GROUNDING GRAPH NETWORK SIMULATORS USING PHYSICAL SENSOR OBSERVATIONS

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ABSTRACT

Physical simulations that accurately model reality are crucial for many engineering disciplines such as mechanical engineering and robotic motion planning. In recent years, learned Graph Network Simulators produced accurate mesh-based simulations while requiring only a fraction of the computational cost of traditional simulators. Yet, the resulting predictors are confined to learning from data generated by existing mesh-based simulators and thus cannot include real world sensory information such as point cloud data. As these predictors have to simulate complex physical systems from only an initial state, they exhibit a high error accumulation for long-term predictions. In this work, we integrate sensory information to *ground* Graph Network Simulators on real world observations. In particular, we predict the mesh state of deformable objects by utilizing point cloud data. The resulting model allows for accurate predictions over longer time horizons, even under uncertainties in the simulation, such as unknown material properties. Since point clouds are usually not available for every time step, especially in online settings, we employ an imputation-based model. The model can make use of such additional information only when provided, and resorts to a standard Graph Network Simulator, otherwise. We experimentally validate our approach on a suite of prediction tasks for mesh-based interactions between soft and rigid bodies. Our method results in utilization of additional point cloud information to accurately predict stable simulations where existing Graph Network Simulators fail.

1 INTRODUCTION

Mesh-based simulation of complex physical systems lies at the heart of many fields in numerical science and engineering (Liu et al., 2022; Reddy, 2019; Rao, 2017; Sabat & Kundu, 2021). Applications include structural mechanics (Zienkiewicz & Taylor, 2005; Stanova et al., 2015), electromagnetics (Jin, 2015; Xiao et al., 2022; Coggon, 1971), fluid dynamics (Chung, 1978; Zawawi et al., 2018; Long et al., 2021) and biomedical engineering (Van Staden et al., 2006; Soro et al., 2018), most of which traditionally depend on highly specialized task-dependent simulators. Recent advancements in deep learning brought rise to more general learned dynamic models such as Graph Network Simulators (GNSs) (Sanchez-Gonzalez et al., 2018; 2020; Pfaff et al., 2021). GNSs learn to predict the dynamics of a system from raw data by encoding the system state as a graph and then iteratively computing the dynamics for every node in the graph with a Graph Neural Network (GNN) (Scarselli et al., 2009; Battaglia et al., 2018; Wu et al., 2020b). Recently, these models were extended to long-term fluid flow predictions (Han et al., 2022) and to model dynamics on different scales (Fortunato et al., 2022). Yet, these approaches assume perfect knowledge of the initial system state, making them ill-suited for applications like model-based control (Camacho & Alba, 2013; Schwenzer et al., 2021) and model-based reinforcement learning (Polydoros & Nalpantidis, 2017; Moerland et al., 2020) where accurate predictions must be made based on an often incomplete initial state and partial observations.

In this work, we address these limitations by providing sensory information to the model to *ground* its prediction in the observations of the scene. More precisely, we extend the graph of the current system state with point cloud data before using it to predict the system dynamics. Point cloud data, however, does not provide correspondences of the points between time steps. Hence, it is very difficult to learn from point-cloud data alone as the dynamics of each point are unclear. To address this challenge, we utilize mesh-based data to learn the dynamics and utilize point-cloud data to correct the predictions.

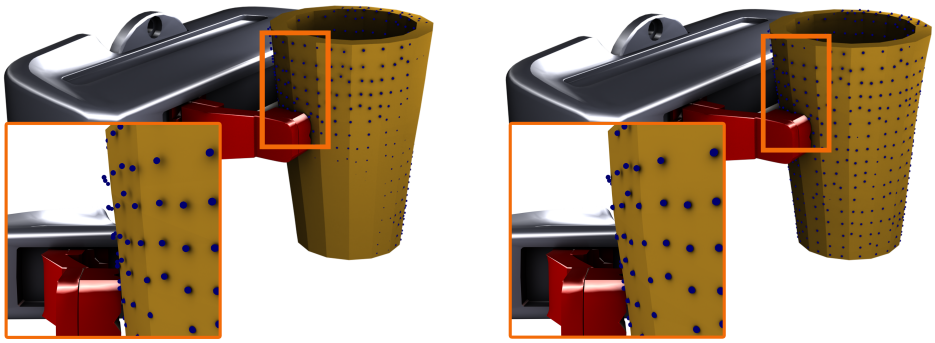


Figure 1: A robot's end-effector (grey, red) grasps a 3-dimensional deformable cavity. The robot maintains an internal simulated prediction of the cavity (orange) for two consecutive simulation steps (left, right). This prediction can deviate from the true state of the cavity over time due to an accumulation of error. However, the true cavity state can infrequently be observed from point cloud data (blue), which the model can use to correct its prediction. Here, the point cloud is used to contract the simulated cavity at the bottom and extend it at the top, causing the points to better align with the mesh surface. We repeat the point cloud from the earlier simulation step for both images for clarity.

As the sensory data is not always available, in particularly not for future predictions, our architecture is trained with imputed point-cloud data, i.e., for each time step the model receives point cloud information with a certain probability. This training scheme allows the model to efficiently integrate the additional information whenever provided. The same model is used for inference by iteratively predicting the next system state, using point clouds whenever available. We find that the resulting model, Grounding Graph Network Simulator (GGNS), greatly improves the simulation quality for simulations with incomplete initial state information, and that it furthermore alleviates common challenges with GNS such as *drift* and error accumulation during long-term predictions.

As a practical example, consider a robot grasping a deformable object. For optimal planning of the grasp, the robot needs to model the state of the deformable object over time and predict the influence of interactions between object and gripper. This prediction not only depends on the initial shape of the object, but also on the forces the robot applies, the kind of material to grasp and external factors such as the temperature, making it difficult to accurately predict how the material will deform over time. However, once the robot starts deforming the object, it may easily observe the deformations in the form of e.g., point clouds. These observations can then be integrated into the state prediction, i.e., they can *ground* the simulation whenever new information becomes available. An example is given in Figure 1. Observation-aided prediction is similar in nature to e.g., Kalman Filters (Kalman, 1960; Jazwinski, 1970; Becker et al., 2019) as the belief of the system state is updated based on partial observations about the system. However, while Kalman Filters explicitly integrate novel information into the belief in a mathematical fashion, we instead simply provide this information to a learned model as additional unstructured sensor input.

We evaluate GGNS on a suite of 2d and 3d deformation prediction tasks created in the Simulation Open Framework Architecture (SOFA) framework (Faure et al., 2012). Comparing our approach to an existing GNS (Pfaff et al., 2021), we find that adding sensory information in the form of point clouds to our model improves the simulation quality for all tasks. This benefit is most apparent when the initial system state is not fully known, e.g., when the exact physical properties of the material are unknown. We investigate this behavior through extensive ablation studies, showing the importance of different parameter choices and design decisions. To facilitate research in this area, we will provide code and data for the camera-ready version.

To summarize, our list of contributions is as follows: (I) We extend the GNS framework to include sensory information to *ground* predicted simulations in observations of the system state. (II) We propose a simple but effective imputation training scheme that allows our model to utilize sensory information whenever available and to resort to a regular GNS otherwise. (III) We construct and experiment on different deformation prediction tasks and find that the inclusion of sensory information improves performance in all settings, and that it is particularly crucial when the initial system state is not fully known.

2 RELATED WORK

Learned Physics Simulation. In recent years there has been a steady increase in research concerning Deep Learning for physical simulations. Early work in Physical Reasoning aims at teaching systems to understand physical relations on N-body systems (Battaglia et al., 2016) and deformable objects (Mrowca et al., 2018). A more direct approach is to instead train a learnable simulator from data provided by some existing ground truth simulator. Here, Convoluational Neural Networks (CNNs) have been extensively studied for fluid flow simulation (Tompson et al., 2017; Chu & Thuerey, 2017; Ummenhofer et al., 2020; Kim et al., 2019; Xie et al., 2018) and aerodynamic flow fields (Guo et al., 2016; Zhang et al., 2018; Bhatnagar et al., 2019). Further approaches use standard neural networks for liquid splash simulations (Um et al., 2018) and latent space physics simulation (Wiewel et al., 2019). Such learned physics simulators are considerably faster than their ground-truth counterparts, and that they are usually fully differentiable. Thus, they have been applied to model-based Reinforcement Learning (Mora et al., 2021) and for Inverse Design problems (Baqué et al., 2018; Durasov et al., 2021; Allen et al., 2022b) .

Graph Network Simulators. Graph Network Simulators (GNS) (Sanchez-Gonzalez et al., 2020) are a special case of learned physics simulators that utilize GNNs (Scarselli et al., 2009) to efficiently encode the graph-like structure of many physical problems. They have found wide-spread application in calculating atomic forces (Hu et al., 2021), particle-based simulations (Li et al., 2019; Sanchez-Gonzalez et al., 2020) and mesh-based simulations (Pfaff et al., 2021; Weng et al., 2021; Han et al., 2022; Fortunato et al., 2022; Allen et al., 2022a). Other work in this field directly solves Partial Differential Equations (Alet et al., 2019), and integrates explicit domain knowledge into the learned simulator to improve the predictions (de Avila Belbute-Peres et al., 2020; Li & Farimani, 2021; 2022). Similarly, CNNs have been used to predict particle masses from images to subsequently simulate physical systems with a GNN (Li et al., 2020) via visual grounding. This approach assumes access to a series of images to predict particles and their behavior, whereas GGNS integrates sensor observations into an existing mesh-based simulation. The work most closely related to our research is MeshGraphNet (MGN) (Pfaff et al., 2021), which combines a graph-based encoding of the system state with the next-step prediction of dynamic quantities to produce realistic predictions of mesh-based simulations.

Simulation from Observation. Another variant of learned physics simulation is simulation from observation. Learning directly from observations instead of a ground truth simulator requires less expert knowledge for the design of the simulator and is more applicable to real-world scenarios. Different approaches exist for this type of simulation, including Physical Reasoning (Li et al., 2020) and particle-based simulation (Martinkus et al., 2021). Point clouds have been used in CNN-based simulation (Watters et al., 2017; Wang et al., 2019), and combined with PointNet (Charles et al., 2017; Qi et al., 2017) to predict object deformations purely from observational data (Park et al., 2021). Further approaches make use of GNNs to predict object relations (Fetaya et al., 2018) and future frames in a point cloud sequence (Gomes et al., 2021).

Simulation of Deformable Objects. Simulating deformable objects is crucial for many applications such as robotic manipulation tasks (Sanchez et al., 2018). Yet, recent approaches do not take explicit deformation into account (Matas et al., 2018), or only consider highly simplified geometries such as ropes (Sundaresan et al., 2020) or a square piece of cloth (Wu et al., 2020a; Lin et al., 2020; 2022). One reason for this is the high computational cost of existing simulators, which may be alleviated by fast and accurate learned simulators (Pfaff et al., 2021; Weng et al., 2021). Another recent work trains the parameters of a differentiable simulator to align its simulations with real-world observations of deformable objects based on point cloud information (Sundaresan et al., 2022). In this work, we instead utilize point cloud information to improve upon existing mesh-based GNSs in settings where additional point cloud data is available.

3 FOUNDATIONS

3.1 MESSAGE PASSING NETWORK

Let $\mathcal{G} = (\mathbf{V}, \mathbf{E}, \mathbf{X_V}, \mathbf{X_E})$ be a directed graph with nodes $\mathbf{V}$, edges $\mathbf{E} \subseteq \mathbf{V} \times \mathbf{V}$, node features $\mathbf{X_V} : \mathbf{V} \to \mathbb{R}^{d_\mathbf{V}}$ of dimension $d_\mathbf{V}$ and edge features $\mathbf{X_E} : \mathbf{E} \to \mathbb{R}^{d_\mathbf{E}}$ of dimension $d_\mathbf{E}$. A Message Passing Network (MPN) (Sanchez-Gonzalez et al., 2020; Pfaff et al., 2021) is a GNN consisting of L

Message Passing Blocks that receives the graph $\mathcal{G}$ as input and outputs a learned representation for each node $\mathbf{V}$. Each block l computes updated features for all nodes $v \in \mathbf{V}$ and edges $e \in \mathbf{E}$ as

$$\mathbf{x}_e^{l+1} = f_{\mathbf{E}}^l(\mathbf{x}_v^l, \mathbf{x}_u^l, \mathbf{x}_e^l), \text{ with } e = (u, v) \text{ and } \mathbf{x}_v^{l+1} = f_{\mathbf{V}}^l(\mathbf{x}_v^l, \bigoplus_{\{e=(v,u)\in\mathbf{E}\}} \mathbf{x}_e^{l+1}),$$

where $\mathbf{x}_v^0$ and $\mathbf{x}_e^0$ are linear embeddings of the initial node and edge features of $\mathcal{G}$ and $\oplus$ is a permutation-invariant aggregation such as a sum, max, or mean operator. Further, each $f_\cdot^l$ is a learned function that is generally parameterized as a simple Multilayer Perceptron (MLP). Previous work (Pfaff et al., 2021) decomposes these learned functions to explicitly represent two different kinds of edges, in their case mesh and world edges. More concretely, they assume an edge partition $\mathbf{E} = \mathbf{E}_1 \dot\cup \mathbf{E}_2$ and separate edge update functions $f_{\mathbf{E}_1}^l$ and $f_{\mathbf{E}_2}^l$. The edge-aggregation for the node update is then computed by aggregating the latent features of both types of edges separately and concatenating the result. Our method, however, omits this explicit representation in favor of a simple one-hot encoding of the type of input edge.

3.2 Graph Network Simulator

GNSs simulate a system's dynamics by repeatedly applying the following three steps. First, they encode the system state $\mathcal{S}$ in a graph $\mathcal{G}$. If the system state is given as e.g., a (triangular or tetrahedral) mesh $\mathcal{M}$ of the underlying entities, this graph is naturally constructed by using the nodes of $\mathcal{M}$ as nodes of the graph, and the connection between these nodes as edges. The node and edge features $\mathbf{X}_{\mathbf{V}}, \mathbf{X}_{\mathbf{E}}$ can be constructed based on the concrete simulation. In general, encoding purely *relative* properties such as relative distances and velocities per edge rather than absolute positions per node have been shown to greatly improve training speed and generalization (Sanchez-Gonzalez et al., 2020). Next, the encoded graph $\mathcal{G}$ is used as input for a learned MPN, which computes final latent representations x_v^L for each node $v \in \mathbf{V}$. These latent representations are interpreted as (potentially higher-order) derivatives of dynamic quantities, which are used by a simple forward-Euler integrator to derive an updated system state $\mathcal{S}'$. Note that for some tasks, only a fraction of mesh nodes need to be predicted, as the others are either fixed or belong to a known entity such as a gripper or collider. In this case, only the latent representations of the nodes with otherwise unknown dynamics are used.

GNSs are trained on a node-wise next-step Mean Squared Error (MSE) objective, i.e., they minimize the 1-step prediction error of the next system state to that of a given ground truth trajectory. During inference, simulations over potentially hundreds of steps can be generated by iteratively repeating the above-mentioned steps, using the updated dynamics of one step as the input for the next. We note that the model does not predict the movement of fixed entities such as e.g., a collider, which is instead assumed to be known and combined with the model's prediction about the unknown parts of the system. Due to this iterative dependence on previous outputs, the model is prone to error accumulation. A common strategy to tackle this limitation is to apply additional noise to the dynamic variables of the system for each training step (Sanchez-Gonzalez et al., 2020; Pfaff et al., 2021). Intuitively, adding training noise acts as a form of data augmentation that allows the learned model to compensate for small prediction errors over time. This kind of error-compensating next-step prediction leads to plausible and visually realistic predictions. However, the resulting predictions can be arbitrarily inaccurate with respect to the true dynamics of the system, since the model has no reference for its simulation other than some potentially incomplete initial state $\mathcal{S}_0$.

4 Observation-Aided Graph Network Simulator

Our approach combines recent advances in graph-based learned physics simulation with additional partial observations of the system state to generate highly accurate simulations from incomplete initial states. To this end, we extend the existing GNS framework to naturally and efficiently integrate auxiliary point cloud data whenever available. This auxiliary information *grounds* the predictions of the model in an observation of the true system state, guiding it towards predictions that not only look realistic but also closely match the actual dynamics of the system. Figure 2 illustrates an overview of our approach. A more detailed description of the GNN-part of the method is found in Appendix A.

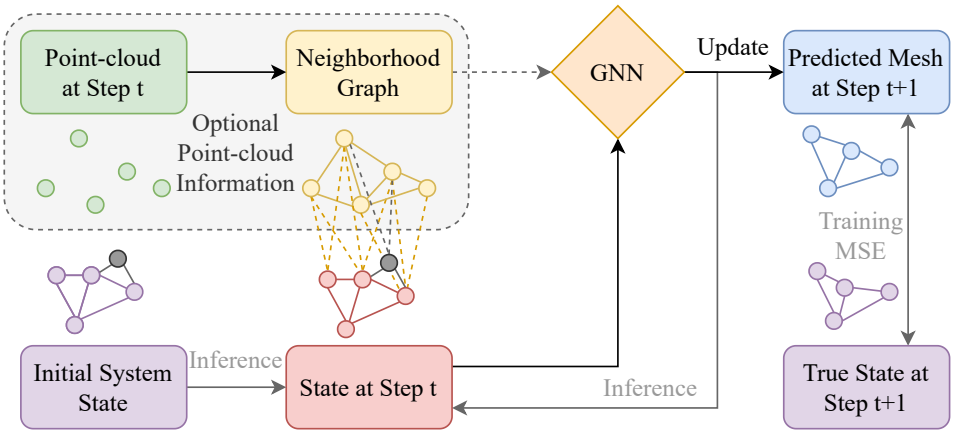


Figure 2: Schematic of GGNS . Given a system state $\mathcal{S}_t$ (red) and optional point cloud observations (green), a GNN (orange) predicts how the system $\mathcal{S}_{t+1}$ will look like at the next step (blue). For object deformation tasks, the state can include boundary conditions (gray) such as colliders or walls. When provided, the point cloud is transformed into a neighborhood graph (yellow) in the same coordinate system as the mesh, connecting each point in the point cloud to the nearest mesh nodes. The model is trained to predict the next system state based on a true state (purple) provided by a ground truth simulator. During inference, the model iteratively predicts updates from a potentially incomplete initial system state (purple), using additional point cloud observations when available.

4.1 Point Clouds and Neighborhood Graphs

In order to utilize point-based data in addition to meshes we have to transfer both into a common graph. Following previous work (Sanchez-Gonzalez et al., 2018), we do this by creating a neighborhood graph based on spatial proximity. Given a graph $\mathcal{G} = (\mathbf{V}, \mathbf{E}, \mathbf{X_V}, \mathbf{X_E})$ that encodes a predicted system state and a point cloud observation $\mathcal{P} = \{p_1, \ldots, p_N\}, p_j \in \mathbb{R}^d$ of the true system state, we set $\mathbf{V}' = \mathbf{V} \cup \mathcal{P}$ and

$$\mathbf{E}' = \mathbf{E} \cup \{(p_i, p_j) \in \mathcal{P}^2 | \mathrm{d}(p_i, p_j) \leq r_\mathcal{P}\} \cup \{(v, p), (p, v) | v \in \mathbf{V}, p \in \mathcal{P}, d(p, v) \leq r_\mathcal{S}\}.$$

Here, d is some distance measure, usually the euclidean distance, and $r_\mathcal{P}$ and $r_\mathcal{S}$ are task-specific neighborhood radii. The corresponding features $\mathbf{X_{V'}}, \mathbf{X_{E'}}$ of the added nodes and edges in $\mathbf{V}'$ and $\mathbf{E}'$ depend on the concrete task. The different node and edge types are one-hot encoded into their respective features to allow the model to differentiate between them. Similar to the original features, information can be encoded in a relative fashion in the form of edge features to aid generalization. More concretely, we encode relative distances in world space along all edges, additionally adding mesh-space distances for edges between two mesh nodes. This connectivity is slightly different from MGN (Pfaff et al., 2021), which make use of additional *world edges* between mesh-nodes by creating a similar radius-based neighborhood graph for the mesh nodes in world space.

4.2 Imputation-based training and inference

For most realistic applications, point clouds are typically not available at each time step during inference. For example, we may have access to observed point clouds from the previous k time steps and want to use them to infer the state of the system in the future. We adapt our model to this constraint by employing an imputation-based training scheme by randomly replacing the graph $\mathcal{G}$ of $\mathcal{S}$ with the corresponding extended graph $\mathcal{G}' = (\mathbf{V}', \mathbf{E}', \mathbf{X_{V'}}, \mathbf{X_{E'}})$ with equal probability during training. In both cases, the model is only trained to predict the system dynamics for the original nodes $\mathbf{V}$. Intuitively, this allows each system node $v \in \mathbf{V}$ to utilize the additional information of close-by points of a point cloud when available, while at the same time forcing it to also make sensible predictions when there is no additional information. During inference, we construct $\mathcal{G}'$ from the (predicted) system state $\mathcal{S}$ and a corresponding observed point cloud $\mathcal{P}$ of the true object whenever available and use $\mathcal{G}$ otherwise. This enables the model to reason about the true system state that is observed via $\mathcal{P}$, adapting its prediction to the otherwise unknown behavior of the system.

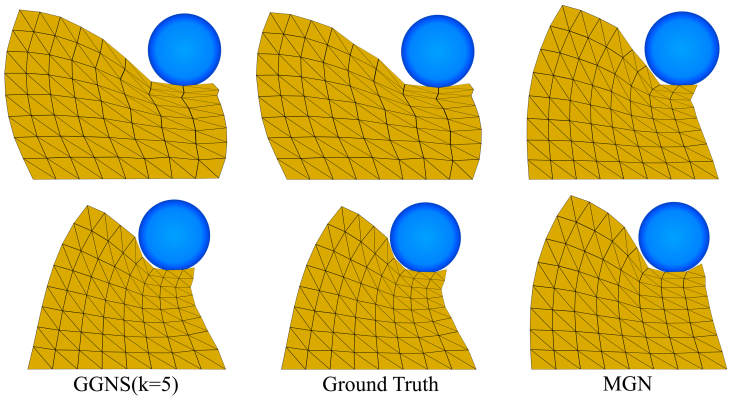


Figure 3: Final simulated meshes ($t = 50$) for GGNS ($k = 5$) (left), the ground truth simulation (middle) and MGN (right) for 2 test rollouts with different material properties for the Deformable Plate task. Our model closely matches the ground truth simulations for both materials, while MGN predicts the same material every time.

This *grounding* of the prediction also alleviates common errors of GNS such as drift and more generally error accumulation. An example can be seen in Figure 1. Here, the system state consists of a predicted mesh and a gripper, and the point cloud consists of points sampled from the true object. The mismatch between point cloud and predicted mesh indicates the prediction error, and the model uses this additional information to correct the current state estimate.

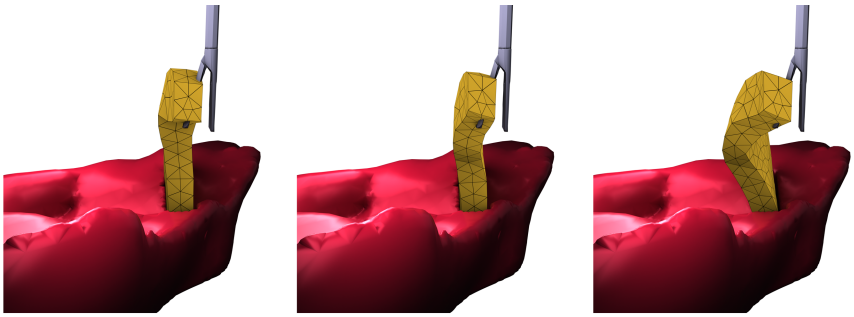
We compare this simple imputation-based method to another training scheme in our experiments, which we call GGNS+LSTM. Here we use an LSTM (Hochreiter & Schmidhuber, 1997) layer on the node output features of the GNN to explicitly include recurrency into the model. This modification allows information such as the material properties to be inferred and propagated over time, which can be utilized to improve the predictions in time steps without point clouds. The resulting model is trained on the same 1-step prediction loss and also uses training noise to generate stable rollouts during inference. However, it is significantly more costly to train, as it makes use of back-propagation in time to compute the gradients for the recurrency. We find experimentally that this recurrent model performs worse than the imputation-based method, likely because the benefit of propagating information over time is offset by the additional training and model complexity.

5 Experiments

We evaluate GGNS on complex 2d and 3d mesh-based object deformation prediction tasks modelled in Simulation Open Framework Architecture (SOFA) (Faure et al., 2012). For each task, the true system state is given by a tetrahedral FEM mesh of a deformable object with rigid boundary conditions combined with a triangular surface mesh of a rigid collider. Environment-specific details, including node and edge features and dataset properties can be found in Appendix B. We assume that, while the initial mesh of the object is known, its material properties are not. We model these unknown properties via the Poisson's ratio (Lim, 2015) $-1 < \nu < 0.5$, which is a scalar value describing the ratio of contraction ($\nu < 0$) or expansion ($\nu > 0$) under compression (Mazaev et al., 2020). For all datasets, we randomly assign Poisson's ratios from $\nu \in \{-0.9, 0.0, 0.49\}$ equally to all rollouts.

We train all models on all tasks using the Adam optimizer (Kingma & Ba, 2015) with a learning rate of 5×10^{-4} and a batch size of 32, using early stopping on a held-out validation set to save the best model iteration for each setting. The models use a LeakyReLU activation function, 5 message passing blocks with 1-layer MLPs and a latent dimension of 128 for node and edge updates. We use a mean aggregation for the edge features and a training noise of 0.01. All tasks use a normalized task space of $[-1, 1]^d$. An overview of the network hyperparameters can be found in Appendix E.

Evaluation Metrics. We evaluate the performance of all trained models on 10 different seeds per experiment. We report the means and standard deviations of the different runs, where, for each run, we average the results over all available steps of a trajectory and over all trajectories in the test set of



GGNS (k=5) Ground Truth MGN

Figure 4: Visualization for a test trajectory at time step $t = 70$ for GGNS (left), the ground truth simulation (middle) and MGN (right). While MGN accumulates a large prediction error over time, GGNS is able to utilize the additional point cloud information to stay close to the ground truth for the full length of the simulation.

the respective data set. For all experiments, we report the *full rollout loss*, where the model starts with the initial state $\mathcal{S}_0$ and predicts the states up to a final state $\mathcal{S}_T$. Here, we provide a point cloud to the model every $k \geq 1$ steps and resort to mesh-only prediction otherwise. This corresponds to a setting in which the deformation of an object is tracked with both high-frequency sensors and low-frequency cameras which provide the position of the rigid collider and point-cloud information respectively.

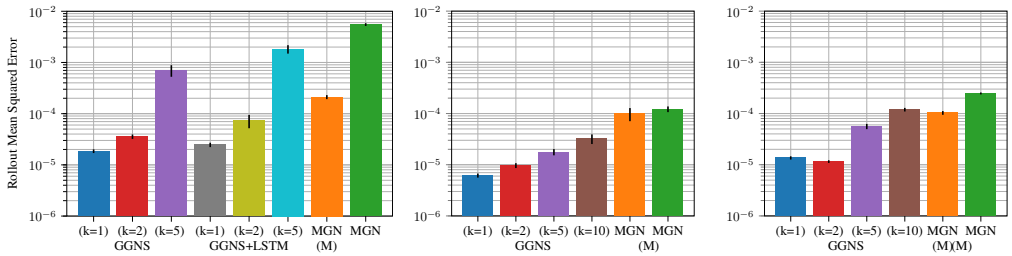
Additionally, we consider an application where a robot observes an object's deformation up to some point in time and then reasons about future deformations without additional point-cloud information. For this setting, the initial system state $\mathcal{S}_0$ is provided to the model, followed by m point clouds for its next m predictions. Then, 10 more steps are predicted without point clouds to predict a state $\mathcal{S}_{m+10}$ and and compute the corresponding 10-*step prediction loss*. The reported losses are the average MSE over every step along the trajectory averaged over all possible rollouts. This metric reduces to the average loss for a $m + 10$-step prediction for methods that can not make use of point cloud data, as the state $\mathcal{S}_{m+10}$ needs to be predicted from the initial $\mathcal{S}_0$.

Baselines. We consider different variants of MGN to compare the performance of our method to that of a state-of-the-art GNS. We compare to MGN, a state-of-the-art GNS, which utilizes additional *world edges* (c.f. Section 4.1) between close-by mesh nodes, but does not incorporate point cloud observations. We find that adding world edges does not improve our method, and instead encode world space in the existing mesh edges. Additionally, we evaluate a variant of MGN that has additional access to the underlying Poisson's ratio υ as an additional node feature, called *MGN (M)*. This additional information leads to a deterministic ground truth simulation w.r.t. the initial system state. We include this baseline as an upper bound of the performance of MGN. We also compare to GGNS+LSTM, which integrates recurrency into our imputation technique. Here, we investigate whether this recurrency helps the model predicting e.g., material properties over time.

As a point cloud based baseline, we use a non-learned method to directly generate a mesh from the point cloud of each time step. We voxel-subsample the point cloud so that we observe approximately the same number of points as nodes in the ground truth mesh and then use *Alpha Shapes* (Akkiraju et al., 1995) to create a (potentially non-convex) mesh for this time step. This baseline shows how much information can be directly inferred from just the point cloud information.

Deformable Plate. We consider a family of 2-dimensional trapezoids that are deformed by a circular collider with constant velocity. Besides the trapezoidal shapes, diversity in the dataset is introduced by varying the size and starting positions of the collider. For this task, we additionally consider the Intersection over Union (IoU) between the predicted and the ground truth mesh as an evaluation metric. We find that this metric is less sensitive to individual mesh nodes and that it instead measures how well the predicted object shape matches that of the real system state. We use a total of $675/135/135$ trajectories for our training, validation and test sets. Each trajectory consist of $T = 50$ timesteps.

Tissue Manipulation. An important application for the prediction of deformable objects is medical robotics. We simulate a robot-assisted surgery scenario where a piece of tissue is deformed by a



(a) Deformable Plate (b) Tissue Manipulation (c) Cavity Grasping

Figure 5: Rollout Mean Squared Error of GGNS and MGN baselines evaluated on the test set of the three datasets. We report the results for GGNS using point clouds in every k-th time step. MGN(mat) indicates the baseline method of MGN that uses the ground truth material as input feature. GGNS outperforms the MGN baseline in all settings and in most cases even if it has access to the complete initial state. For the Deformable Plate task we additionally report the errors for GGNS+LSTM, which perform worse than GGNS for all k but still outperforming the MGN baseline.

solid gripper. Varying the direction of the gripper's motion and its gripping position on the tissue results in additional diversity. Here, $600/120/120$ trajectories are used, each of which is rolled out for $T = 100$ timesteps. This task is visualized in Figure 4.

Cavity Grasping. Robotic manipulation of deformable objects is an important application of deformable physics simulation. Here, a simulated Panda [1] robot gripper grasps and deforms a cavity. For this purpose, we randomly generate cone-shaped cavities with different radii, which are deformed by a gripper from different positions. An example simulation step by GGNS for this task is illustrated in Figure 1. We use the same amount of samples and the same data split as in the Tissue Manipulation task. A visualization can be seen in Figure 1.

6 Results

Main Results. We test our method on the three deformation prediction tasks described in Section 5 and compare it to MGN with and without material information. We find that GGNS can use the point cloud information to produce high quality rollouts that closely match the true system states. An example is shown in Figure 3, which visualizes the final simulated meshes for our method and the ground truth simulation. Additionally, GGNS outperforms the baselines even when they have access to the complete initial state, which our model has not. Figure 4 shows the qualitative differences between GGNS and MGN on the Tissue Manipulation task. Additional visualizations for all tasks and both methods can be found in Appendix C. The evaluations for full rollouts are given in Figure 5. Table 1 shows results for the $m + 10$-step evaluation. Appendix D shows the performance of GGNS for different model hyperparameters. Similar to Pfaff et al. (2021), we find that the model is robust to most parameter choices, and that a modest amount of training noise is crucial for long-term rollouts. On the Deformable Plate dataset, we additionally evaluate the mean Intersection over Union (IoU) during the rollouts. Here, the main emphasis is laid on compliance with the overall shape of the object rather than that of individual mesh nodes, highlighting, for example, the simulation of the correct material. The results are illustrated in Figure 6a.

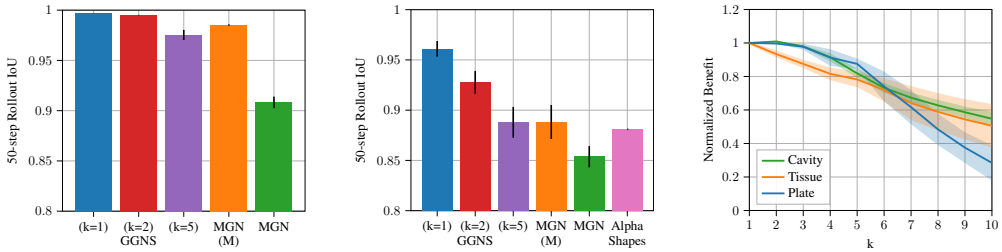
Recurrent Imputation Model. For the $2d$ data of the Deformable Plate task, we additionally compare our imputation model to the GGNS+LSTM approach, which can use the recurrence of LSTMs to pass information over time. In Figure 5a shows that GGNS outperforms this alternative approach for each k. We find that our simple architecture performs outperforms the recurrent one while requiring significantly less time to train, likely due to the additional complexity of training the recurrent model.

Initial Mesh Generation. Using the IoU metric, we can compare objects across different mesh representations. The results in Figure 6b show that GGNS produces accurate rollouts even if the initial mesh is generated from the initial point cloud. For this, we compute a mesh with similar resolution

[1] FRANKA EMIKA GmbH, Munich, Germany

Approach	$m + 10$-step MSE $\times 10^{-5}$		
	Plate	Tissue	Cavity
GGNS	2.907 ± 0.172	0.514 ± 0.052	0.923 ± 0.040
MGN(mat)	10.663 ± 1.063	5.027 ± 1.489	6.294 ± 0.668
MGN	282.684 ± 18.112	5.885 ± 0.723	11.528 ± 0.747

Table 1: Evaluation on the $m + 10$-step prediction setting on the test set for all three tasks. GGNS clearly outperforms the baselines on all tasks even if they have access to the full initial simulation state.



(a) Deformable Plate IoU (b) IoU without initial mesh (c) Different grounding frequencies

Figure 6: (a) Rollout IoU for the Deformable Plate dataset for GGNS and the MGN baseline. The main findings here are similiar to the MSE results but enable to compare against the values in (b), where the initial mesh is created from initial the point cloud. The achieved IoUs are lower compared to using the ground truth mesh, but GGNS ($k \leq 2$) still outperforms all baselines including the Alpha Shapes in this setting. (c) Normalized benefit of using a point cloud in every k-th timestep.

to the training meshes from the convex hull of the initial point cloud, avoiding the dependence on *any* simulation data. This procedure marks an important step towards using these models on real world data. As can be seen from our results, generating the initial mesh from point cloud information naturally results in a degradation of the performance compared to an evaluation that uses a provided mesh. Yet, it still allows for a high-quality prediction of the deformation. The comparison to Alpha Shapes shows that combining infrequent point cloud information ($k = 5$) with a simulator leads to better and more consistent results than directly creating the mesh from the point cloud in each time step.

Grounding Frequency. Figure 6c shows the normalized performance of GGNS for grounding frequencies $k \in \{1..10\}$ across tasks. Here, a value of 1.0 corresponds to the performance for $k = 1$, and 0.0 to the performance MGN. For all tasks there is a clear advantage in utilizing the point cloud information, where the performance increases with increasing frequency of available point clouds.

7 CONCLUSION

We propose Grounding Graph Network Simulator (GGNS), an extension of the popular Graph Network Simulator framework that can utilize auxiliary observations to accurately simulate complex dynamics from incomplete initial system states. Utilizing a neighborhood graph computed from point cloud information and an imputation-based training scheme, our model is able to *ground* its prediction in an observation of the true system state. We show experimentally that this leads to high-quality simulations in challenging $2d$ and $3d$ object deformation tasks, outperforming existing approaches even when these are provided with full information about the system.

In future work, we will extend GGNSs to explicitly model uncertainty and maintain a belief over the latent variables of the system, e.g., by employing a Kalman filter in a learned latent space (Becker et al., 2019). Another promising direction is to adapt the current next-step prediction loss to instead predict a trajectory over a small period of time to increase the long-term consistency of the model. Finally, we will employ our model for Model Predictive Control and Model-based Reinforcement Learning in both simulation and on a real robot.

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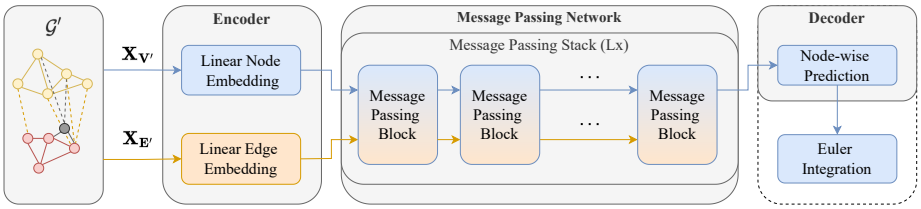


Figure 7: A detailed view of the GNN part of GGNS . Given a graph $\mathcal{G}'$, the node and edge features $\mathbf{X_{V'}}$ and $\mathbf{X_{E'}}$ are linearly embedded into a latent space and then updated with L Message Passing Blocks. The resulting predictions are interpreted as dynamical quantities that are used to update the system.

A Model Details

The Message Passing Network employed by GGNS is displayed in 7. As node-wise predictions we use velocities, which are Euler-integrated once to update the positions of the mesh of the deformable object.

B Environment Details

Here, we describe all key aspects, which are valid for all three environments. All datasets are simulated using SOFA and include different material properties. Therefore, we choose discrete Poisson's ratios from $\nu \in \{-0.9, 0.0, 0.49\}$ for one-third of all simulated trajectories each. The required point clouds are not directly available in SOFA, but instead rendered from the scene of the meshes using Raycasting from Open3D (Zhou et al., 2018). We therefore place virtual cameras around and on top of the scene to generate partial point clouds from different directions. For the Deformable Plate dataset one camera is sufficient, while the other two tasks rely on four cameras around and one camera on top of the scene. The resulting point clouds are then fused and subsampled accordingly to achieve a processable number of points. For this we use voxel subsampling, as this leads to the most structured results, which helps the model to account for correspondences between points over time. In addition to encoding the node or edge type as one-hot features, we add an encoding to static nodes and encode the velocity of the collider in its node features. We encode the positions in space as relative features in the edges instead of absolute encodings in the node features following previous work (Sanchez-Gonzalez et al., 2020). All edges thus receive their relative world coordinates, while mesh edges additionally contain relative coordinates in mesh space.

B.1 Deformable Plate

For this environment, we simulate a family of 2-dimensional trapezoids deformed by a circular collider with constant velocity. We vary the size the collider by sampling from a triangular distribution between 15 and 60 $\%$ of the edge length of the deformable object. For the collider start position we sample from a uniform distribution between the left and right corner of deformable object. We record 50 time steps per trajectory and 945 trajectories in total, which are split in $675/135/135$ trajectories per train/evaluation and test set. A single data sample contains approx. 700 nodes: 57 nodes for the collider, 81 nodes for the mesh oft the deformable object and around 600 points in the subsampled point cloud. The mesh itself consists of 416 edges, the total number of edges is about 3 K depending on the deformation in the according time step. In contrast to the Poisson's ratio, the other adjustable material parameter in SOFA, the Young's modulus is kept constant for all samples at $E = 5\,000\text{Pa}$. It describes the compressive stiffness when a force is applied lengthwise. The different material properties together with the different trapezoidal shapes introduce uncertainty in the form of multi-modality into the data. The reason for this is that different deformations result in states that cannot be clearly assigned to a single trapez-material combination. We construct this dataset because it comes with lower computational cost due to the restriction to 2d, but already allows for more general statements due to the non-trivial deformations and the multi-modality. Therefore, it is especially suitable as a proof-of-concept and for ablations.

B.2 TISSUE MANIPULATION

Here, a piece of tissue is deformed by a rigid gripper which could be part of a robot-assisted surgery scenario. To generate diversity, we generate random motions in a $2d$ plane and sample a random gripping point from the 19 top mesh points. We record 100 time steps per trajectory and 840 trajectories in total, which we split in $600/120/120$ trajectories per train/evaluation and test set. A single data sample consists of approx. $1\,200$ nodes: 361 for the mesh, one for the gripper and about 850 for the point cloud. The mesh consists of $2\,154$ edges, which leads to a total number of about $3\,800$ edges depending on the time step. To ensure physically plausible deformation, each Poisson's ratio is assigned its specific Young's modulus from $E \in \{10\,000, 80\,000, 30\,000\}\mathrm{Pa}$. If instead it were kept the same for each Poisson's ratio, the gripper could penetrate the deformable object or pull it without touching it. The uncertainty in this dataset is mainly in the initial state, which can result in different deformations depending on the material from the same initial state.

B.3 CAVITY GRASPING

We randomly generate cone-shaped cavities with radii between 87.5% and 50% of the maximum possible gripping width. The cone shape helps to increase uncertainty in the form of multi-modality in the data, because the states resulting from deformation cannot be clearly assigned to a single cone-material combination. The deformable cavities are deformed by a gripper located at random positions in space. The positions are sampled form a hexahedron around the geometrical center of the cavity ensuring collision free starting positions. For the grasping, the gripper moves as quickly as it is allowed to the gripping position and then closes its fingers with constant velocity. We record 100 time steps per trajectory and 840 trajectories in total, which are split in $600/120/120$ trajectories per train/evaluation and test set. A single data sample consists of approx. 2.4 K nodes: 750 for the mesh, 636 for the gripper and about 1 K for the point cloud. The mesh consists of $4\,500$ edges, the overall number of edges in the graph is about 8.5 K depending on the exact time step. The motivation for the creation of this environment is that a successful use of our method in this setting is an important step on the way to a real-world application.

C QUALITATIVE RESULTS

We provide example visualizations for a test rollout over time for the Deformable Plate task in Figure 8, for the Tissue Manipulation task in Figure 9, and for the Cavity Grasping in Figure 10. Throughout all tasks, GGNS closely matches the ground truth simulation for the complete rollout, achieving close to optimal results when provided with frequent point cloud information ($k = 2$). Opposed to this, MGN sometimes fails to predict the correct material, leading to poor predictions over time and large mismatches in the final system states.

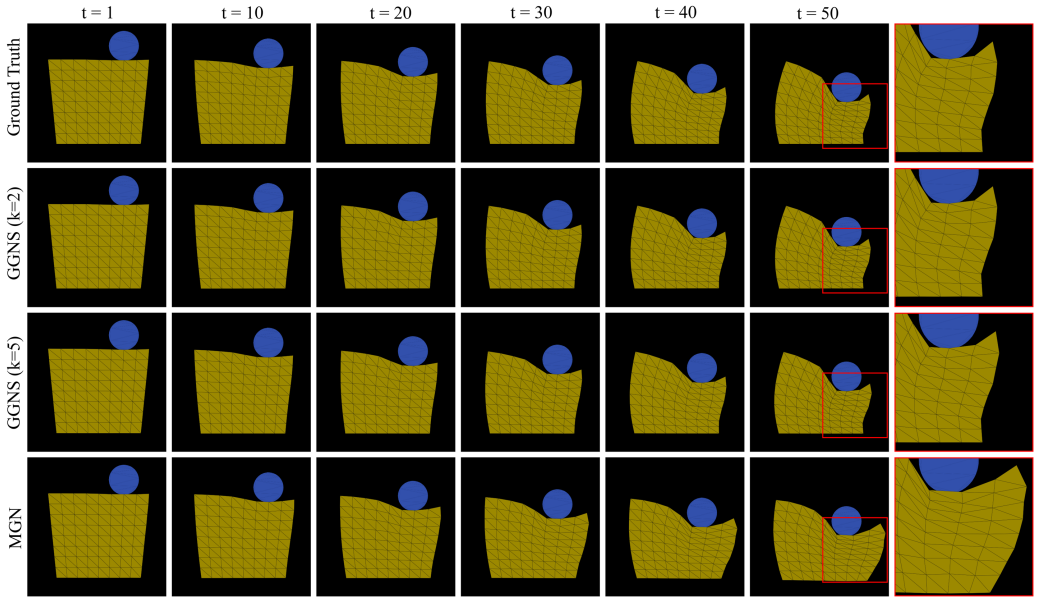


Figure 8: Test rollout visualization for the Deformable Plate task. The last column depicts a close-up of the final time step, which is shown in full in the previous column.

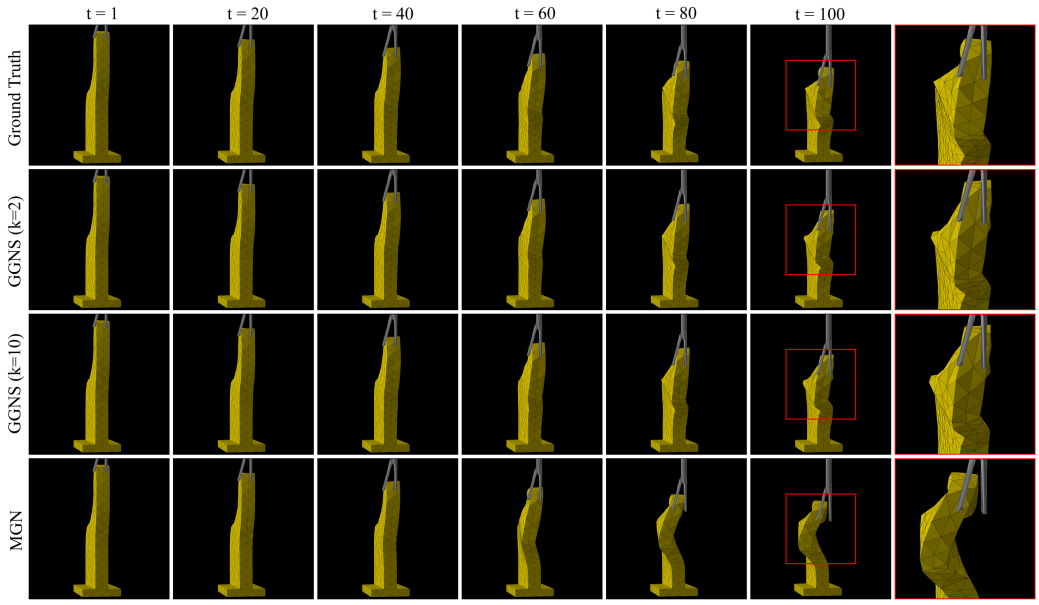


Figure 9: Test rollout visualization for the Tissue Manipulation task. The last column depicts a close-up of the final time step, which is shown in full in the previous column.

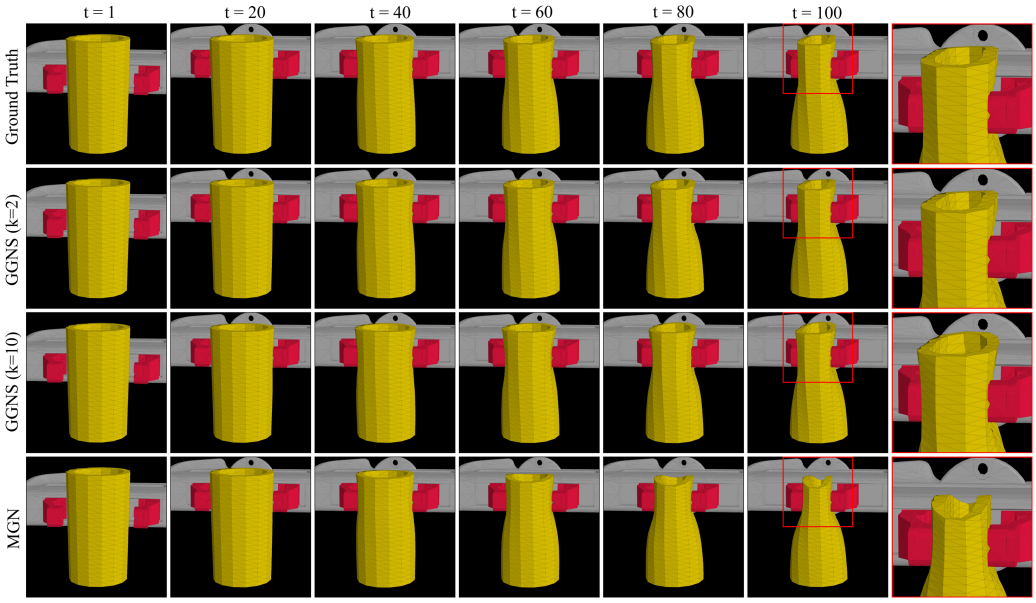


Figure 10: Test rollout visualization for the Cavity Grasping task. The last column depicts a close-up of the final time step, which is shown in full in the previous column.

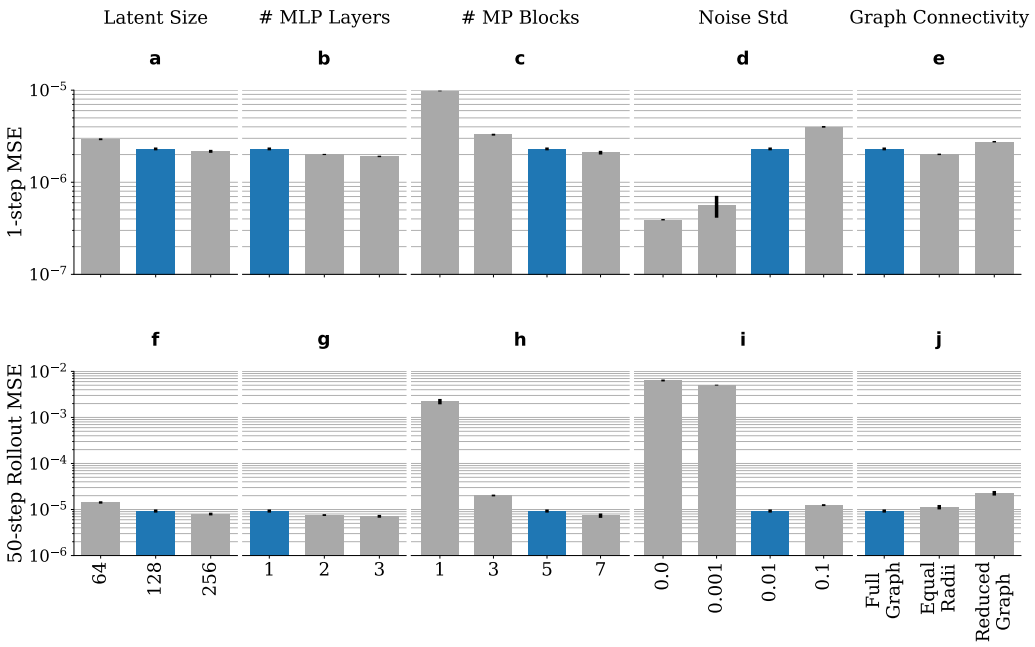


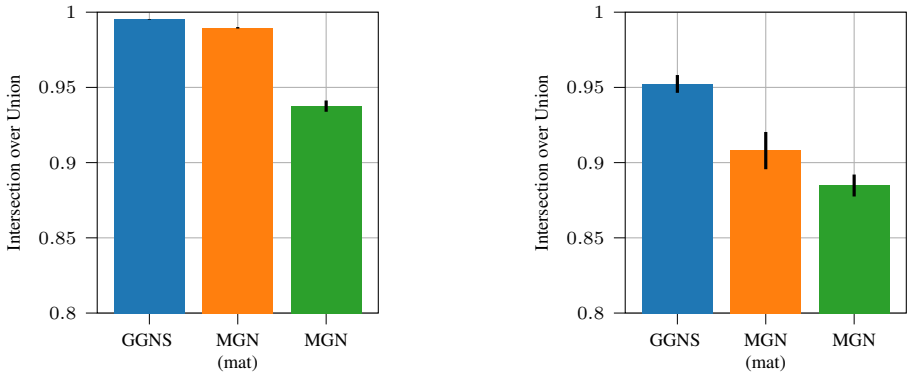
Figure 11: Performance for different changes in hyperparameter choices (grey) on the Deformable Plate dataset in comparison to our default model (blue) with $k = 1$. Error bars indicate one standard deviation. The top row shows the error for the next-step prediction, the bottom row that of full rollouts. We find that a suitable noise scale is crucial for stable rollouts, and that more information in the form of additional edges between the different types of graph nodes generally improves performance. Given enough Message Passing (MP) blocks, further increases in model capacity only lead to modest improvements.

Table 2: Edge radii for the connectivities between point clouds $\mathcal{P}$ and meshes $\mathcal{M}$ on the 2D Deformable Plate Dataset.

Setting	$\mathcal{P} - \mathcal{P}$	$\mathcal{M} - \mathcal{P}$	World
Full Graph	0.1	0.08	-
Equal Radii	0.2	0.2	-
Reduced Graph	0.0	0.08	-
MGN	0.0	0.0	0.35

D ABLATIONS

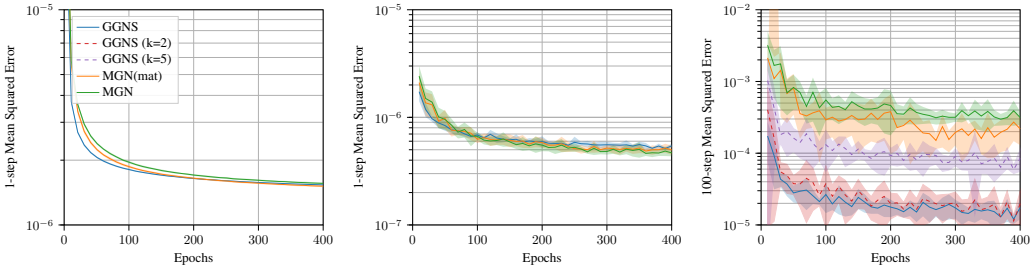
Figure 11 compares the performance of GGNS for different hyperparameter choices. We find that the most importance parameters are the number of Message Passing (MP) blocks and the scale of the noise used in training. Both are crucial to achieve a good performance over multi-step rollouts. In terms of training noise, there is a 1-step/multi-step loss trade-off. Other than that, our approach is robust to variations of the different hyperparameters. In terms of graph connectivity, it can be seen that all settings achieve similar performance. Additional information in the form of more local edges helps slightly, while larger connectivity radii do not do much. A detailed listing of the used edge radii is display in Table 2. In particular, the use of significantly more edges in the *Equal Radii* setting does not provide a significant advantage, which is why we use weaker connectivity *Full Graph* that saves computation time. The results for the *Reduced Graph* settings show that edges within the point cloud are not mandatory. For this reason, we omit these edges in the more complex $3d$ tasks in favor of shorter computation time.



(a) $m + 10$-step IoU Evaluation

(b) $m + 10$-step IoU Evaluation without initial mesh

Figure 12: (a) Comparison of our model to the baseline results on the Plate cataset using the $m + 10$-step Evaluation routine. (b) Results when using an initial mesh generated from the point cloud. GGNS outperforms the MGN baseline even if it has access to the initial ground truth mesh.



(a) Train loss

(b) 1-step Evaluation Loss

(c) 100-step Evaluation Loss

Figure 13: Exemplary learning curves for the Cavity Grasping task. The light shaded area indicates one standard deviation. Both GGNS and the baselines learn the task pretty similarly in terms of 1-step predictions. Our model is only evaluated for the $k = 2$ and $k = 5$ variant during full rollout evaluation. Here, we can clearly see the advantage of using the point cloud information.

Table 3: Configuration of the hyperparameters and key information of the training of our model for all experiments.

Parameter	Value
Batch Size	32
Optimizer	Adam
Learning Rate	5×10^{-4}
Activation Function	LeakyReLU
Aggregation Function	Mean
Encoder	Linear Layer
MP-Blocks	5
MLP Layers	1
Latent Dimension	128
Decoder	1-layer MLP
Residuals Connections	Around each MP block
Training Noise Std	0.01

Table 4: Task specific configuration and hyperparameters for our experiments. We vary the graph connectivity and the number of training epochs for different tasks to control the total training time of our method.

Parameter	Plate	Tissue	Cavity
Connectivity Setting	Full Graph	Reduced	Reduced
Number of Epochs	1000	800	400
Approx. Training Time	$21:00$ h	$40:00$ h	$38:00$ h

E HYPERPARAMETERS

Table 3 gives an overview of hyperparameters shared across tasks. Since GNS are generally robust to the choice of hyperparameters (c.f. D), we use the same hyperparameters for all task and for both, GGNS and MGN for simplicity. The only hyperparameters that vary over tasks are the graph connectivity and the number of training epochs, as shown in Table 4. We adapt these parameters to control for the total training time on a single GPU.