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Artificial Intelligence and
Machine Learning

Bachelor's Thesis

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Abstract

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Introduction

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The field of ML on graph-structured data has recently become an active topic of research. One reason for this is the wide range of domains and problems that are expressible in terms of graphs.

1.1 Motivation

1.2 Research Questions

1.3 Structure

Chapter 2: Related Work   Some text

Chapter 3: Implementation   Some text

Chapter 4: Evaluation   Some text

Chapter 5: Conclusion   Finally, the results of this thesis are summarized and a brief outline of promising directions for future research is given.

Related Work

Before describing the problem, and later on the experimental setup, we first

1. Introduce three common prediction tasks in graph neural networks (GNNs).

2. Give a general overview of how GNNs organize and process graph structured data.

3. We further discuss the relation of messasge passing mechanism to the WL-test, an algorithm for inspecting whether two graphs are isomorph.

4. Give a formal definition and description of two GNN architectures which will be used in our experiments.

5. Discuss typical issues which occur in GNNs and methods for adressing those issues.

2.1 Prediction Tasks and Typical Problems

Graphs naturally appear in numerous application domains, ranging from social analysis, bioinformatics to computer vision. A Graph $G = (V, E)$, where $V = \{v_1, ..., v_n\}$ is a set of $N = |V|$ nodes and $E \subseteq V \times V$ a set of edges betwen those nodes. The unique capability of graphs enables capturing the structural relations among data, and thus allows to harvest more insights compared to analyzing data in isolation [Zha+19]. Graphs therefore can be seen as a general language for describing entities and relationships between those entities. Graph neural networks (GNNs) then organize graph structured data to tackle various prediction and classification tasks. Typically, one is interested in one of the following three tasks:

1. **Link prediction:** Predict whether there are missing links between two nodes e.g., knowledge graph completion.

2. **Vertex classification & regression:** Predict a property of a node e.g., categorize online users/items.

3. **Graph classification & regression:** Here, we are interested in classifying or predicting a continuous value for the entire graph, e.g., predicting a property of a molecule.

In this work the main focus will be on node classification (NC), graph classification (GC) and graph regression (GR) for small- as well as medium-sized graphs.

2.2 Passing Messages in GNNs

Graphs, by nature, are unstructured. Vertices in graphs have no natural order and can contain any type of information. In order for machine learning algorithms to be able to make use of graph structured data, a mechanism is needed to organize them in a suitable way [Zho+20a; HYL17; Zha+19].

Message passing is a mechanism, which embeds into every node information about it's neighbourhood [Xu+19; Zho+20a]. This can be done in several ways. One way of classifying a GNN is by looking at the underlying message passing machanism. In this paper we will look at a network, where message passing is done via convolutions (graph convolutional network (GCN)). We will however ocasionally use the more general term message passing, as the separation is rather blurred and message passing describes a neighborhood aggregation scheme which is seen as a generalisation of other, more specific mechanisms.

Formally, message passing in a GNN can be described as using two functions: AGGREGATE and COMBINE. The expressive and representational power of a GNN can then be determined by looking at the concrete functions and their properties, used to implement aggregation and combination. AGGREGATE mixes the hidden representation of every node's neighborhood in every iteration. COMBINE then combines the mixed representation togheter with the representation of the node. Each node uses the information from its neighbors to update its embeddings, thus a natural extension is to use the information to increase the receptive field by performing AGGREGATE and COMBINE multiple times.

$$a_v^k = \text{AGGREGATE}^{(k)}(\{h_u^{(k-1)} : u \in \mathcal{N}_{(v)}\})$$

$$h_v^{(k)} = \text{COMBINE}^{(k)}(h_v^{(k-1)}, a_v^{(k)})$$

For graph-level predictions, an additional READOUT- operation is used:

$$h_G = \text{READOUT}(\{h_v^{(K)} \mid v \in G\})$$

One useful type of information, which the message passing framework should be able to capture, is the local graph structure. This can be done by choosing functions with appropriate properties. A more detailed explanation will follow in section 2.2.2. In spatial GNNs we make the assumption of the similarity of neighbor nodes. To exploit this spatial similarity, we perform composition by stacking multiple layers togheter increasing the receptive field.
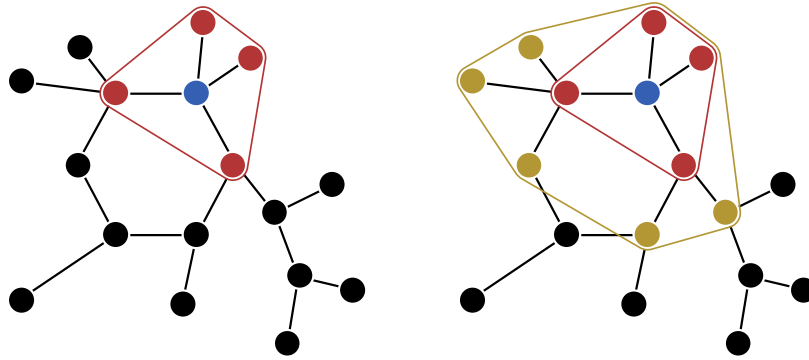
Abbildung 2.1.: By performing aggregation k-times, we can reach and capture the structural information of the k-hop neighborhood

2.2.1 Weisfeiler-Lehman Graph Colorings

The Message passing mechanism is closely related to the way the Weisfeiler-Lehman (WL) test [WL68; DMH20; HV22] works, an algorithm for deciding if two graphs are isomorphic. Before describing the algorithm, we introduce notations and preliminaries.

Let $G = (V, E, X)$ denote an undirected graph, where $V = \{v_1, ..., v_n\}$ is a set of $N = |V|$ nodes and $E \subseteq V \times V$ a set of edges between those nodes. For simplicity, we represent an edge $\{v, u\} \in E$ by $(v, u) \in E$ or $(u, v) \in E$. $X = [x_1, ..., x_n]^T \in \mathbb{R}^{n \times d}$ is the node feature matrix, where $n = |V|$ is the number of nodes and $x_v \in \mathbb{R}^d$ represents the d-dimensional feature of node v. $\mathcal{N}_v = \{u \in V \mid (v, u) \in E\}$ is the set of neighboring nodes of node v. A multiset is denoted as $\{\!\{...\}\!\}$ and formally defined as follows.

Definition 2.1 (Multiset)**.** A multiset is a generalization of a set allowing repeating elements. A multiset $\mathcal{X}$ can be formally represented by a 2-tuple as $X = (S_X, m_X)$, where S_X is the underlying set formed by the distinct elements in the multiset and $m_X : S_X \to \mathbb{Z}^+$ gives the multiplicity (i.e., the number of occurrences) of the elements. If the elements in the multiset are generally drawn from a set X (i.e., $S_X \subseteq \mathcal{X}$), then $\mathcal{X}$ is the universe of X and we denote it as $X \subseteq \mathcal{X}$ for ease of notation.

Definition 2.2 (Isomorphism)**.** Two Graphs $\mathcal{G} = (V, E, X)$ and $\mathcal{H} = (P, F, Y)$ are *isomorphic*, denoted as $\mathcal{G} \simeq \mathcal{H}$, if there exists a *bijective* mapping $g : V \to P$ such that $x_v = y_{g(v)}$, $\forall v \in V$ and $(v, u) \in E$ iff $(g(v), g(u)) \in F$.

The 1-dimensional WL algorithm (color refinement)

In the 1-dimensional WL algorithm (1-WL), a label, called *color*, c_v^0 is assigned to each vertex of a graph. Then, in every iteration, the colors get updated based on the multiset representation of the neighborhood of the node until convergence. If at some iteration the colorings of the graphs differ, 1-WL decides that the graphs are not isomorphic.

$$c_v^l \leftarrow \text{HASH}\,(c_v^{l-1}, \{\!\{c_u^{l-1} \mid u \in \mathcal{N}_v\}\!\})$$

Algorithmically, this can be expressed as follows:

Algorithm 1 1-dim. WL (color refinement)

Input: $G = (V, E, X_V)$

1: $c_v^0 \leftarrow hash(X_v)$ for all $v \in V$
2: **repeat**
3:      $c_v^l \leftarrow hash(c_v^{l-1}, \{\!\{c_w^{l-1} : w \in \mathcal{N}_G(v)\}\!\})$ forall $v \in V$
4: **until** $(c_v^l)_{v \in V} = (c_v^{l-1})_{v \in V}$
5: **return** $\{\!\{c_v^l : v \in V\}\!\}$

The 1-WL is a heuristic method that can efficiently distinguish a broad class of non-isomorphic graphs [BK79]. However, there exist some corner cases, where the algorithm fails to classify simple shapes as non-isomorphic. This is the case for non-isomorphic graphs with the same number of nodes and equivalent sets of node-degrees, as shown in fig. 2.3.
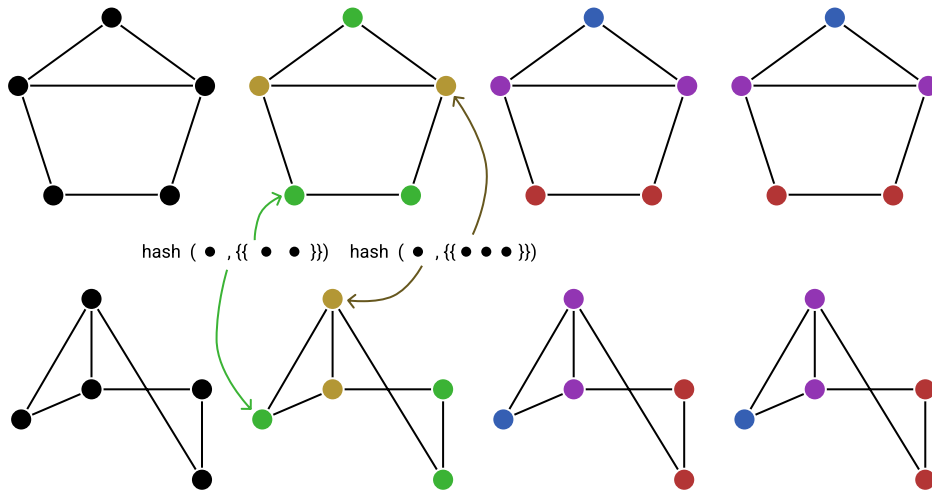
Abbildung 2.2.: Two isomorphic graphs. 1-WLassigns the same representation to those graphs.
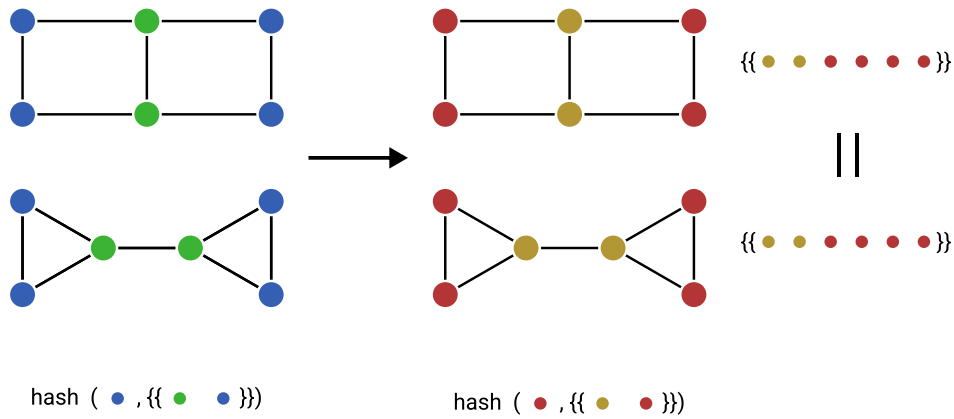
Abbildung 2.3.: 1-WL assigned the same labeling to two non-isomorphic graphs [LYJ22].

2.2.2 GNN Architectures in this Paper

In the following section we briefly introduce and motivate the choice of two types of networks, which we have chosen to experimentally verify the efficacy of several regularization techniques, which will be discussed in section 2.2.4.

Since all GNNs encorporate message passing in a way, we decided to chose two architectures for our experiments, which are powerful, efficient, scalable and broadly used.

Graph Convolutional Network (GCN)

Graph convolutional network (GCN) was originally proposed by Kipf und Welling [KW17] to tackle the problem of semi-supervised node classification, where lables are available for a small subset of nodes. GCN is a simple, but powerful architecture, that scales linearly in the number of graph edges and learns hidden layer representations that encode both local graph structure and features of nodes.

A GCN can formally be expressed via the following layer-wise propagation rule:

$$H^{(l+1)} = \sigma(\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}H^{(l)}W^{(l)})$$

Where $\tilde{A} = A + I_N$ is the adjacency matrix of the undirected graph $\mathcal{G}$ with added self-connections. I_N is the identity matrix. $\tilde{D}_{ii} = \sum_j \tilde{A}_{ij}$ and W^l is a layer-specific trainable weight-matrix. $\sigma(\cdot)$ denotes an activation function, such as $ReLU(\cdot) = max(0, \cdot)$. $H^l \in N \times D$ is the matrix of activations in the lth layer; $H^0 = X$.

Because we consider every neighbor to be of equal importance and therefore normalization is accomplished by dividing by the number of neighbours, one can view this operation as performing an element-wise mean-pooling [Xu+19].

$$h_v^{(k)} = \text{ReLU}(\text{W} \cdot \text{MEAN}\{h_u^{k-1} \mid \forall u \in \mathcal{N}_{(v)} \cup \{v\}\})$$

An application of a two-layer GCN is given by:

$$Z = f(X, A) = \text{softmax}(\hat{A}\,\text{ReLU}(\hat{A}XW^0)W^l)$$

where $\hat{A} = \tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}$ is calculated in a preprocessing step. The model uses a single weight matrix per layer and deals with varying node degrees through an appropriate normalization of the adjacency matrix. This model consisting of a 2-layer GCN performed well in a series of experimental tasks, including semi-supervised document classification, semi-supervised node classification in citation networks and semi-supervised entity classification in a bipartite graph extracted from a knowledge graph. The prediction accuracy was evaluated on a set of 1000 examples and additional experiments on deeper models with up to 10 layers have been also provided. Being capable of encoding both graph structure and node features, GCN outperformed numerous related methods by a significant margin [KW17].

Graph convolutional networks (GCNs) are widely and successfully used today in many fiels due to their simplicity and scalability.

Graph Isomorphism Network (GIN)

To overcome the lack of expressivity of popular GNN architectures, Xu et al. [Xu+19] designed a new type of GNN, graph isomorphism network (GIN). They prove that GINs are strictly more expressive than a variety of previous GNN architectures and that they are in fact as powerful as the commonly used 1-dimensional Weisfeiler-Lehman (WL)-test.

Two requirements must be met for a network to have the same expressive and representational power as the WL isomorphism test:

1. The framework must be able to represent the set of feature vectors of a given nodes neighbors as a multiset.

2. Choosing an injective function for the aggregation step. Such a function would never map two different neighborhoods to the same representation.

The more discriminative the multiset function is, the more powerful the representational power of the underlying GNN.

Formally, a graph isomorphism network (GIN) can be expressed as follows:

$$h_v^{(k)} = \text{MLP}^{(k)} \left((1 + \epsilon^{(k)}) \cdot h_v^{(k-1)} + \sum_{u \in \mathcal{N}(v)} h_u^{(k-1)} \right)$$

The choice of such an architecture, is motivated by the necessity to learn two functions with certain properties, f and ϕ. This task can be accomplished using a multilayer perceptron (MLP). The following lemma and corollary, proven by Xu et al. [Xu+19] show the properties and application of the functions:

Theorem 2.3. *Let $A : G :\to \mathbb{R}^d$ be a GNN. With a sufficient number of GNN layers, A maps any grphs G_1 and G_2 to different embeddings, the WL-test of isomorphism decides as non-isomorphic, to different embeddings if the following conditions hold:*

(a) A aggregates and updates node features iteratively with

$$h_v^{(k)} = \phi(h_v^{(k-1)}, f(\{h_u^{(k-1)} \mid u \in \mathcal{N}_{(v)}\}))$$

where the functions f, which operates on multisets and, and ϕ are injective.

(b) A's graph-level readout, which operates on the multiset of node features $\{h_v^{(k)}\}$, is injective.

Lemma 2.4. *Assume $\mathcal{X}$ is countable. There exists a function $f : \mathcal{X} \to \mathbb{R}^n$ so that $h(X) = \sum_{x \in X} f(x)$ is unique for each multiset $X \subseteq \mathcal{X}$ of bounded size. Moreover, any multiset function g can be decomposed as $g(X) = \phi(\sum_{x \in X} f(x))$ for some function ϕ.*

Corollary 2.5. *Assume $\mathcal{X}$ is countable. There exists a function $f : \mathcal{X} \to \mathbb{R}^n$ so that for infinetly many choices of ϵ, including all irrational numbers, $h(c, X) = (1 + \epsilon) \cdot f(c) + \sum_{x \in X} f(x)$ is unique for each pair (c,X), where $c \in \mathcal{X}$ and $X \subseteq \mathcal{X}$ is a multiset of bounded size. Moreover, any function g over such pairs can be decomposed as $g(c, X) = \varphi(1 + \epsilon) \dot{f}(c) + \sum_{x \in X} f(x)$ for some function φ.*

GIN is as powerful as 1-dimensionalWL

GIN is a neural network-based approach designed to handle graph data and detect graph isomorphisms. It operates on each vertex and updates its representation based on its own features and the aggregated features of its neighbors. There exists a fundamental similarity between the GIN and the way the 1-WL algorithm works

2.2.3 Weaknesses and Obstacles in GNNs

Because of the way GNNs operate, they tend to suffer from two main obstacles: Overfitting and oversmoothing.

Overfitting hinders the generalization ability of a neural network (NN), making it perform poorly on previously unseen data. This occurs expecially when using small datasets, since the model thends to 'memorize' instead of learn the pattern.

Oversmoothing is a condition, where the performance and predictive power of a NN does not improve or even gets worse when more layers are added. This happens because by stacking multiple layers togheter aggregation is being performed over and over again. This way, the representation of a node is being smoothed, i.e., mixed with features of very distant, possibly unrelated nodes. Oversmoothing is a problem mainly for node classification tasks. There is a trade-off between the expressiveness of the model (capturing graph structure by applying multiple layers) and oversmoothing, which leads to a model where nodes have the same

representation, because they all converge to indistinguishable vectors [Zho+20b; Has+20].[1]

A closer examination of underlying causes of oversmoothing was conducted by Chen et al. [Che+20], who suggested, that not message passing itself, but the type of interacting nodes cause this issue. For node classification (NC) tasks, intra-class communication (interaction between two nodes sharing the same class) is useful (signal), whereas inter-class communication (the communication between two nodes sharing different lables) is considered harmful, because it brings interference noise into the feature-representations by mixing unrelated features and therefore making unrelated nodes more similar to each other. Because of that, the the quality of shared information is essential and should therefore be considered as a benchmark for improvement.

2.2.4 Regularization Techniques

Kukacka et al. [KGC17] define regularization as any supplementary technique that aims at making the model generalize better, i.e., produce better results on the test set, which can include various properties of the loss function, the loss optimization algorithm, or other techniques.

One subgroup of regularization is via data, where the training set $\mathcal{D}$ is transformed into a new set $\mathcal{D}_R$ using some stochastic parameter π, which can be used in various ways, including to manipulate the feature space, create a new, augmented dataset or to change e.g, thin out the hidden layers of the NN.

An example of such a transformation is corruption of inputs by Gaussian noise.

$$\tau_0(x) = x + \theta, \theta \backsim \mathcal{N}(0, \Sigma)$$

In this work we focus on stochastic regularization techniques, which perform data augmentation in one way or another and whose main benefits lie in the alleviation of overfitting and oversmoothing [Has+20]. We will use the following notation:

---

[1]In spatial GNNs we make the assumption of relatedness by proximity.

| Notation	Description
$H^{(l)} = [h_0^{(l)}, \ldots h_n^{(l)}]^T \in \mathbb{R}^{n \times f_l}$	Output of the l-th hidden layer in GNN
n	Number of nodes
f_l	The number of output features at the l-th layer
$H^0 = X \in \mathbb{R}^{n \times f^0}$	Input matrix of node attributes
f_0	Number of nodes features
$W^l \in \mathbb{R}^{f_l \times f_{l+1}}$	The GNN parameters at the l-th layer
$\sigma(\cdot)$	Corresponding activation function
$\mathcal{N}(v)$	Neighborhood of node v
$\tilde{\mathcal{N}}(v) = \mathcal{N}(v) \cup v$	$\mathcal{N}(v)$ with added self-connection
$\mathfrak{N}(\cdot)$	Normalizing operator
$\odot$	Hadamard product

DropOut (Srivastava et al.)

DropOut (DO)[Sri+14] randomly removes elements of its previous hidden layer $H^{(l)}$ based on independent Bernoulli random draws with a constant success rate at each training iteration:

$$H^{(l+1)} = \sigma(\mathfrak{N}(A)(Z^{(l)} \odot H^{(l)})W^{(l)})$$

where Z^l is a random binary matrix, with the same dimensions as H^l, whose elements are samples of Bernoulli(π).

The random drop of units (along with their connections) from the neural network during training prevents units from co-adapting too much. A neural net with n units can be seen as a collection of 2^n possible networks. Applying dropout with a certain probability π can be interpreted as sampling "thinned" networks from all possible 2^n networks. In the end, since averaging over all possible networks is computationally expensive, an approximation for combining the prediction is used. This averaging method entails using a single neural net with weights, which are scaled-down weights obtained during training time.
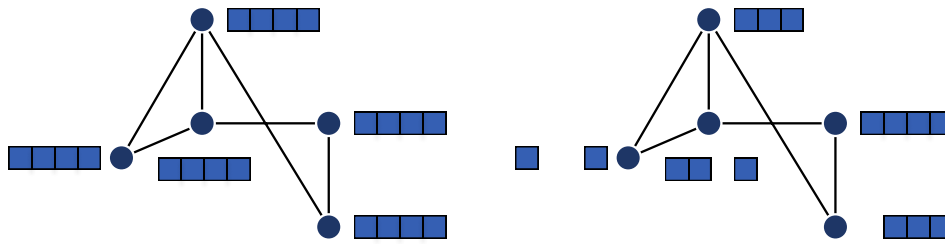
Abbildung 2.4.: DropOut (DO) preserves connections between nodes as well as the nodes itself, unless we chose a large probability π, which drops all of the nodes features.

DropEdge (Rong et al.)

DropEdge (DE) [Ron+20] randomly removes a certain number of edges from the input graph at each training epoch and can be formally expressed as follows:

$$H^{(l+1)} = \sigma(\Re(A \odot Z^{(l)})H^{(l)}W^{(l)})$$

The random binary mask Z^l has the same dimensions as A. Its elements are the random samples of Bernoulli(π) where their corresponding elements in A are non-zero and zero everywhere else.

Message passing in GNNs happens along the edges between neighbours. Randomly removng edges makes the connections more sparse, which leads to slower convergence time and thus prevents the network from oversmoothing and allows for a deeper architecture. Intuitively this makes sence, since removing an edge means, that the node, previosely connected by that edge stops being a neighbor. Consequently the representation of this former neighbor does not get mixed with the representation of the node.

DE also acts like a data augmenter, since by randomly dropping edges we manipulate/change the underlying graph data. Since the data is now augmented with noise, it is harder for the network to overfit the data by "memorising" rather than learning complex relationships. The combination of DO and DE reaches a better performance in terms of mitigating overfitting in GNNs than DE on it's own.

NodeSampling (Chen et al.)

This method of regularization, also known as FastGCN [CMX18] was developed to improve the GCN [KW17] architecture and to adress the bottleneck issues of GCNs
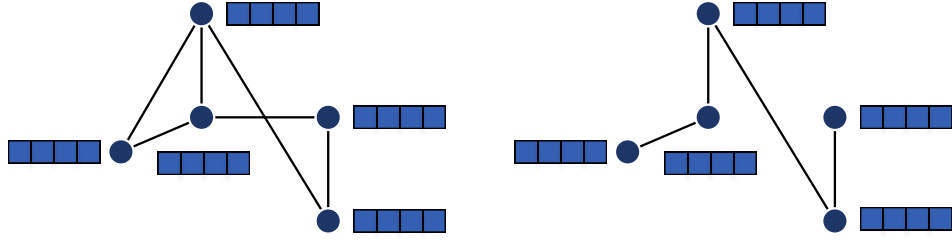
Abbildung 2.5.: DropEdge (DE) preserves nodes and all of nodes featurs, but randomly removes edges, leading to a smaller number of neighbors, which results in slower convergence times and allowes for architectures with more hidden layers.

caused by recursive expansion of neighborhoods.It reduces the expensive computation in batch training of GNN by relaxing the requirement of simultaneous availability of test data. Graphs can be very large and therefore require large computational and processing capacities. By randomly dropping out nodes, we reduce the amount of data in such a manner, that it alleviates the expensiveness of the computation reduces and bottleneck issue while preserving important relations.

$$H^{(l+1)} = \sigma(\mathfrak{R}(A)diag(z^{(l)})H^{(l)}W^{(l)})$$

Here, $z^{(l)}$ is a random vector whose elements are drawn from Bernoulli(π). This is a special case of DO, since all of the output features are either kept or completely dropped.
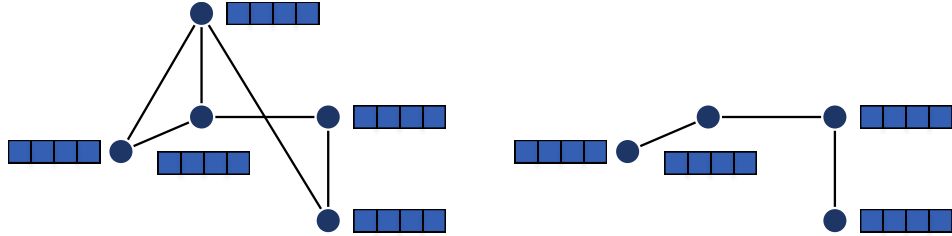
Abbildung 2.6.: In NodeSampling (NS), a node is either removed or preserved along with the whole feature vector with a certain probability π.

GraphDropConnect (Hasanzadeh et al.)

Finally, GraphDropConnect (GDC) [Has+20], which can be seen as a generalization of all the above proposed methods, is a stochastic regularization approach,

which has been shown to be the most effective among all the above and even more effective than the combination of DO and DE. The regularization is done via adaptive connection sampling and can be interpreted as an approximation of Bayesian GNNs.

$$H^{(l+1)}[:,j] = \sigma \left(\sum_{i=1}^{f_l} \Re \left(A \odot Z_{i,j}^{(l)} \right) H^{(l)}[:,i] W^{(l)}[i,j] \right)$$
$$\text{for } j = 1, ..., f_{l+1}$$

where f_l and f_{l+1} are the number of features at layers l and $l+1$, respectively, and $Z_{i,j}^{(l)}$ is a sparse random matrix (with the same sparsity as A), whose non-zero elements are randomly drawn from Bernoulli(π_l), where π_l can be different for each layer. GDC is a regularization technique, that combines all of the above by drawing different random masks for each channel and edge independently, which yield better performance results then all of the previous methods or even combinations of them. GDC, as it is expressed in the formula above has not been implemented and evaluated yet. Instead, a special case of GDC has been implemented:

Under the assumption, that $Z_{i,j}^{(l)}$ are the same for all $j \in \{1, 2, \ldots, f_{l+1}\}$, we can omit the indices of the output elements at layer $l + 1$ and rewrite the above formula as follows:

$$H^{(l+1)} = \sigma(\sum_{i=1}^{f_l} \Re(A \odot Z_i^{(l)}) H^{(l)}[:,i] W^{(l)}[i,:])$$
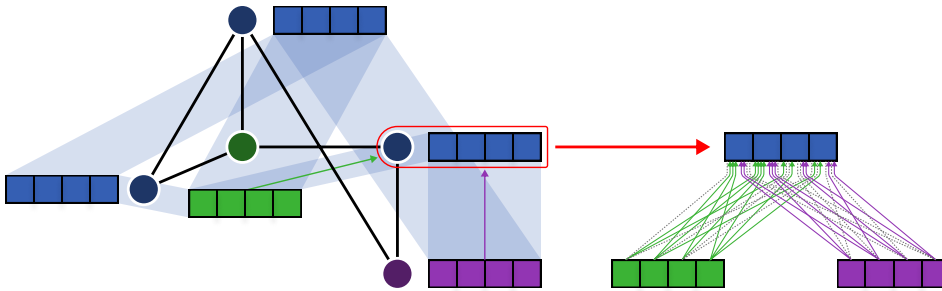
Abbildung 2.7.: GraphDropConnect (GDC)can be thought of as duplicating every existing edge between features of the feature-vectors of existing nodes and then randomly removing every edge with a certain probability π before the convolution.

All the methods are somewhat related and share some similarities [Ron+20]. DropOut (DO) has been successful in alleviating overfitting by perturbing the feature matrix and setting some entries to zero. The issue of oversmoothing is not affected by this measure. DropEdge (DE) achieved great results in reducing both overfitting as well as oversmoothing. Intuitively this makes sense, because smoothing comes from the aggregation of the neighbours of a certain node and by dropping the connections to some neighbours, the feature vectors of those neighbours are no longer aggregated and combined with the hidden representaion of the node.

NodeSampling (NS) is a special case of DropOut (DO), as all of the output features for a node are either completely kept or dropped while DO randomly removes some of these related output elements associated with the node. Also, along with the dropped node, the edges of this node are dropped. The method itself, however is node-oriented and the edge-drop is a ßide-effect".

GraphDropConnect (GDC) generalizes existing stochastic regularization methods for training GNNs and is effective in dealing with overfitting and oversmoothing. GDC regularizes neighbourhood aggregation in GNNs at each chanel separately. This prevents connected nodes in graph from having the same learned representations in GNN layers; hence better improvement without serious oversmoothing can be achieved [Has+20].

2.3 Assesment of Graph regularization approaches

To make systematic and quantitative statements about the positive effects of oversmoothing by using different regularization techniques, one has to be able to monitor the smoothness of nodes at different execution steps during training. Therefore, choosing a suitable metric is of great importance, as it helps to assess the extent of the effect produced by various regularization techniques and compare them against each other in terms of efficacy.

Mean Average Distance (MAD) [Che+20] is a metric for smoothness, the similarity of graph node representations. In that sense, over-smoothness is the similarity of node representations among different classes. While smoothing to some extent is desired (we assume spatial similarity between nodes), mixing features of nodes with different labels over several iterations leads to over-smoothing.

It is therefore important to differentiate between different types of messages between nodes. Signal/information is the messaging of nodes, which share the same class/label, i.e., intra-class communication and noize denotes intra-class comunication. Having too many inter-class edges leads to much noise by encorporating messages from other classes, which results in oversmoothing.

Because of that it is crucial to have a measure of the quality of the recieved messages. A way to do that is to consider the information-to noise ratio i.e., the fraction of intra-class node pairs and all node pairs that have interaction trough GNN model. That way it is possible to differentiate between remote and neihbouring nodes and calculate the **MADGap (MADGap)**, which is strongly positive correlated with a models accuracy.

MAD is calculated as follows:

Given the graph representation matrix $H \in \mathbb{R}^{n \times h}$ we first obtain the distance matrix $D \in \mathbb{R}^{n \times n}$ for H by computing the cosine distance between each node pair.

$$D_{i,j} = 1 - \frac{H_{i,:} \cdot H_{j,:}}{\mid H_{i,:} \mid \cdot \mid H_{j,:} \mid} \quad i,j \in [1, 2, \ldots, n],$$

where H_k is the k-th row of H. The reason to use cosine distance is that cosine distance is not affected by the absolute value of the node vector, thus better reflecting the smoothness of graph representation. Then we filter the target node pairs by element-wise multiplication D with a mask matrix M^{tgt}

$$D^{tgt} = D \odot M^{tgt},$$

where $\odot$ denotes the element-wise mutliplication: $M^{tgt} \in \{0, 1\}^{n \times n}; M_{i,j}^{tgt} = 1$ only if node pair (i, j) is the target one. Next we access the average distance $\bar{D}^{tgt}$ for non-zero values along each row in D^{tgt} :

$$\bar{D}_t^{tgt} = \frac{\sum_{j=0}^{n} D_{i,j}^{tgt}}{\sum_{j=0}^{n} \mathbb{1}(D_{i,j}^{tgt})}$$

where where $1(x) = 1$ if $x > 0$ otherwise 0. Finally, the MAD value given the target node pairs is calculated by averaging the non-zero values in tgt MAD gives access to the smoothness of a node and pairs of nodes throughout iterations, which makes it easy to "track down"over smoothing. First, the cosine similarity is calculated, showing how similar the corresponding feature vectors are. By subtracting the cosine similarity from one, we get the cosine distance, which tells us the difference between the nodes.

Implementation 3

This section overviews the implementation and aims to motivate the choice of libraries and frameworks. We also deliver an in-depth explanation of the implementation of GDC, as it is the main focus of our work.

3.1 Scope and Limitations

Our research is concerned only with graph-level prediction tasks on two types of GNNs, GCN and GIN. We implemented both networks as described by Kipf und Welling [KW17] and Xu et al. [Xu+19] respectively. We evaluate five different scenarios, among them four different regularization techniques DO, NS, DE, and GDC, and we also train the networks using no regularization. GDC is implemented as described in eq. (3.2) since this allows for better time and space complexity, which was also done by Hasanzadeh et al. [Has+20]. We perform our experiments using five datasets from the OGB dataset collection [Hu+20], all within the molecular realm. Two datasets are for classification, and the rest for regression tasks.

3.2 Sparse Implementation of Graph Dropout Layers

This section is concerned with implementing our regularization techniques and explaining how those have been embedded into a convolutional step. First, we take a look at TensorFlow's gather and scatter operations. Then, we explain how these operations are used to implement sparse graph convolutions. For that, an algorithmic description and a text explanation will be presented. We then explain the implementation of the sparse graph convolutions before we explain how regularization is embedded in a convolutional step.

3.2.1 Gather and Scatter

In GNNs, communication between nodes is achieved via message passing (see section 2.2). For messages to be passed along between nodes, we need first to extract and second to pass information on. For this purpose, we utilize two of TensorFlow's functions *gather* and *scatter* [He+07; DMH20].

Formally, the *gather* operator takes two inputs: A list X of n row vectors and a list R of m pointers into X. It returns a list X of m row vectors $X[i] = Z[R[i]]$ for $i \in [m]$. The gather operation in TensorFlow extracts specific elements from a tensor along a given axis. Given an input tensor and a list of indices, the gather operation selects elements based on the provided indices from the input tensor. Given a tensor representing node features in a graph and a list of node indices, the gather operation extracts the corresponding node features. The gather operation can extract node features, adjacency information, or other relevant data based on specific graph node indices.

The $scatter_\Sigma$ operator can be understood as the opposite of *gather*. $scatter_\Sigma$ takes a list X of m row vectors and a list R of m pointers from the range $[n]$. It returns a list Z of n row vectors $Z[i] = \sum_{j \in [m] \wedge R[j]=i} X[j]$ for $i \in [n]$. The scatter operation in TensorFlow is the inverse of the gather operation. It updates the elements of an existing tensor based on the provided indices. Given an input tensor, a list of indices, and a tensor containing values, the scatter operation replaces elements in the input tensor at the specified indices with the corresponding values from the values tensor. Gather and scatter operations are crucial for tasks involving graph neural networks GNNs where information aggregation and dissemination across nodes are essential. Information from nodes or subgraphs is gathered and aggregated for graph classification tasks to represent the entire graph. GNNs can use gather operations to pool information from nodes and perform graph-level predictions.

3.2.2 Sparse Implementation of Graph Convolutions

In our study, the fundamental mechanism for information exchange among nodes in both GNNs is implemented through the message-passing mechanism via graph convolutions. GNNs capture complex relationships in convolutional steps within graph-structured data. The detailed algorithm for implementing this message-passing mechanism using graph convolutions is described in Algorithm 2. Algorithm

2 outlines the Sparse Graph Convolution operation, where information is efficiently exchanged between nodes utilizing gather and scatter operations. In this algorithm, the gather operation extracts feature information from neighboring nodes, while the scatter operation aggregates and updates the node representations. The resulting updated node features are the foundation for subsequent graph convolutional layers.

The fundamental operation in our GNNs is the graph convolution operation, which allows nodes to aggregate and exchange information with their neighboring nodes. The sparse implementation of graph convolutions can be described algorithmically as follows:

Algorithm 2 Sparse Graph Convolution using Gather and Scatter

1: **function** $SparseGraphConvolution(X \in \mathbb{R}^{n \times d}, R \in [n]^{m \times 2})$
2:    $X_a := gather(Z, R[:, 0])$ $\triangleright$ Gather Operation: $\mathbb{R}^{n \times d} \times [n]^m \to \mathbb{R}^{m \times d}$
3:    $X_b := gather(Z, R[:, 1])$
4:    $X_{\Sigma a} := scatter_\Sigma(X_a, R[:, 1])$ $\triangleright$ Scatter Operation: $\mathbb{R}^{m \times d} \times [n]^m \to \mathbb{R}^{n \times d}$
5:    $X_{\Sigma b} := scatter_\Sigma(X_b, R[:, 0])$
6:    $X_{\text{conv}} := \sigma\left(X + X_{\Sigma a} + X_{\Sigma b}\right)$ $\triangleright$ Result with added self-connections
7:    **return** X_{conv} $\triangleright$ Result with added self-connections
8: **end function**

Note that algorithm 2 assumes bidirectional edges. Hence, the gather and scatter operations are performed twice. This operation can be efficiently implemented using gather and scatter operations, enabling the network to learn expressive node representations while considering the graph's topology. In graph convolutions, the gather operation extracts feature information from neighboring nodes. For each target node v_i, the gather operation assembles feature vectors from its neighboring nodes in the graph line 2 and **??**. These gathered features are then scattered into the feature vector of each target v_i. The scatter operation aggregates the gathered features by adding them to each target's feature vector. It takes the computed features and distributes them back to the corresponding nodes in the graph line 4 and **??**. This step ensures that the updated node representations, enriched with information from neighboring nodes, are propagated throughout the graph.

Lastly, the feature vector of the node itself is added, forming the basis for computation in the subsequent convolutional layer line 6. By selecting and aggregating features from neighboring nodes using the gather and scatter operations, the model

captures the local neighborhood information critical for graph-based tasks. With each convolution, one additional neighborhood can be captured. This way, both local and global patterns are captured.

3.2.3 Adding Dropout to Sparse Graph Convolutions

Four of our regularization techniques, described in section 2.2.4, have been integrated into this gather/scatter-based graph convolution. To better understand the connection between our implementation, we propose to look at two parameters, $row - wise?$ and $gather - first?$. The $row - wise?$ parameter tells us if the dropping of entities on a certain position is done for the whole row of one of two feature vectors. The feature matrix X, where each row represents a node, and the entry in such a row represents a feature of the node. This vector is masked when we perform DO or NS. Each row of the gathered matrices X_a and X_b contains the feature vector of the start node of an edge. We perform DE and GDC by masking those gathered matrices. Masking is implemented as element-wise multiplication with the corresponding vectors.

So, when $row - wise?$ is true, the whole node is dropped. This is the case for NodeSampling (NS) and for DropEdge (DE). NS removes the whole node, along with every feature of this node, and DE is concerned with dropping edges, i.e., connections to the entire node, not only to some of the features. So, this type of dropout is also performed row-wise. DropOut (DO) drops just some features of a gíven node, so the $row - wise?$ parameter is set to false. This is also the case for GDCs as it draws random masks, i.e., performs drops for each channel independently.

The different types of regularization are all performed in each gather/scatter-based convolutional step. It is done by masking some values from the feature vector X or X_a and X_b. In the case of DO and GDC, The X vector is masked. The difference is that, unlike in the case of GDC for DO, the masking is performed row-wise.

We implement regularization by integrating it in each gather/scatter-based convolutional step

Regularization	row-wise?	gather-first?
DropOut (DO)	false	false
DropEdge (DE)	true	true
NodeSampling (NS)	true	false
GraphDropConnect (GDC)	false	true

Before we describe our implementation in Python, we look at the two proposed variants of GDC and provide an intuition for them. As stated previously, this version of GDC allows drawing different random masks for each channel and edge independently, giving more flexibility and increasing the time and space complexity.

$$H^{(l+1)}[:,j] = \sigma \left(\sum_{i=1}^{f_l} \Re \left(A \odot Z_{i,j}^{(l)} \right) H^{(l)}[:,i] W^{(l)}[i,j] \right)$$

$$\text{for } j = 1, ..., f_{l+1}$$

(3.1)

Here, we calculate the new feature matrix $H^{(l+1)}$ by stacking the column vectors of each iteration. One can think of the calculations that are being performed as a 4-dimensional matrix with the dimensions $n \times n \times f_l \times f_{l+1}$

To understand what is being done, we can look at what is being performed when calculating one column of the resulting matrix. First, a random mask is applied to the connection from the i-th to the j-th. Regarding node features communicating with each other, we look at the edge between the i-th and j-th features between connected nodes. By applying the random mask, we drop those connections selectively. Because we sample the random binary mask Z f_{l+1} times, one time for every feature in the $l+1$-th iteration, we differentiate between the connection $i \rightarrow j$ between two nodes and the connection $j \rightarrow i$ between the same two nodes. Thus, the same edge can be dropped as a connection and remain as a connection in the opposite direction. The masked adjacency is then multiplied by the corresponding column and weight. One may think of it as performing a random sampling across each channel since in each iteration from $i = 1$ to f_{l+1}, we perform multiplication with the $i - th$ column of H.

As for the implementation of GDC, we decided to implement the less complex version, as shown below, since this implementation reduces the runtime completely and is also the one that was originally implemented for testing the efficacy of GDC
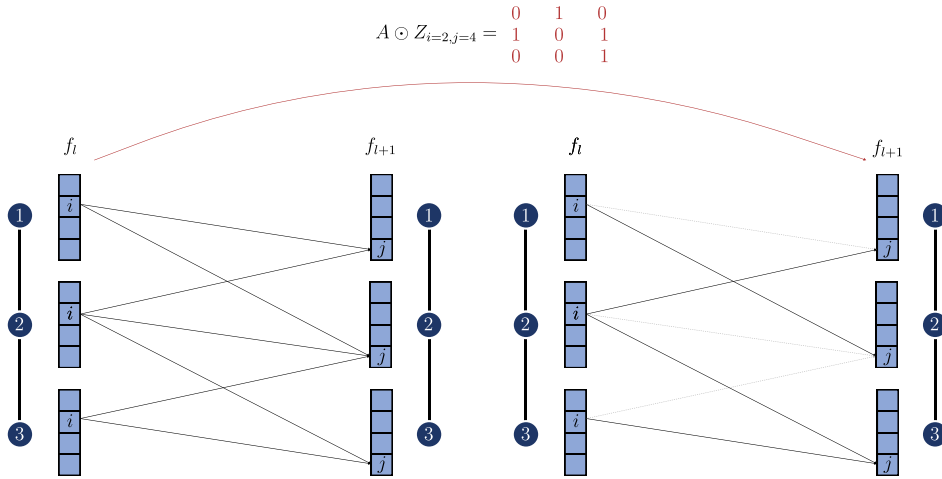
$$A \odot Z_{i=2,j=4} = \begin{matrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 0 & 1 \end{matrix}$$

Abbildung 3.1.: GDCNote: self connection are assumed

$$H^{(l+1)} = \sigma(\sum_{i=1}^{f_l} \mathfrak{N}(A \odot Z_i^{(l)})H^{(l)}[:,i]W^{(l)}[i,:]) \tag{3.2}$$

Here, we compute the new feature matrix in one go instead of doing f_l iterations for all f_l columns.

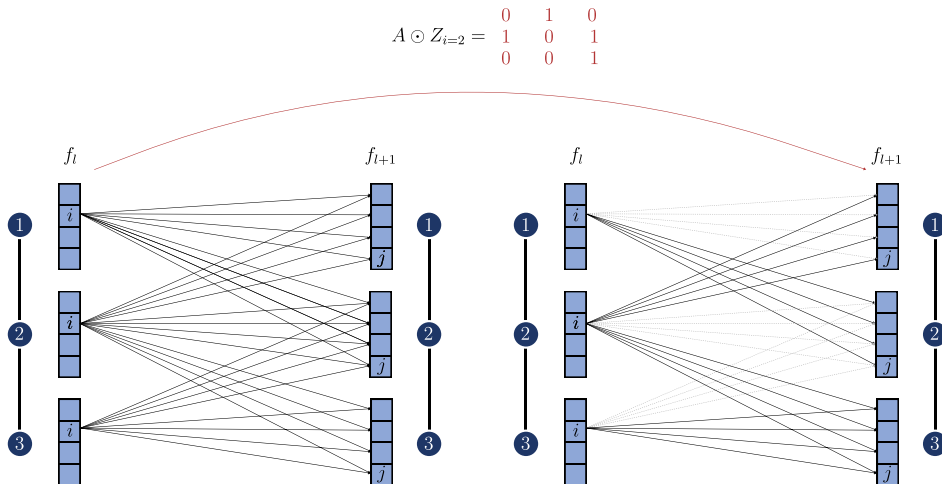$$A \odot Z_{i=2} = \begin{matrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 0 & 1 \end{matrix}$$

Abbildung 3.2.: Originally proposed GDCNote: self connection are assumed

3.3 Choice of Libraries and Frameworks

Below, we briefly overview used datasets and frameworks and motivate the choice.

Even though machine learning on graph-structured data is carried out in many areas and has many interesting use cases ranging from social networks to molecular graphs, manifolds, and source code [Hu+20], there is no unified framework for working with graph-structured data. Furthermore, commonly used datasets and evaluation procedures suffer from multiple issues that negatively affect the quality of predictions and the reliability of evaluations of models. Machine learning algorithms rely heavily on data. For a GNN to be able to make accurate predictions, there is a need for a sufficient amount of properly prepared training data. Standardized splitting and evaluation methods are needed to compare different models against each other.

Today, most of the frequently used graph datasets are extremely small compared to graphs found in real applications. The same datasets, such as Cora, CiteSeer, and PubMed, are used repeatedly to train various models, leading to poor scalability in most cases. Small datasets also make it hard to rigorously evaluate data-hungry models, such as graph neural networks (GNNs). The performance of a GNN on these datasets is often unstable and nearly statistically identical to each other, due to the small number of samples the models are trained and evaluated on [KW17; Xu+19; Hu+20].

Open Graph Benchmark (OGB) offers a wide range of different-sized graph datasets from different domains for a variety of varying classification tasks and provides a unified pipeline for working with the datasets in ML tasks. The unified experimental protocol with standardized dataset splits, evaluation metrics, and cross-validation protocols makes it easy to compare performance reported across various studies [Hu+20].

Working with OGB consists of following steps:

1. OGB provides realistic, different-scaled graph benchmark datasets that cover different prediction tasks from diverse applications.

2. Dataset processing and splitting is fully automated. OGB data loaders automatically download and process graphs and further split the datasets in a

standardized manner. This is compatible with multiple libraries and provides a library-agnostic option.

3. This step includes developing an ML model to train on the OGB datasets.

4. OGB evaluates the model in a dataset-dependent manner and outputs the model performance appropriate for the task at hand.

5. OGB provides public leaderboards to keep track of recent advances.

Abbildung 3.3.: **Overview of the standardized OGB pipeline** adapted from [Hu+20]

For machine learning tasks, TensorFlow, a powerful and versatile open-source machine learning framework, was a fundamental tool for developing and training intricate machine learning models. TensorFlow's extensive set of libraries and tools simplifies the process of building, training, and deploying machine learning models, making it a preferred choice. The framework's adaptability to various tasks, ranging from image recognition to natural language processing, underscores its universal applicability, positioning it at the forefront of modern machine learning research. In addition to TensorFlow, this study leveraged NetworkX, a Python package designed to create, manipulate, and analyze complex networks. NetworkX was used as a tool for graph representation.

Evaluation

In this section, we delve into the critical evaluation of the machine learning experiments conducted as part of this research. The main postulated question of this study was to determine whether GDC is effective in solving the problem of overfitting and over-smoothing for graph-level prediction tasks, as there is already a wide range of conducted studies, which answer the question of various regularization techniques for node level prediction tasks. Other regularization techniques have also been evaluated for this type of task. The investigation encompassed classification and regression tasks, with a comprehensive analysis of two types of neural networks, GCN and GIN. The datasets of choice were all molecular datasets. In the evaluation, we will mainly focus on two manipulated parameters: the number of layers and the dropout rate, since the number of layers is important in concluding overfitting, especially the issue where additional layers do not make the network perform better. The dropout rate since this parameter indicates the efficacy of various types of dropouts and if higher rates have an impact at all.

4.1 Datasets and Metrics Overview

Before proceeding to the experimental findings, we present a quick overview of the used datasets and metrics to ensure a better understanding of the subject matter. We have used five datasets, all from the molecular realm. Molhiv and molpcba are small and medium-size classification datasets, respectively. The other three, OGB-molesol, -mollipo and -molfreesolv are regression datasets. They contain 1128, 4200, and 642 molecular structure graphs, respectively. The regression task is to predict the solubility of a molecule in different substances. To evaluate the performance of molhiv, we used ROC-AUC, for molpcba AP was used and we used MAE for all the regression datasets.

Tabelle 4.1.: Experimental results for graph-level prediction tasks. With ROC-AUC metric for OGB-molhiv, AP for -molpcba and MSE for the three remaining regression datasets.

		OGB-molhiv	-molpcba	-molesol	-molfreesolv	-mollipo
GCN	None	0.51 ± 0.12	0.11 ± 0.00	1.67 ± 0.20	10.01 ± 1.71	0.69 ± 0.02
	DropOut	0.47 ± 0.03	0.06 ± 0.00	3.97 ± 0.31	13.84 ± 0.77	1.11 ± 0.01
	NodeSampling	0.51 ± 0.03	0.07 ± 0.00	2.96 ± 0.12	12.54 ± 0.59	1.06 ± 0.02
	DropEdge	0.48 ± 0.10	0.10 ± 0.00	1.92 ± 0.07	8.79 ± 1.08	0.82 ± 0.05
	GDC	0.54 ± 0.03	0.08 ± 0.00	2.88 ± 0.13	13.29 ± 1.19	1.02 ± 0.03
GIN	None	0.70 ± 0.01	0.10 ± 0.02	1.74 ± 0.10	8.36 ± 0.70	0.75 ± 0.05
	DropOut	0.50 ± 0.03	0.07 ± 0.00	3.46 ± 0.24	20.32 ± 1.15	1.10 ± 0.02
	NodeSampling	0.55 ± 0.04	0.08 ± 0.00	3.02 ± 0.59	13.10 ± 1.80	0.94 ± 0.04
	DropEdge	0.52 ± 0.04	0.11 ± 0.00	2.16 ± 0.21	7.94 ± 0.17	0.78 ± 0.05
	GDC	0.52 ± 0.03	0.09 ± 0.00	2.54 ± 0.20	20.10 ± 3.50	1.06 ± 0.04

4.2 Experimental Setup

4.2.1 Parameter Grid

In this study, a comprehensive exploration of the model's hyperparameters was conducted to optimize the performance of the graph neural network. The hyperparameter search space was defined through a parameter grid, denoted as param_grid, encompassing various configurations. The param_grid was meticulously designed to contain many possibilities, enabling a systematic investigation of the model's behavior under different settings.

This parameter grid contained a number of layers ranging from 1 to 6, representing the depth of the neural network architecture. The learning rate alternated between three different values (0.0001, 0.001, 0.01) for the learning rate optimization of the model. We chose the Adam optimizer exclusively for its robust performance in optimizing complex neural networks. As mentioned previosly, we looked at four regularization technique described in **??**, DO, NS, DE, GDC, and also looked at the performance, when no regularization was applied.

Regularization Technique (regularization): Examining the impact of various regularization methods, including 'None', 'DropOut', 'NodeSampling', 'DropEdge', and 'GDC', to mitigate overfitting and enhance model generalization. Dropout Probability (probability): Investigating three dropout probabilities (0.3, 0.5, 0.7) to regulate the dropout rate during training, preventing co-adaptation of feature detectors. Activati-

on Function (activation): Considering three activation functions ('relu', 'sigmoid', 'tanh') to introduce non-linearity into the model, capturing complex relationships within the data. Number of Units in Hidden Layers (units): Exploring two different configurations (32, 64) for the number of units in the hidden layers, determining the capacity of the neural network. Graph Convolution Type (convo_type): Investigating two graph convolution types ('gcn', 'gin') to assess their impact on capturing graph-structured data effectively. To comprehensively explore the hyperparameter space, all possible combinations of these parameters were generated, resulting in a list denoted as param_combos. Each configuration within param_combos represented a unique set of hyperparameters for the graph neural network. By exhaustively evaluating these combinations, this study aimed to identify the most suitable hyperparameter configuration, providing valuable insights into the optimal setup for graph-based machine learning tasks.

4.2.2 Finding the Best Set of Hyperparameters

For hyperparameter optimization, we use grid search grid search (GS) [Lor+17; YS20; ZH21].GS is a model-free method of automated hyperparameter selection, which systematically explores the configuration space performing an exhaustive search.

1. Poor scalability for large configuration spaces due to its exponential complexity in the number of hyperparameters and corresponding values. Assuming that there are k parameters, and each of them has n distinct values, its computational complexity is $O(n^k)$

2. Lack of consideration of the hierarchical hyperparameter structure leads to many redundant configurations.

Despite its two major drawbacks,GS is well-suitable for small search spaces and can easily be implemented and parallelized.

4.3 Some Additional Section

4.4 Experimental Results

Some insights we can gather from the results table: The best results are achieved using no regularization techniques for graph-level prediction tasks on both types of networks GCN and GIN. This holds for both datasets – classification and regression – indicating that any regularization type is unsuitable for both graph-level prediction tasks independently of the network of choice. For both classification datasets, the variance is very small; the network performance is stable. Out of the three regression datasets, only the mollipo dataset has low variance in performance for both types of GNNs, and we have rather a high variance on the remaining datasets. GCN and GIN perform better on classification tasks for graph-level predictions. This high variance of molesol and mollipo is an interesting trend, which would be nice to investigate further. Despite achieving the best result when using no regularization, we can point out a clear second-place 'winner' among the different regularization methods on both networks and across all datasets.DE performs the second best in all cases, with the second place being GDC for classification tasks and NS for regression tasks, apart from one exception on the mollipo dataset where the second best performing regularization is GDC. However, as all the results are very close in range, we cannot point out any notable advantages of using GDC above other regularization methods, as their performance varies depending on the task and dataset. Despite the GIN network being more powerful than GCN and as powerful as the 1-dimWL test, the performance on both networks is very similar, with only a significant difference in performance on the molhiv dataset.

4.5 Conclusion

Our study examined the impact of various regularization techniques, particularly GDC, on graph-level prediction tasks across two different network types. Regularization techniques are commonly employed in node-prediction tasks across diverse networks to mitigate over-smoothing and overfitting issues. These methods perturb the values and introduce randomness, leading to improved results.

In graph-level tasks, the final output is a readout of aggregated nodes, making over-smoothing less problematic as the focus shifts from distinguishing individual nodes to capturing collective behavior. Consequently, introducing controlled randomness might seem unnecessary for such predictive tasks. This shift in focus from individual nodes to aggregated outcomes challenges the conventional wisdom of applying regularization methods in graph-level prediction tasks.

Despite this counterintuitive aspect, our study aimed to empirically validate the effectiveness of regularization techniques in graph-level prediction tasks. Our exploration of this uncharted territory was motivated by a desire to challenge existing assumptions and gain a nuanced understanding of the relationship between regularization methods and graph-level predictions. This unconventional approach enabled a rigorous assessment of current methodologies, providing valuable insights into graph-based machine learning.

4.6 Insights from Plots

This analysis aims to gain insights into the phenomenon of over-smoothing. To achieve this, we investigate the variations in performance corresponding to changes in the number of layers within the network architecture.

4.6.1 Effect of the Number of Layers

Upon analyzing five distinct datasets, discernible patterns in performance relative to the number of network layers become evident. Except for the molhiv and molfree-solv datasets, a weak positive correlation between increased layers and improved performance is observable. This trend is consistent across both GCN and GIN models. Typically, optimal performance is achieved at the 5th or 6th layer. However, it is noteworthy that the overall differences in performance are marginal.

This observed trend persists across various regularization techniques, including scenarios without regularization. Interestingly, insufficient evidence supports that regularization effectively mitigates over-smoothing for graph-level classification tasks on the GCN, specifically concerning these datasets. Additionally, substantial
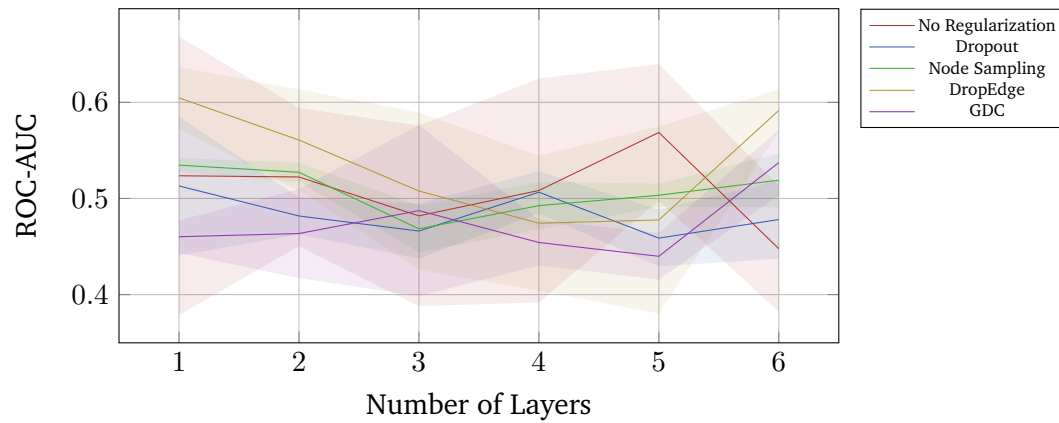
Abbildung 4.1.: molhiv (GCN Model)

fluctuations are observed in the molhiv dataset, introducing complexity to the observed trends.

In regression datasets, the molfreesolv dataset presents a unique case where optimal performance is attained with a single layer, contrary to the general trend where 5-6 layers yield high performance. Importantly, consistent trends emerge across all regularization techniques and without regularization, suggesting that regularization does not induce unexpected network behavior.

Regarding variance, apart from substantial variance and high fluctuations observed in the molhiv dataset, across both networks and all types of regularization, including scenarios without any regularization. Overall, higher variance is evident in instances without regularization, whereas regularization techniques tend to stabilize performance, resulting in lower variance. This finding underscores the stabilizing influence of regularization techniques on model performance in graph-level classification tasks.
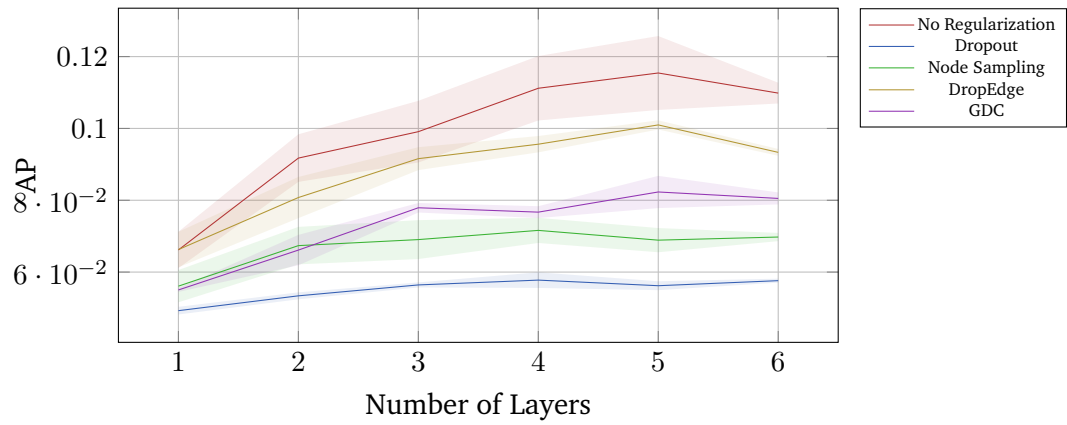
Abbildung 4.2.: molpcba (GCN Model)
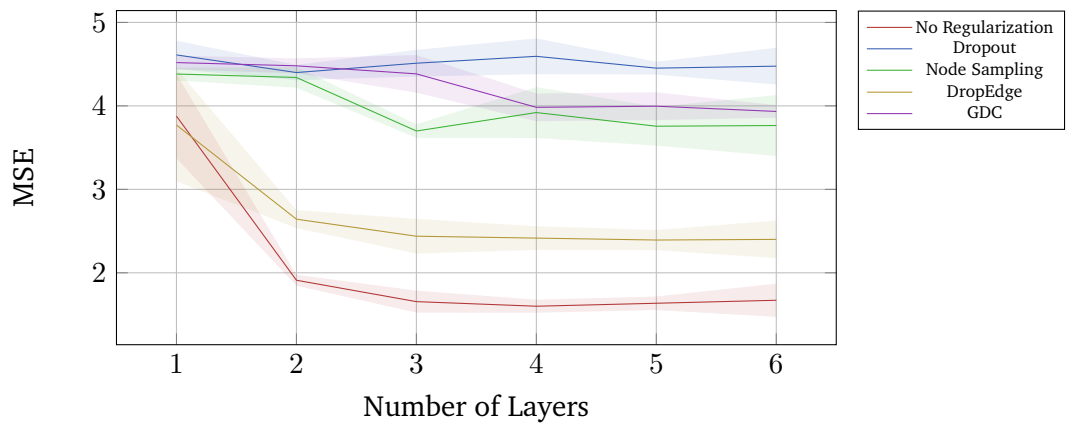
Abbildung 4.3.: molesol(GCN Model)
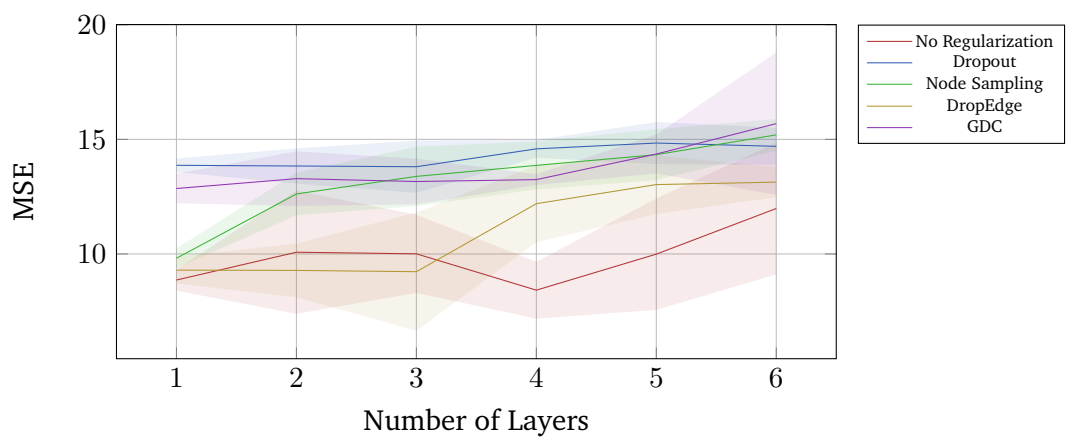
Abbildung 4.4.: molfreesolv (GCN Model)
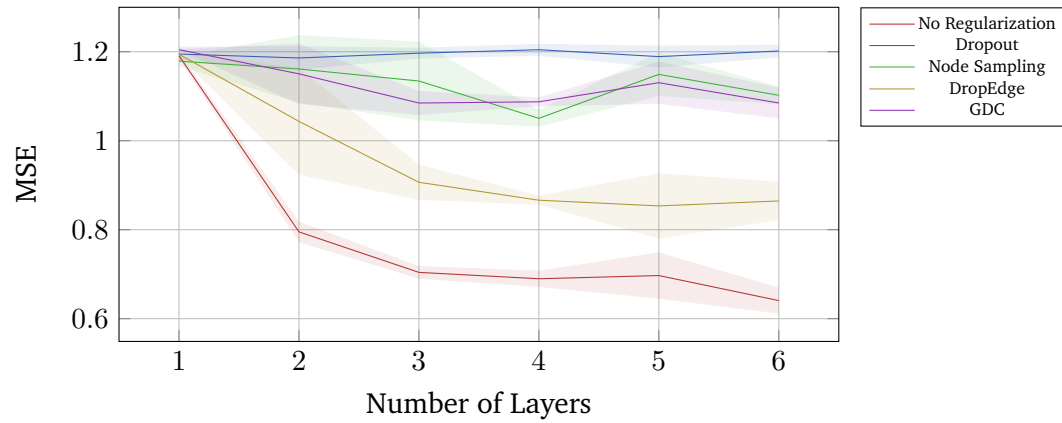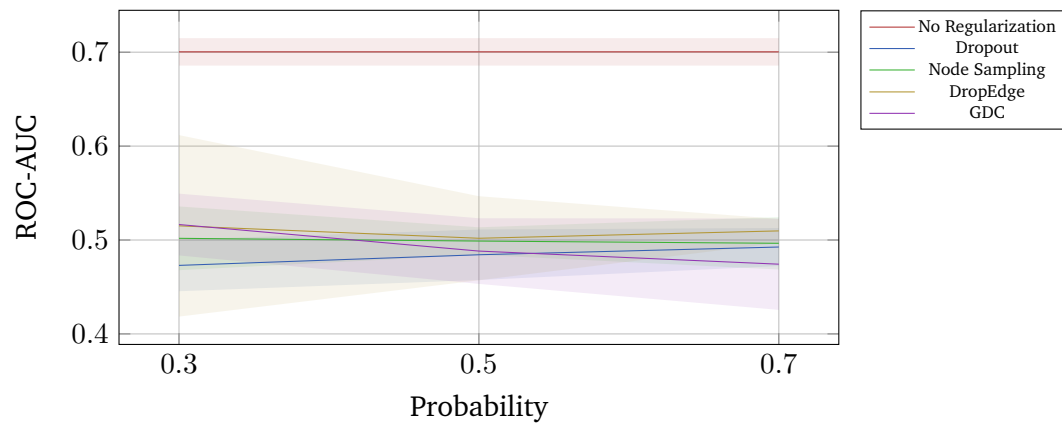
Abbildung 4.5.: mollipo (GCN Model)
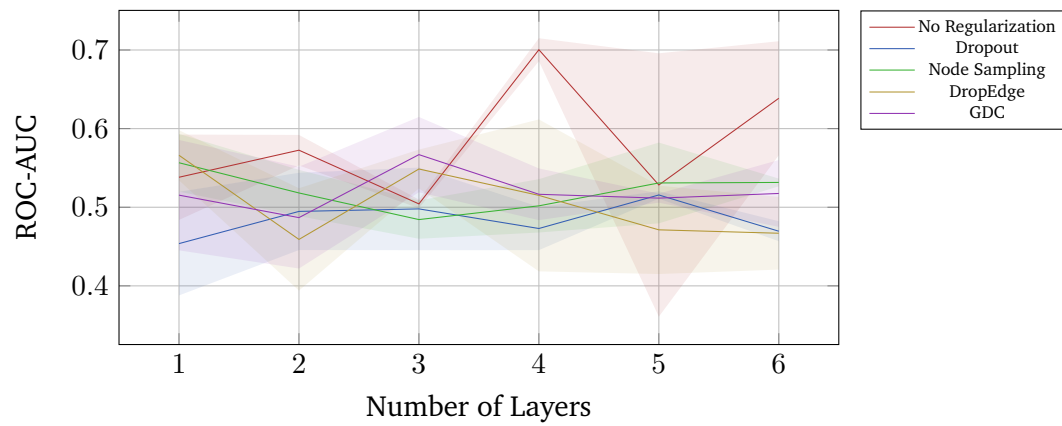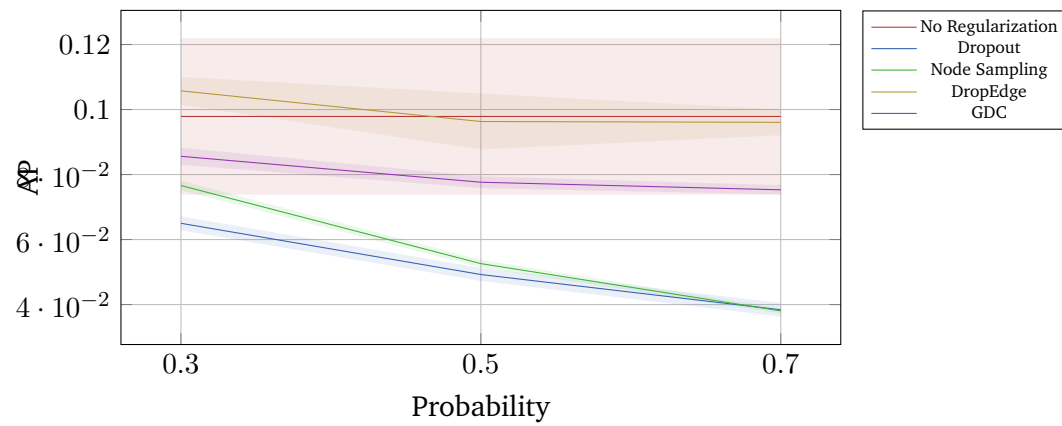

Abbildung 4.6.: molhiv (GIN Model)
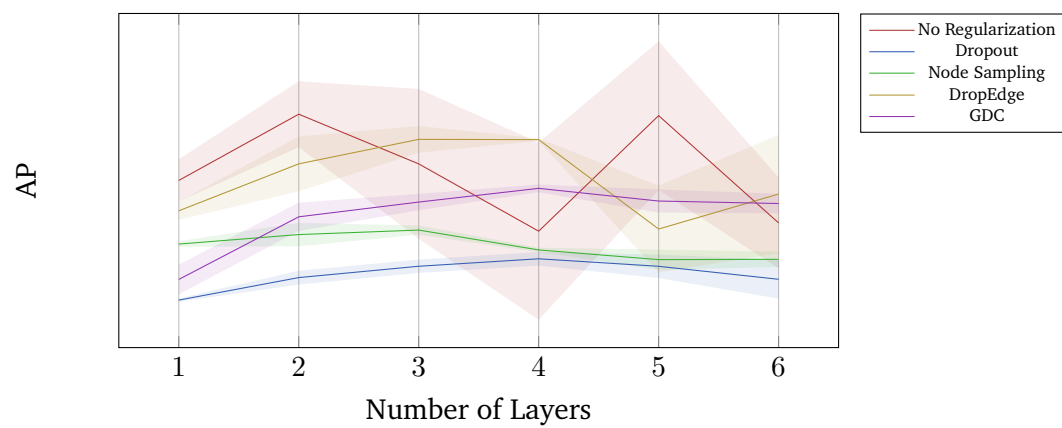
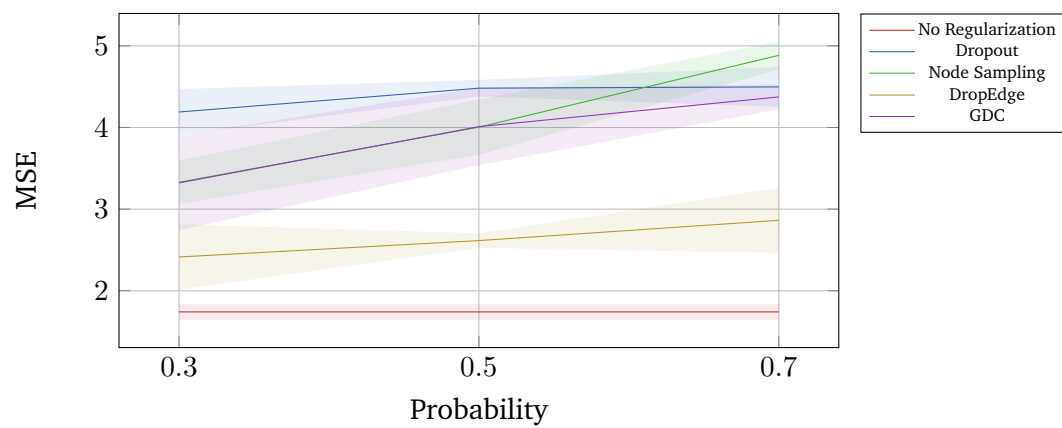**Abbildung 4.7.:** molpcba (GIN Model)
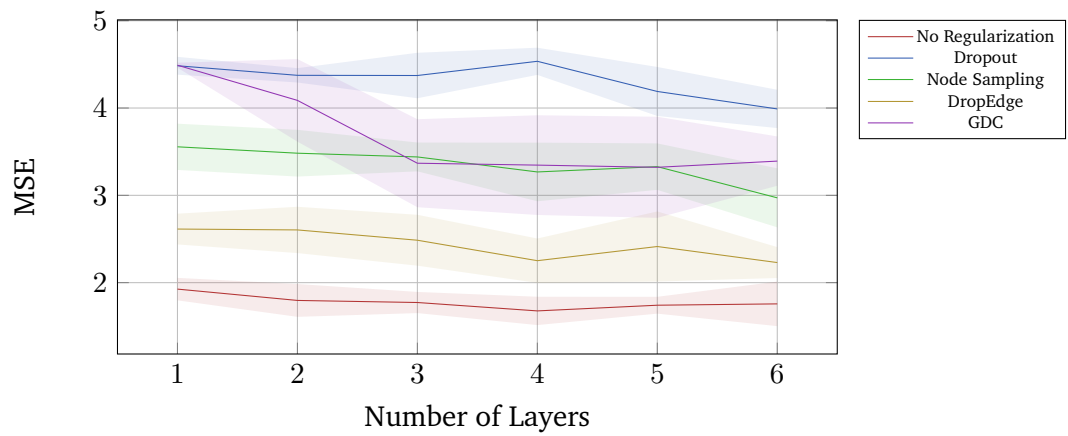
Abbildung 4.8.: molesol (GIN Model)
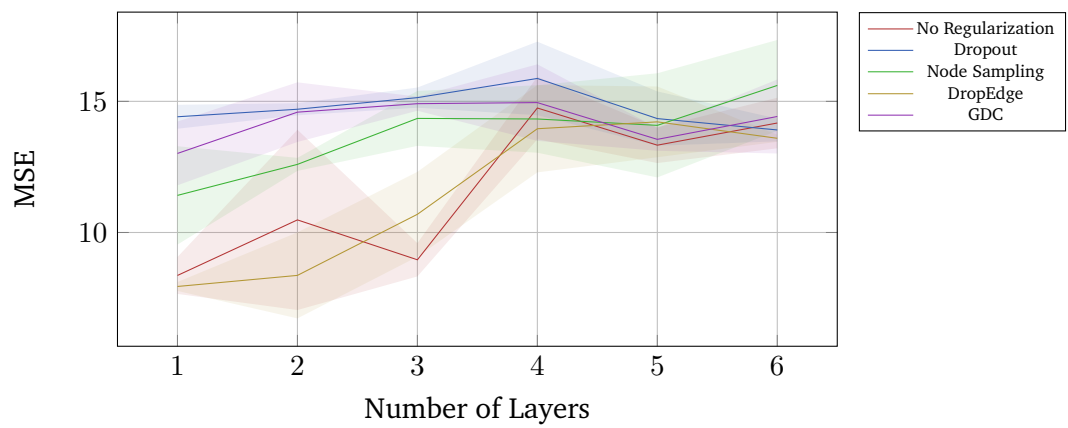
Abbildung 4.9.: molfreesolv (GIN Model)
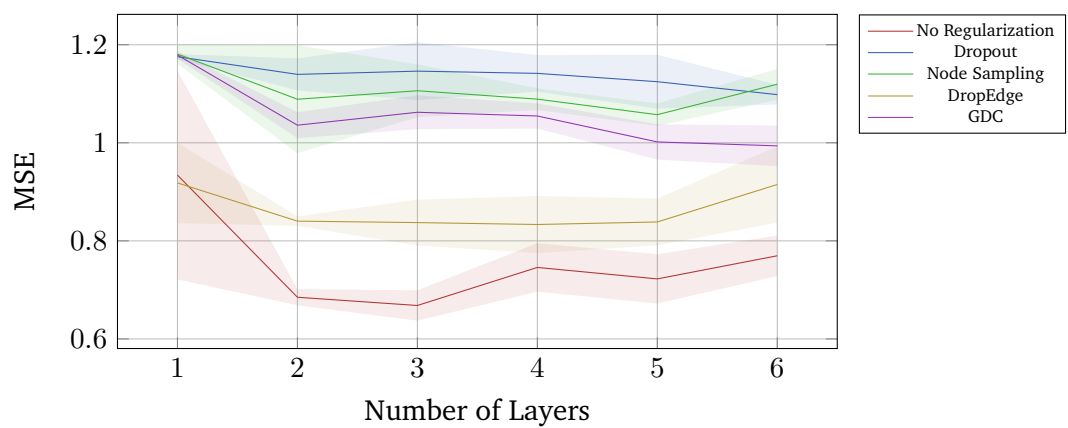
Abbildung 4.10.: mollipo (GIN Model)
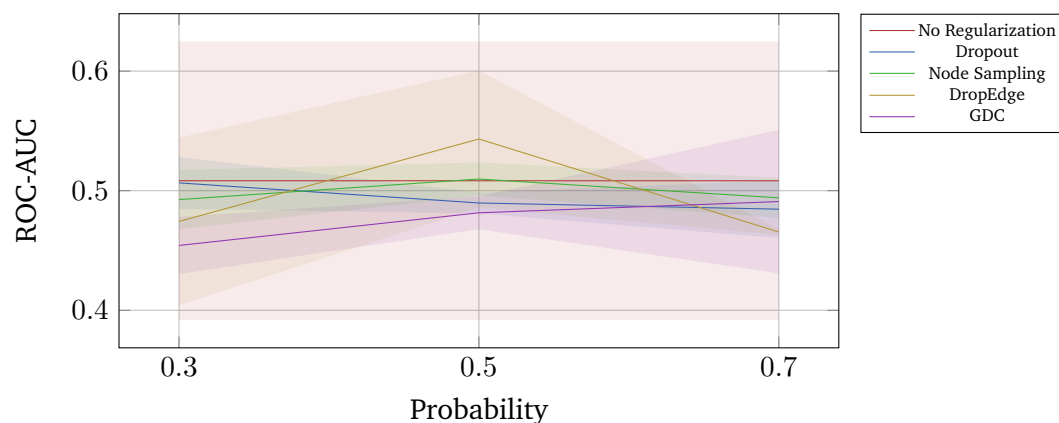
Abbildung 4.11.: molhiv (GCN Model)
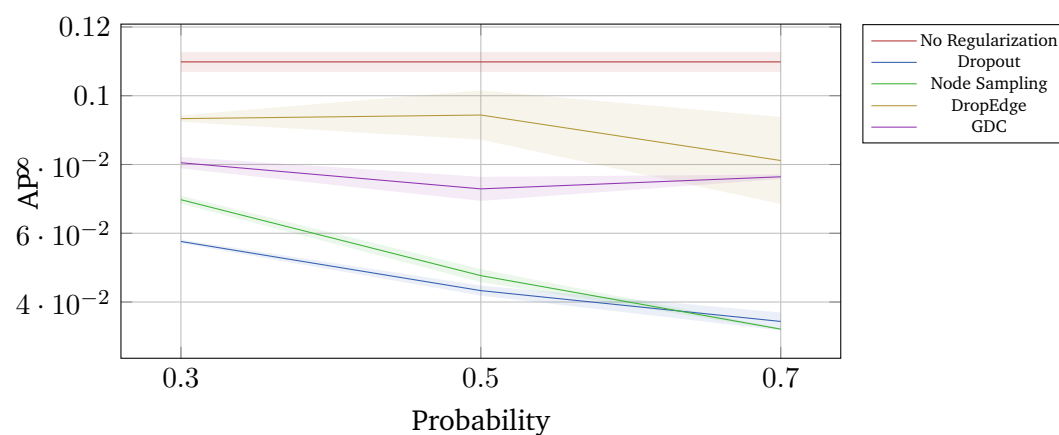
Abbildung 4.12.: molpcba (GCN Model)

Probability Manipulation

4.7 Insights Regression Datasets

4.7.1 Effect of the probability of regularization

Concerning the dropout probability, we found that a lower dropout probability leads to better performance. This makes sense since the best performance is achieved without regularization. This trend can clearly be observed in the regression datasets on the GCN and the GINnetwork. This trend also holds for the classification dataset molpcba on both networks. On the molhiv dataset, the dropout probability does not lead to any substantial differences in performance.
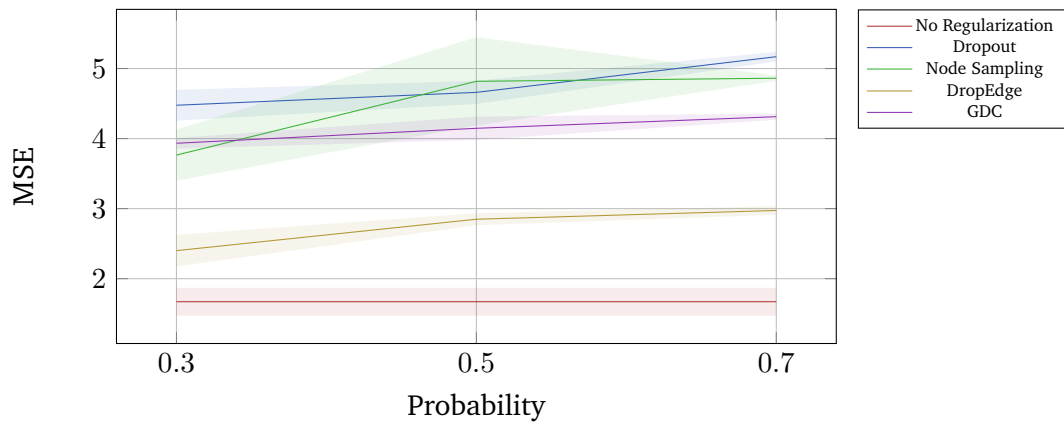
Abbildung 4.13.: molesol (GCN Model)
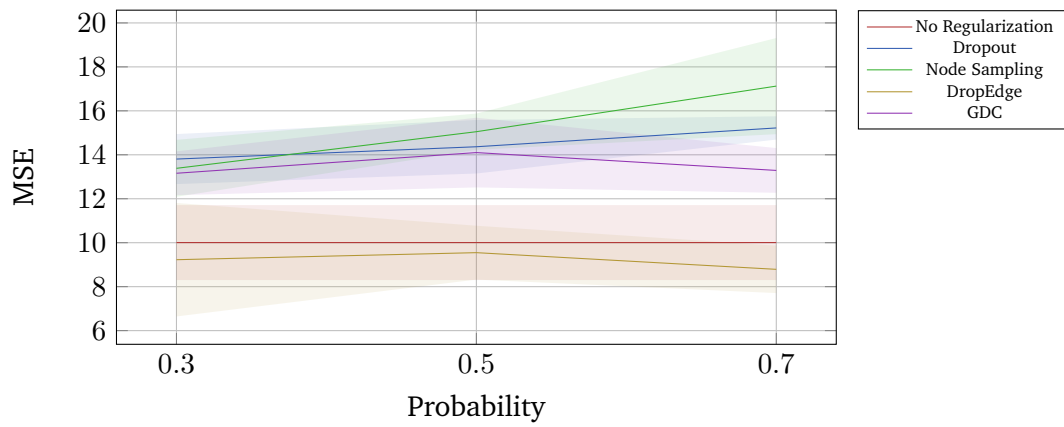
Abbildung 4.14.: molfreesolv (GCN Model)
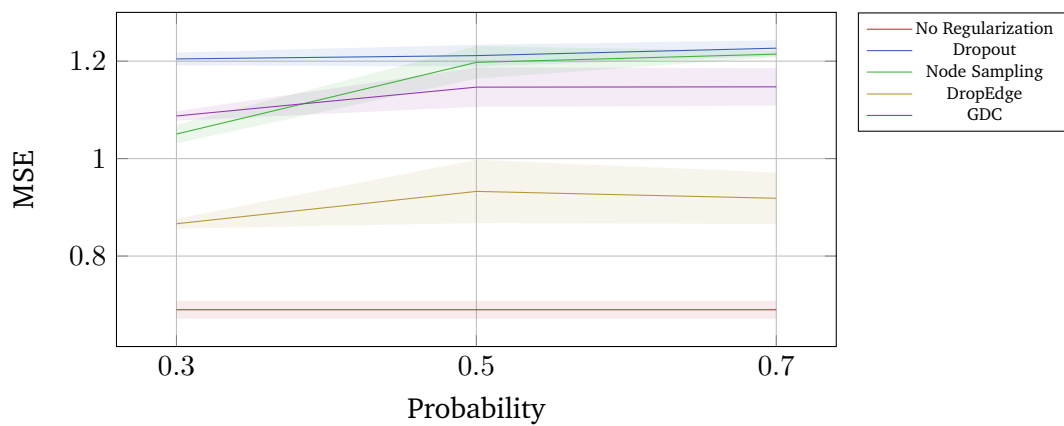
Abbildung 4.15.: mollipo (GCN Model)

Abbildung 4.16.: molhiv (GIN Model)

Abbildung 4.17.: molpcba (GIN Model)

Abbildung 4.18.: molesol (GIN Model)
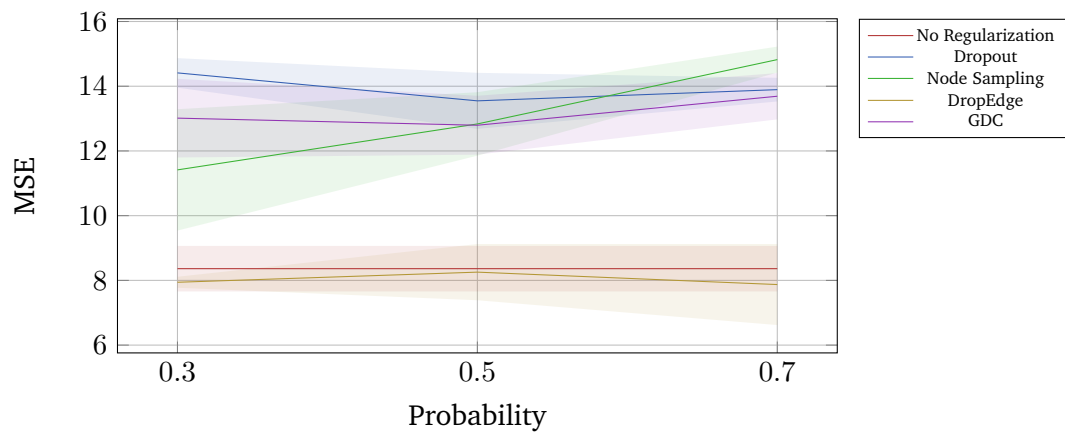
Abbildung 4.19.: molfreesolv (GIN Model)
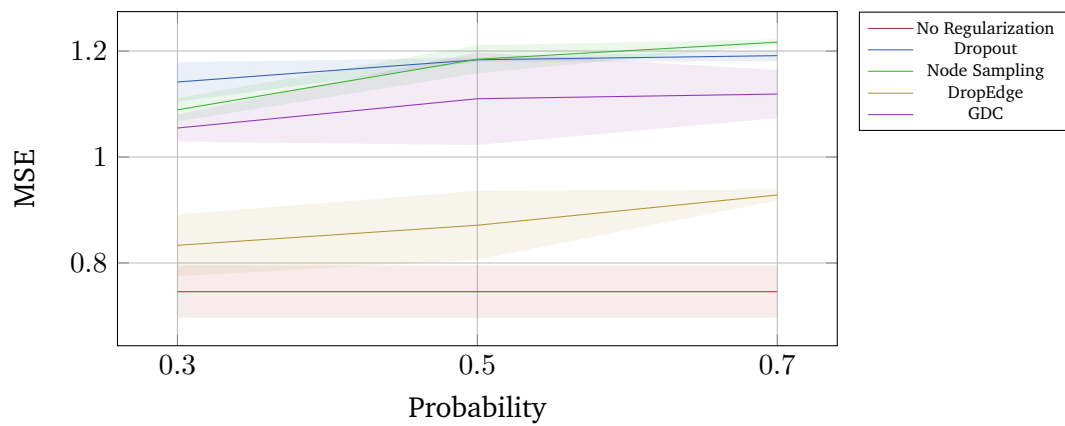
Abbildung 4.20.: mollipo (GIN Model)

Among the datasets, the classification dataset molhiv and the regression dataset molfreesoolv

As mentioned earlier, the results are very close in range, and together with the limited number of datasets- all from the same molecular realm- we cannot draw any general conclusions. However, we can describe some emerging trends from our findings: The trends: Overall, regularization seems to smoothen the line, i.e., to reduce the differences in performance depending on the number of layers. Also, the performance variance is much higher when we use no regularization.

Conclusion

5.1 Future Work

Another proposed regularization technique https://arxiv.org/pdf/2106.07971.pdf

Appendix A

Literatur

[BK79]   László Babai und Ludek Kucera. "Canonical Labelling of Graphs in Linear Average Time". In: *20th Annual Symposium on Foundations of Computer Science, San Juan, Puerto Rico, 29-31 October 1979*. IEEE Computer Society, 1979, S. 39–46 (zitiert auf Seite 7).

[Che+20]   Deli Chen, Yankai Lin, Wei Li et al. "Measuring and Relieving the Over-Smoothing Problem for Graph Neural Networks from the Topological View". In: *The Thirty-Fourth AAAI Conference on Artificial Intelligence, AAAI 2020, The Thirty-Second Innovative Applications of Artificial Intelligence Conference, IAAI 2020, The Tenth AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2020, New York, NY, USA, February 7-12, 2020*. AAAI Press, 2020, S. 3438–3445 (zitiert auf den Seiten 12, 17).

[CMX18]   Jie Chen, Tengfei Ma und Cao Xiao. "FastGCN: Fast Learning with Graph Convolutional Networks via Importance Sampling". In: *6th International Conference on Learning Representations, ICLR 2018, Vancouver, BC, Canada, April 30 - May 3, 2018, Conference Track Proceedings*. OpenReview.net, 2018 (zitiert auf Seite 14).

[DMH20]   Clemens Damke, Vitalik Melnikov und Eyke Hüllermeier. "A Novel Higher-order Weisfeiler-Lehman Graph Convolution". In: *Proceedings of The 12th Asian Conference on Machine Learning, ACML 2020, 18-20 November 2020, Bangkok, Thailand*. Hrsg. von Sinno Jialin Pan und Masashi Sugiyama. Bd. 129. Proceedings of Machine Learning Research. PMLR, 2020, S. 49–64 (zitiert auf den Seiten 5, 22).

[HYL17]   William L. Hamilton, Rex Ying und Jure Leskovec. "Representation Learning on Graphs: Methods and Applications". In: *IEEE Data Eng. Bull.* 40.3 (2017), S. 52–74 (zitiert auf Seite 4).

[Has+20]   Arman Hasanzadeh, Ehsan Hajiramezanali, Shahin Boluki et al. "Bayesian Graph Neural Networks with Adaptive Connection Sampling". In: *CoRR* abs/2006.04064 (2020). arXiv: 2006.04064 (zitiert auf den Seiten 12, 15, 17, 21).

[He+07]   Bingsheng He, Naga K. Govindaraju, Qiong Luo und Burton Smith. "Efficient gather and scatter operations on graphics processors". In: *Proceedings of the 2007 ACM/IEEE conference on Supercomputing - SC '07*. ACM Press, 2007 (zitiert auf Seite 22).

[Hu+20]   Weihua Hu, Matthias Fey, Marinka Zitnik et al. "Open Graph Benchmark: Datasets for Machine Learning on Graphs". In: *CoRR* abs/2005.00687 (2020). arXiv: 2005.00687 (zitiert auf den Seiten 21, 27, 28).

[HV22]   Ningyuan Huang und Soledad Villar. "A Short Tutorial on The Weisfeiler-Lehman Test And Its Variants". In: *CoRR* abs/2201.07083 (2022). arXiv: 2201.07083 (zitiert auf Seite 5).

[KW17]   Thomas N. Kipf und Max Welling. "Semi-Supervised Classification with Graph Convolutional Networks". In: *5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings*. OpenReview.net, 2017 (zitiert auf den Seiten 8, 9, 14, 21, 27).

[KGC17]   Jan Kukacka, Vladimir Golkov und Daniel Cremers. "Regularization for Deep Learning: A Taxonomy". In: *CoRR* abs/1710.10686 (2017). arXiv: 1710.10686 (zitiert auf Seite 12).

[LYJ22]   Meng Liu, Haiyang Yu und Shuiwang Ji. "Your Neighbors Are Communicating: Towards Powerful and Scalable Graph Neural Networks". In: *CoRR* abs/2206.02059 (2022). arXiv: 2206.02059 (zitiert auf Seite 8).

[Lor+17]   Pablo Ribalta Lorenzo, Jakub Nalepa, Michal Kawulok, Luciano Sánchez Ramos und José Ranilla Pastor. "Particle swarm optimization for hyper-parameter selection in deep neural networks". In: *Proceedings of the Genetic and Evolutionary Computation Conference, GECCO 2017, Berlin, Germany, July 15-19, 2017*. Hrsg. von Peter A. N. Bosman. ACM, 2017, S. 481–488 (zitiert auf Seite 31).

[Ron+20]   Yu Rong, Wenbing Huang, Tingyang Xu und Junzhou Huang. "DropEdge: Towards Deep Graph Convolutional Networks on Node Classification". In: *8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020*. OpenReview.net, 2020 (zitiert auf den Seiten 14, 17).

[Sri+14]   Nitish Srivastava, Geoffrey E. Hinton, Alex Krizhevsky, Ilya Sutskever und Ruslan Salakhutdinov. "Dropout: a simple way to prevent neural networks from overfitting". In: *J. Mach. Learn. Res.* 15.1 (2014), S. 1929–1958 (zitiert auf Seite 13).

[WL68]   Boris Weisfeiler und Andrei A. Lehman. "A reduction of a graph to a canonical form and an algebra arising during this reduction". In: *Nauchno-Technicheskaya Informatsia* 2.9 (1968), S. 12–16 (zitiert auf Seite 5).

[Xu+19]   Keyulu Xu, Weihua Hu, Jure Leskovec und Stefanie Jegelka. "How Powerful are Graph Neural Networks?" In: *7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6-9, 2019*. OpenReview.net, 2019 (zitiert auf den Seiten 4, 9, 10, 21, 27).

[YS20]   Li Yang und Abdallah Shami. "On hyperparameter optimization of machine learning algorithms: Theory and practice". In: *Neurocomputing* 415 (2020), S. 295–316 (zitiert auf Seite 31).

[Zha+19]   Si Zhang, Hanghang Tong, Jiejun Xu und Ross Maciejewski. "Graph Convolutional Networks: A Comprehensive Revew". In: *Computational Social Networks* (2019) (zitiert auf den Seiten 3, 4).

[Zho+20a] Jie Zhou, Ganqu Cui, Shengding Hu et al. "Graph neural networks: A review of methods and applications". In: *AI Open* 1 (2020), S. 57–81 (zitiert auf Seite 4).

[Zho+20b] Kaixiong Zhou, Xiao Huang, Yuening Li et al. "Towards Deeper Graph Neural Networks with Differentiable Group Normalization". In: *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual*. Hrsg. von Hugo Larochelle, Marc'Aurelio Ranzato, Raia Hadsell, Maria-Florina Balcan und Hsuan-Tien Lin. 2020 (zitiert auf Seite 12).

[ZH21] Marc-André Zöller und Marco F. Huber. "Benchmark and Survey of Automated Machine Learning Frameworks". In: *J. Artif. Intell. Res.* 70 (2021), S. 409–472 (zitiert auf Seite 31).

Abbildungsverzeichnis

Tabellenverzeichnis

Colophon

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Declaration

Ich, Olga Yakobson (Matrikel-Nr. 11591478), versichere, dass ich die Masterarbeit mit dem Thema SerialExperimentsOlga selbstständig verfasst und keine anderen als die angegebenen Quellen und Hilfsmittel benutzt habe. Die Stellen der Arbeit, die ich anderen Werken dem Wortlaut oder dem Sinn nach entnommen habe, wurden in jedem Fall unter Angabe der Quellen der Entlehnung kenntlich gemacht. Das Gleiche gilt auch für Tabellen, Skizzen, Zeichnungen, bildliche Darstellungen usw. Die Bachelorarbeit habe ich nicht, auch nicht auszugsweise, für eine andere abgeschlossene Prüfung angefertigt. Auf § 63 Abs. 5 HZG wird hingewiesen.

München, 8. November 2023

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Olga Yakobson