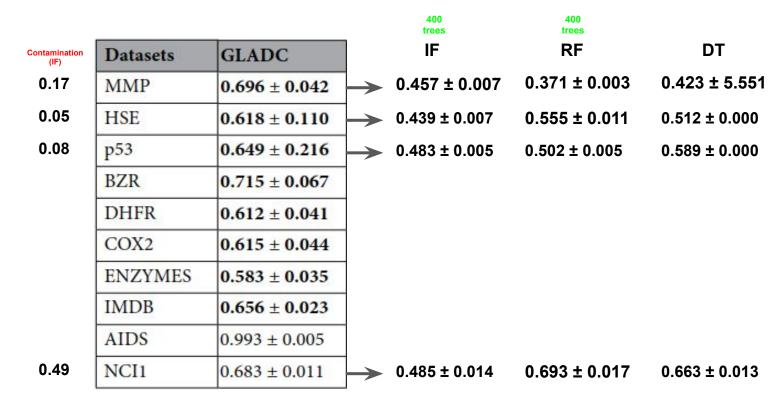
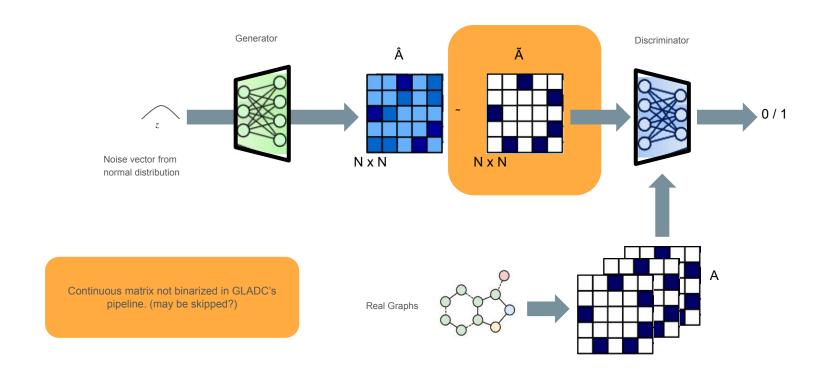
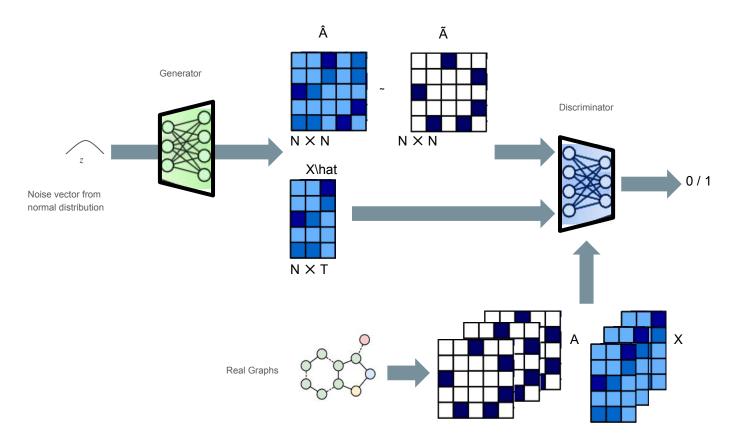
### **Updated Classifiers**



# Generation Pipeline (plain graphs)



# Generation Pipeline (attributed graphs)



# Pipeline (details)

#### Generator

- Consists of a "multi dense" layer followed by one/two final linear layer(s).
  - Two if dealing with attributed graphs (one for the edges or A\hat and the other for the nodes X\hat).
  - One for plain graphs (edges or A\hat).
- Dropout layers in between.
  - Prevents the model from becoming too dependent on particular neurons.
- Loss: log(1 D(G(z)))

#### Discriminator

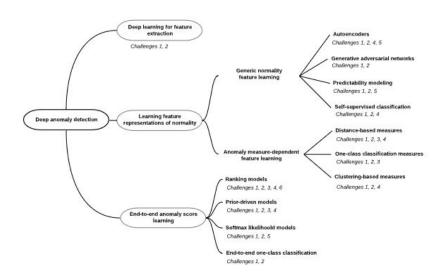
- Possibly inspired from PatchGAN.
  - Classifies patches (local parts) of an image, or in this case a graph and its subgraphs.
- Consists of graph convolution (for node representation), custom graph aggregation (for graph representation), "multi dense" layer and a final classification linear layer.
- Fed both real and fake inputs for loss computation.
  - Loss obtained from sum of the losses for real and fake inputs.

### **Brainstorm**

- As stated earlier, GLADC does not binarize the adjacency matrices before computing the loss.
  - Is this worth looking into?
  - MolGAN does suggest binarizing the adjacency matrices before feeding into discriminator.
  - Continuous adjacency matrices will simply tell the probability of an edge being present or not.
  - MolGAN applies categorical sampling.
    - This won't work in our case since we don't have differentiable categories of nodes or edges.
    - Will need to define a threshold for the probability of an edge being enough to consider it present.
- Try out discriminator as anomaly detection module?
- In fact, if we go for GAN generation, using the Discriminator as anomaly detection might be the only viable approach.
  - GLADC passes a graph as input to its auto encoder and returns a new graph from said input.
    - GANs only take noise.
  - GLADCs judges a graph's anomaly potential by comparing the input with the generated fake graph.

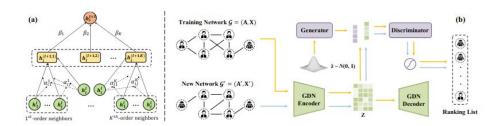
### Brainstorm (cont.)

- Nice taxonomy of strategies for anomaly detection.
  - <u>https://arxiv.org/abs/2007.02500</u>



## Brainstorm (cont.)

- Following previous taxonomy, GLADC lands in the "Generic normality feature learning".
  - As it only uses normal graphs during learning.
  - In the Autoencoders sub-branch.
- Example of "Anomaly measure-dependent feature learning"
  - Inductive node level anomaly detection.
    - https://www.google.com/url?sa=t&source=web&rct=j&opi=89978449&url=https://www.ijc ai.org/proceedings/2020/0179.pdf&ved=2ahUKEwjWvtO\_gJqIAxWAg\_0HHUt1CYEQFn oECBcQAQ&usq=AOvVaw3v-lfqYuDISW8ryHdNPHOa



### Brainstorm (cont.)

- Going back three slides, are there other ways to utilize GANs' power?
- Latent space searching.
  - https://www.google.com/url?sa=t&source=web&rct=j&opi=89978449&url=https://kdd.org/exploration\_files/p29-GAN\_base\_d\_anomaly\_detection\_review\_including\_reviewer\_suggestions.pdf&ved=2ahUKEwjX5NGSjJqlAxWbiv0HHbWtANEQFno\_ECBYQAQ&usg=AOvVaw05Yi7lSdjry2lvbgWnZ3FN
  - For any input data x, search your Generator's latent space Z for a z that closely resembles x.
    - If there is none, there is a chance you are looking at an anomalous graph.
  - This step can result particularly computationally expensive.
    - Some optimizations...
    - Usually used for image generation
      - Images are big matrices, we are dealing with small graph matrices A\hat and X\hat
  - Fast Ano-GAN.
    - https://pubmed.ncbi.nlm.nih.gov/30831356/
    - Additional network to optimize latent space searching.
    - Only applied for images?

