DiPol-GAN: Generating Molecular Graphs Adversarially with Relational Differentiable Pooling

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1 Problem Background and Methods

The extension of deep learning to graph data structures has become a popular research topic with compelling applications to the field of chemistry [1]. Of particular interest is the impact of deep generative models to *de novo* drug discovery. Drug discovery describes the process by which new candidate medications are found with the goal of identifying a new target molecule with specific desired properties. The key challenge presented is the vast size of the chemical space and the discrete nature of molecular structures [2]. The drug discovery process is expensive as even *de novo* approaches rely on some semblance of brute force. Improvements in methods to discover new drugs with desired properties would have great impact. Our work presents a method to generate previously undiscovered molecular graphs with specific desired properties.

Generative models have been making astounding progress in the field of computer vision and natural language processing showing significant improvements in the quality of generated samples. Prominent approaches to generative modeling are autoregressive models [3], variational autoencoders (VAEs) [4], and generative adversarial networks (GANS) [5], each excelling in solving very specific types of problems. For the task of image synthesis autoregressive models generate high quality images but can be slow to evaluate and do not have a latent representation. VAEs train via maximum likelihood estimation making them more numerically stable; however, they can produce lower quality results [6]. GANs implicitly learn model parameters without having to specify a likelihood [7] and are known to produce higher quality results but are susceptible to generating lower diversity samples (a.k.a. mode collapse), and are prone to numerical instability making them difficult to train even with recent advances in adversarial training theory [8, 9, 10, 11].

Generative models have started to make their way into the domain of graphs with works such as [7, 12, 13, 14, 15, 16]; however, learning to generate graphs presents problems for gradient based learning due to the discrete nature of graphs because of their arbitrary connectivity [16]. Likelihood-based models for graph generation are known to be stable but require expensive approximate graph matching procedures as seen in GraphVAE [16] or require some fixed ordered representations of the graph as seen in Junction Tree VAE (JT-VAE) [14], which often is not feasible. Autoregressive models suchs as presented in GraphRNN [15] offer an interesting approach building a graph by conditionally modeling sequences of nodes where the sequence generators are jointly aware of each other; however, they lack a latent representation that would allow us to optimize for a desired chemical property.

GANs seem to present a clear advantage for the task of graph generation because they allow us to implicitly learn the data generation distribution without having to formalize a likelihood that necessitates a graph matching strategy as in the likelihood-based models (*e.g.* VAEs) while also allowing for the optimization of the learned distribution towards a desired chemical property.

In this work we present DiPol-GAN, summarized in Figure 1, which is a GAN-based approach to generating complete graph structures that are resistant to graph isomorphisms by learning to predict discrete connections. Through the use of a reinforcement learning objective DiPol-GAN's learned generation distribution is encouraged towards a desired chemical property. DiPol-GAN implements

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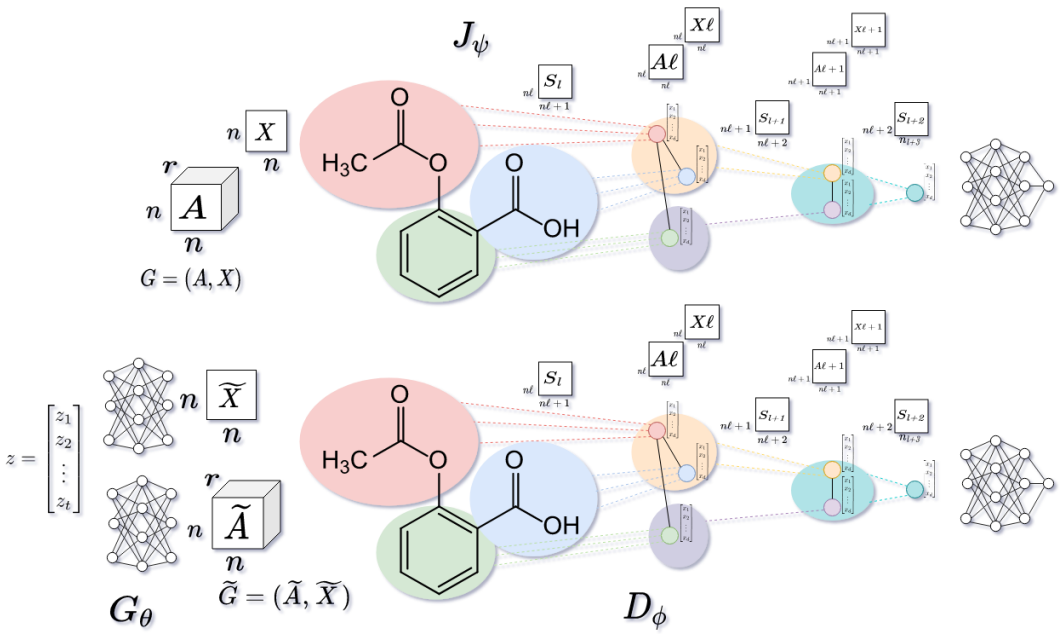

Figure 1: Proposed model architecture. J_ψ is a policy network, G_θ is the generator, and D_ϕ is the discriminator in a graph-based generative adversarial network. The generator is a graph $G = (\mathbf{A}, \mathbf{X})$ where $\mathbf{A}$ is the adjacency matrix, and $\mathbf{X}$ is the features matrix. The model implements a reinforcement learning reward mechanism.

Differentiable Pooling (DIFFPOOL) [17] in its discriminator, which learns to aggregate nodes on the molecular graph in a hierarchical way improving classification accuracy and the quality of learned graph embeddings. We believe that, through improving the discriminator's architecture, it will encourage the generator to learn higher quality graph representations.

2 Results and Conclusions

Table 1 shows the results obtained with the proposed model on the QM9 dataset [18]. Reportedly, the proposed solutions are highly unique and diverse, which means that the molecules produced are not simply regurgitations of the existing (and known to be) valid molecules. However, in spite of the great results obtained, there are a few performance remarks that need to be noted. Using the QM9 dataset for the task of goal directed molecular graph generation can be problematic in that there are 134k molecular graph structures lacking software to calculate chemical properties on a GPU in a timely manner. However, nearly all related work reports lengthy training times with GraphVAE.

Table 1: Comparisons with related molecular graph generation work, presented are test results.

Algorithm	Valid (%)	Uniqueness	Diversity	Druglikeliness	Time (s)
MolGAN	77.5 ± 42.0	0.098 ± 0.16	0.877 ± 0.21	0.513 ± 0.22	16473 ± 651
DiPo (WGAN)	100 ± 0.0	0.883 ± 0.01	0.999 ± 0.45	0.648 ± 0.21	19484 ± 134

In summary, DiPOLGAN presents a method for generating molecular graphs with specific chemical properties via hierarchical differentiable pooling to improve discriminator performance while also optimizing towards a a reinforcement learning objective via the policy network. Through learning hierarchical graph representations it is our intuition from representation learning that our discriminator and policy networks are learning to hierarchically filter learned representations toward information present to improve each specific network's objective and therefore implicitly encourage the generation of realistic molecular graphs.

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