Motivation:

Recent methods have employed simplified camera feeds as states, and regressed these states to small delta pose control. In the last ten years, classification and regression tasks for statistics have been tackled using convolutional neural nets, which combine signal processing intuition with highly expressive learned models. While deep learning offers the offers an opportunity to handle and learn more complex states and policies, highly expressive models also have the weakness of overfitting and weakness to noise, especially with fairly limited data. With regards to theses problems, researchers often employ a collection of techniques referred to as "data cleaning" in order to limit and correct for systematic noise. Employing an appropriate combination of these techniques can often greatly improve the error rate of a machine learning model. The use case of machine learning differs in several key ways from robotic learning, however. First, the nature of the data produced by robotic learning models differs from those in generalized machine learning. In robotic learning, certain properties of the data can be enforced, such as smooth robotic deltas, since different sets of data have clear relationships: robotic trajectories have local physical constraints, making low pass filters particularly applicable. Second, robotic data is often much harder to collect, and with fewer data points than machine learning datasets, since a robotic policy, in the worst case, has a different distribution at each time step. A learning model most determine the behavior at each of these distributions (though not without some amount of locality), which implies that robotic learning data scales in the number of timesteps (as well as the shared entropy of the distributions). Furthermore, because the data must be collected on the physical robotic system, this data is often difficult to gather, compared to the large aggregated data available to machine learning datasets. Third, robotic learning data might not be easy to identify as difficulty, because the "dirtiness" of the policy is based on how well the user performed the demonstration, which is often not easy to measure. This is compared to messy or incorrect labels, which can often be easily computed. For these reasons, model free robotic learning from demonstration has the potential to benefit from unique forms of data cleaning: more intensive data cleaning has the capacity to compensate for more expensive robotic learning, robotic data cleaning has the potential to highlight trajectory-based relationships, and dirty robotic data might not be easy to evaluate.

Key Insight:

Hard to learn data points often produce high test errors, and trajectories with especially high numbers of these hard to learn data point have the potential to be more dirty. However, determining whether these hard to learn trajectories are hard to learn because they are necessarily more complex, or because they are dirty, is hard for a learning model to determine automatically. Thus, in these cases we employ the user to compare this cleaning method with the data. I propose an iterative meta-algorithm, loosely derived from ActiveClean [1], which iterates between the three steps:

Step 1: Determine hard data points using the cross-validation test error of the learned model

Step 2: The human is displayed these hard states, and corrects them based on either: choosing the regressed delta, producing a new delta, removing the data point or keeping the data point.

Step 3: Using the human actions a model is learned that discriminates hard data (kept points) from dirty data (removed, or modified deltas). Use the new dataset for the next iteration, preferring dirty points.

State of the art:

Robotic learning generally employs data cleaning in the context of sensor readings [2] and torque control [3]. However, the direct application of data cleaning to model free state to control regression robotic learning is quite limited, perhaps even non-existent. On the other hand, data cleaning in machine learning and statistics is well studied. Data cleaning has historically employed several methods, including: smoothing using probabilistic models [4], cleaning with hand crafted features [5], and performing learnability analysis [6]. In addition, the effect of noise on neural nets[7], as well as their high expressiveness [8,9] have been well studied. Finally, iterative data cleaning methods have been proposed before, with some success, in the context of machine learning [1, 10, 11]

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