others, resulting in a large loss term. Therefore, the validation loss should be interpreted in conjunction with other metrics.
We know that the network aims to predict grasp success for each pixel location and gripper rotation, but even if the model doesn't predict exact grasp location, but predicts nearby location that is also valid grasping. The network might correctly identify a grasp location, but the loss might be large due to orientation of the grasp, or the shape of the object. Hence, to get accurate measures of grasp prediction, we should rely on metrics like precision/recall/f1-score.

c) Success Rate before data augmentation:

```
    )
  )
)
Success rate = 36.0%: 100%|
numActiveThreads = 0
stopping threads
Thread with taskId 0 exiting
Thread TERMINATED
destroy semaphore
semaphore destroyed
destroy main semaphore
main semaphore destroyed
finished
numActiveThreads = 0
btShutDownExampleBrowser stopping thread
```

After running evaluate model.py ->

A)In the dataset ->

the objects’ primary axes (L x W x H) are aligned with the coordinate axes of the image (horizontal and vertical axis). The objects appear in their "standard" orientations, which can make it easier for the model to recognize and train.

B) In the evaluation simulator -> places objects at arbitrary rotations.

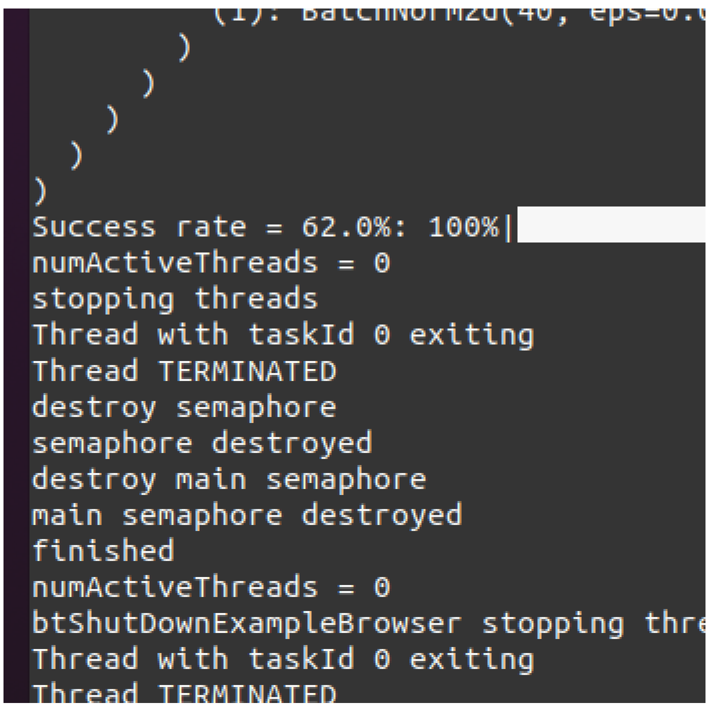
The objects can be found at any angle in the scene, this will lead to the variety in the object placements. This makes the model more challenging for recognition and prediction.

Q4)

b)

After implementing the data augmentation,

Success rate = 62%



```
          (1): BatchNorm2d(40, eps=0.
        )
      )
    )
  )
)
Success rate = 62.0%: 100%|
numActiveThreads = 0
stopping threads
Thread with taskId 0 exiting
Thread TERMINATED
destroy semaphore
semaphore destroyed
destroy main semaphore
main semaphore destroyed
finished
numActiveThreads = 0
btShutDownExampleBrowser stopping thre
Thread with taskId 0 exiting
Thread TERMINATED
```

c)

To improve generalization to translations of the objects in the scene:

1.Gripper Rotations and pixel location -

For gripper rotation, we can randomly rotate the gripper around its axis to simulate different grasping orientations. For pixel location, we can add random noise to the pixel coordinates to simulate small variations in the position of the objects in the scene. We can add noise by jittering.

2.Image Transformations -

We can use data augmentation techniques such as random cropping, flipping, and rotation or scaling to generate new training examples with different translations of the objects.