6.857 Final Project: Milestone 5

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I. Introduction

Our goal is to use neural networks to classify whether a particular grasp will succeed on an object. We utilize the Dexerity Network (DexNet) 2.0 data set [1], that has 6.7 million synthetic point clouds with parallel-jaw grasps (a common robot hand type of two parallel fingers) and analytical grasp metrics. The authors of the data set trained a Grasp Quality Convolutional Neural Network (GQ-CNN), which achieved 85.7% accuracy on their classification task. To accomplish the same task, we will be experimenting with new architectures, intput formats, other modifications described in Sec. IV. Most of the recent machine learning papers in robotics present a problem, dataset and, usually, an optimized convolutional neural network with some architecture and input format. Our goal is to explore the process of finding that CNN and exploring the factors that effect performance. While our results will only be verified according to this data set, and therefore cannot be generalized to all CNNs, we hope to gain intution, understanding, and, hopefully, a higher accuracy. Having explored various components, we will optimize our final, best architecture.

We will first describe the data set generation process and the features provided in the data set Sec. II. Understanding and processing this data set has become a larger element of our project then previously anticipated. We next discuss our results thus far Sec. III, which are preliminary. We will continue to explore these results, as well as our research questions Sec. IV.

II. Data Set

We are using the Dex Net 2.0 data set as first presented in [1]. We first briefly summarize their data generation process before describing how we manipulated the data.

Mahler et al define a generative graphical model defined over the camera pose, object shape and pose, friction coeffient, grasp, depth image and success metric. To generate the data set they make i.i.d (independent and identically distributed) samples from their generative graphical model, resulting in 6.7 million data points.

The data set is defined over 1,500 object meshes that were used in Dex-Net 1.0 [2], collected from a variety of other data bases and standardized with respect to position. For each object, they generated 100 parallel jaw grasps via rejection sampling of antipodal pairs and evaluated a grasp metric on each grasp. Additionally, each object is paired with a rendered depth image (2.5D point cloud [1]) from the sampled camera pose.

The GQ-CNN takes two images as input. The first is the depth image, called the "aligned image", transformed to center and axis align according the grasp point. Hence this image captures the scene and grasp in one representation. The second image, the "z image" is untransformed and represents the distance from the gripper to the camera.

The data set of 6.7 million data points has 21.1% positive examples. This is unsurprising, since it is much more difficult to find successful grasps, as compared to failed grasps.

The published Dex-Net 2.0 data set contains both sets of images for each data point in addition to grasp quality metrics and the grasp, represented by a 7-dimensional vector, specifying details of the grasp center, angle, object center and gripper width and several over parameters. Our label is given by the robust epsilon quality grasp metric (defined in [3]), which is thresholded by the value 0.002 to create binary labels.

From the 6.7 million data points, we create two types of data sets:

- **Unbalanced.** We randomly sample 10,000 data points from our entire set. We expect to sample approximately 20% positive examples, matching the distribution of the original set.
- **Balanced.** We randomly sample data points until we have 10,000 data points that are 50% positive examples and 50% negative examples.

We further discuss the motivation for this distinction in Sec. IV. For all data sets we include all possible features, although some architectures might not leverage all features.

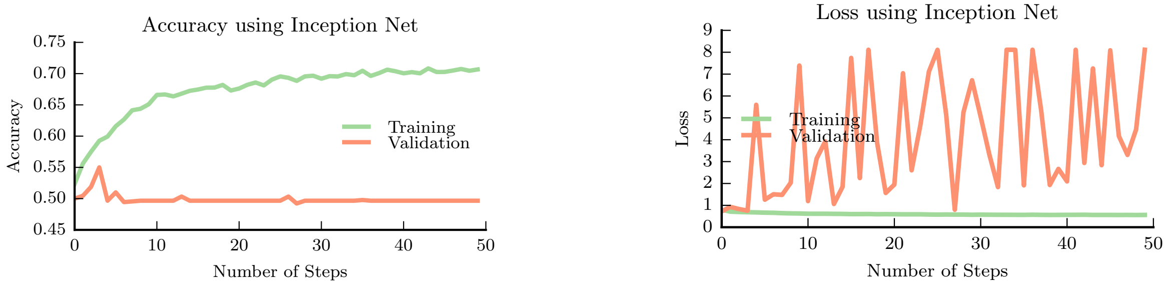
Since we are sampling our data sets, we will sample multiple copies and average the final results across each version [2].

III. Results

RH: give the results from the architectures that we have

[1] The images are 2D matrics that are referred to as 2.5D in robotics literature because they display depth information.

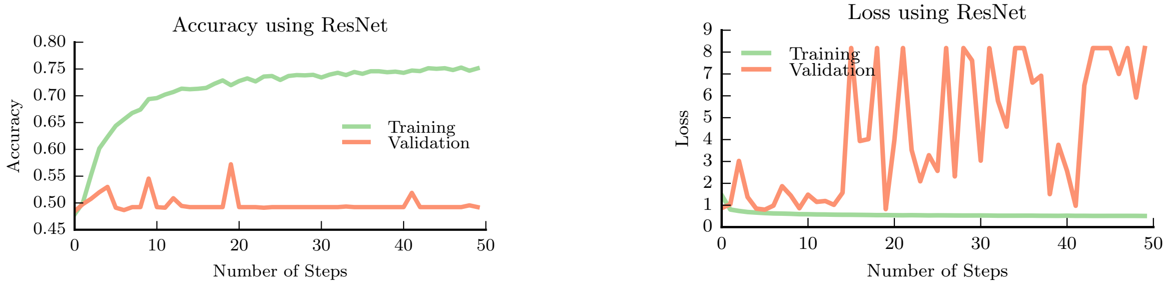
[2] This was not done for this milestone, but will be done in the final report.



(a) Accuracy

(b) Loss

Fig. 1: The Loss and Accuracy across the Training and Validation Sets for our Inception Net



(a) Accuracy

(b) Loss

Fig. 2: The Loss and Accuracy across the Training and Validation Sets for our ResNet using the balanced data set.

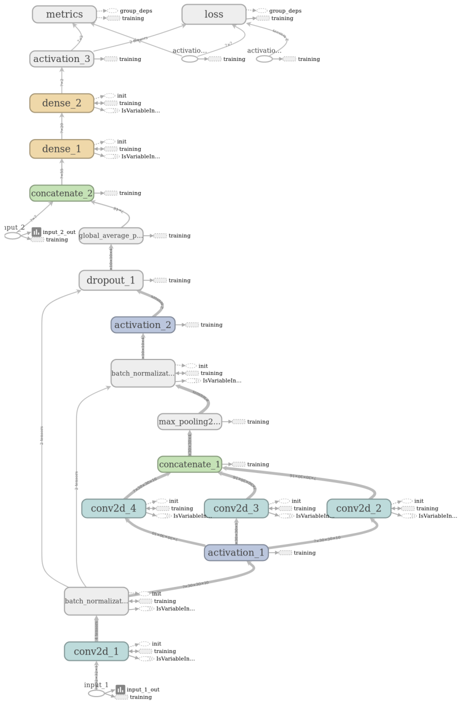


Fig. 3: Network Structure of Inception Net

IV. Research Questions

A. Input Format

One of the benefits of the Dex-Net data set is that it provides many features, allowing us to vary what we use as input to the network. We are and will continue to experiment with various inputs. Some inputs might be particularly informative but costly to collect when running the system on a real robot. **RH: say what we use above**

B. Balancing Data Sets

As mentioned previously, Dex-Net 2.0 contains approximately 20% positive examples. This is not inherenely problematic given that the training and testing sets are drawn from the same distribution, with this same ratio. However, by sampling subsets of our data set, we can achieve any positive-to-negative ratio and thus explore how changing this ratio effects accuracy. Furthermore, we can explore what happens when the distributions of the training and testing set don't match. When utilizing these learning architectures on a real robotic system, (hence making a new test set), we might not be able to accurately predict our positive-to-negative distribution. If so, how should we construct our training set to handle this?

C. Data Set Size

The Dex-net data set contains 6.7 million data points. For computational reasons, we are sampling a subset of these points. However, we can vary the size of this subset to compare the trade-off between the accuracy and the size of the training set. How much does this relationship vary between input formats and architectures? Are some combinations more data-hungry?

D. Architecture Structure

One of the largest sources of experimentation thus far and continuing forward is our choice of architecture.

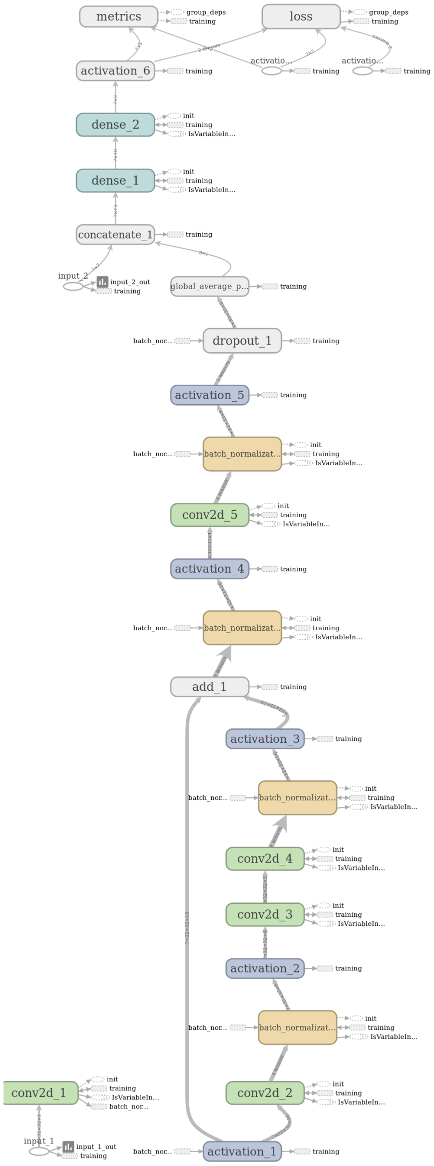


Fig. 4: Network Structure of ResNet

RH: list a few examples

V. Work Distribution

RH: give basically same thing as before

References

[1] J. Mahler, J. Liang, S. Niyaz, M. Laskey, R. Doan, X. Liu, J. A. Ojea, and K. Goldberg, "Dex-net 2.0: Deep learning to plan robust grasps with synthetic point clouds and analytic grasp metrics," *arXiv preprint arXiv:1703.09312*, 2017.

[2] J. Mahler, F. T. Pokorny, B. Hou, M. Roderick, M. Laskey, M. Aubry, K. Kohlhoff, T. Kröger, J. Kuffner, and K. Goldberg, "Dex-net 1.0: A cloud-based network of 3d objects for robust grasp planning using a multi-armed bandit model with correlated rewards," in *ICRA*, pp. 1957–1964, IEEE, 2016.

[3] D. Seita, F. T. Pokorny, J. Mahler, D. Kragic, M. Franklin, J. Canny, and K. Goldberg, "Large-scale supervised learning of the grasp robustness of surface patch pairs," in *SIMPAR*, pp. 216–223, IEEE, 2016.