1 Key Ideas

1. An interpretable intuitive physics model where dimensions in the bottleneck layer corresponds to different physical properties.
2. Intuitive as in the model is not able to predict the precise value of the physical properties, but still able to predict the approximate change in the world following a change in physical properties.
3. The NN architecture seems standard, the key to success is the training procedure and loss fnc.
4. Benefit is generalization to unseen conditions and interpretable latent dimensions. For example, the latent dimension can be interpolated, where interpolation in a specific dimension leads to meaningful and accurate change in the final prediction of the properties associated with that dimension.

2 Grouping of training samples based on changes in specific physical properties

1. Since training data is generated in simulation, they know what the values for the physical properties are for each training sample.
2. In each training mini-batch, they only include samples which differ in their values for one specific physical property while the remaining physical properties are the same.
3. For each mini-batch, they encourage only the dimensions in the latent space corresponding to the physical properties which vary in the mini-batch to change. The rest of the dimensions are encouraged to stay constant.
4. Their obj fnc thus consists of 2 terms, a standard MLE term for reconstruction and a term which encourages the appropriate dimensions in the latent space to stay constant.

3 Staggered training procedure

1. They argue that the observed physical dynamics are dependent across the set of underlying physical properties, which confound training. This probably meant that training was unstable.
2. The same sequence of input-output pair can correspond to different combinations of the values for the physical properties. For example, both large friction and slow initial speed can explain the slow movement of an obj after a collisions.
3. They thus propose curriculum learning, where they train the network to only "infer" one new physical property at a time.
4. They divide the training set into subset, where in each subset, only the values for one physical parameter change. Within each subset are the training mini-batch as discussed in the previous sections.
5. They begin by training the network with one subset and progressively add more subsets with different properties into training.

4 Experiment

4.1 Generalization to unseen conditions

1. There are 2 axis of variations in the data: combination of different values of the physical properties and the combinations of objects that are colliding.
2. They shown that the prediction made by the learnt model generalize to unseen conditions in either of this axis.

4.2 Interpolation between 2 ground truth values

1. This experiment is to show that the learned bottleneck layer is meaningful and smooth.

2. Given two ground truth input, they convert them to their respective latent representation. They then interpolate linearly between the two latent representations and obtain the output of the model conditioned on the interpolated latent. They show that the predicted output roughly matches the corresponding ground truth value.

4.3 Scaling the physics parameter by a vector

1. They ask: can the model predict the future if mass is doubled while all other physics condition remain the same?

2. To do this, they train a new network to scale the physics parameter by a factor.

3. The label for this network is the embedding of the already trained physics model! So neat!

5 Question

1. The approach works because the data is generated in simulation, so it's "easy" to control the data generation process and divide the training set into mini-batches where only one physical properties vary. Can similar ideas be used for sim-to-real?

2. Intuitive physics learnt in simulation + sim-to-real are a good match. The hard thing about sim-to-real is that if the model tries to learn anything precise in sim, it will fail because the values will be different in real. But intuitive physics' goal is not learning precise values, but a general understanding. Such understanding can bootstrap training in real.

3. A benefit of the disentangled representation is generalization to unseen conditions. Will a policy trained on top of such representation generalize better as well?