Applications

Applications

Diffusion Models: A Comprehensive Survey of Methods and Applications

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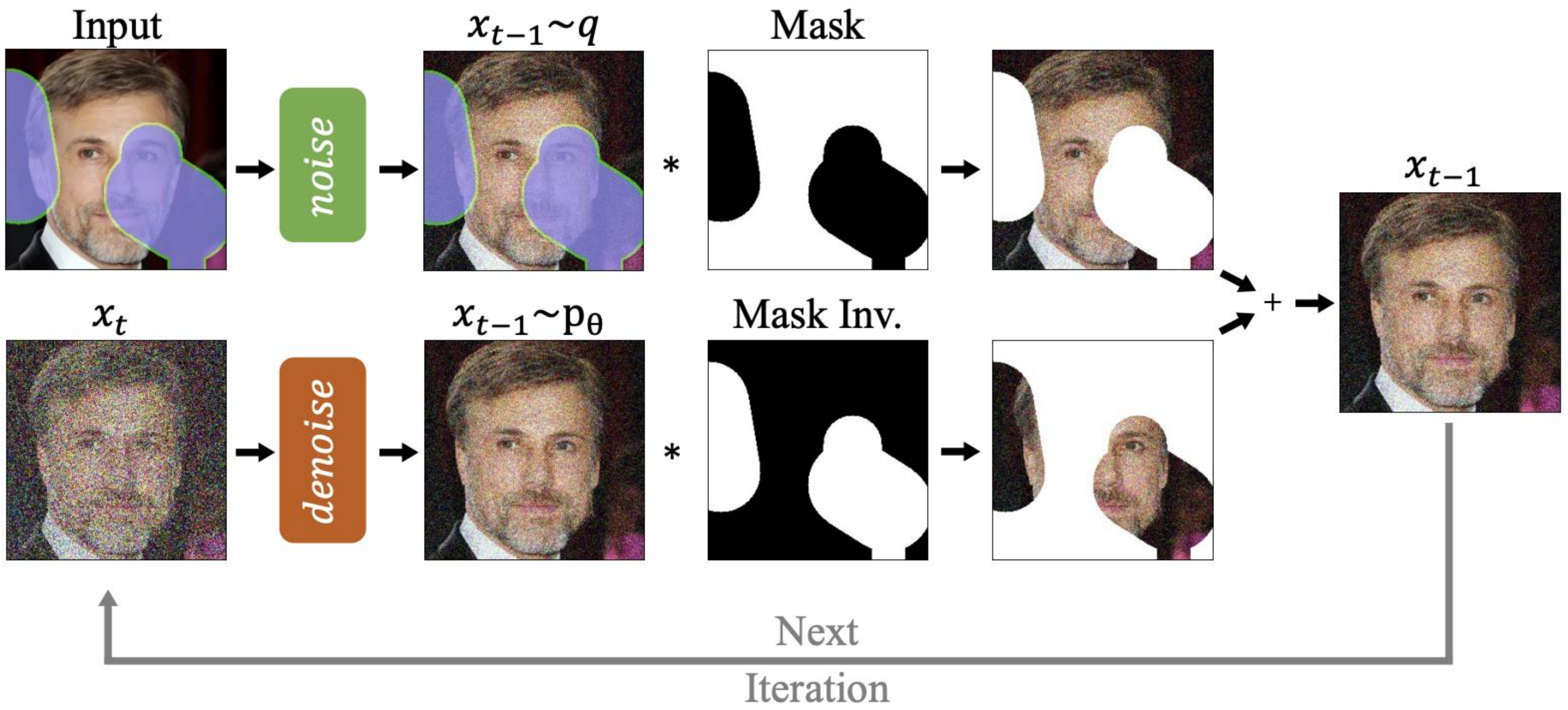
Applications

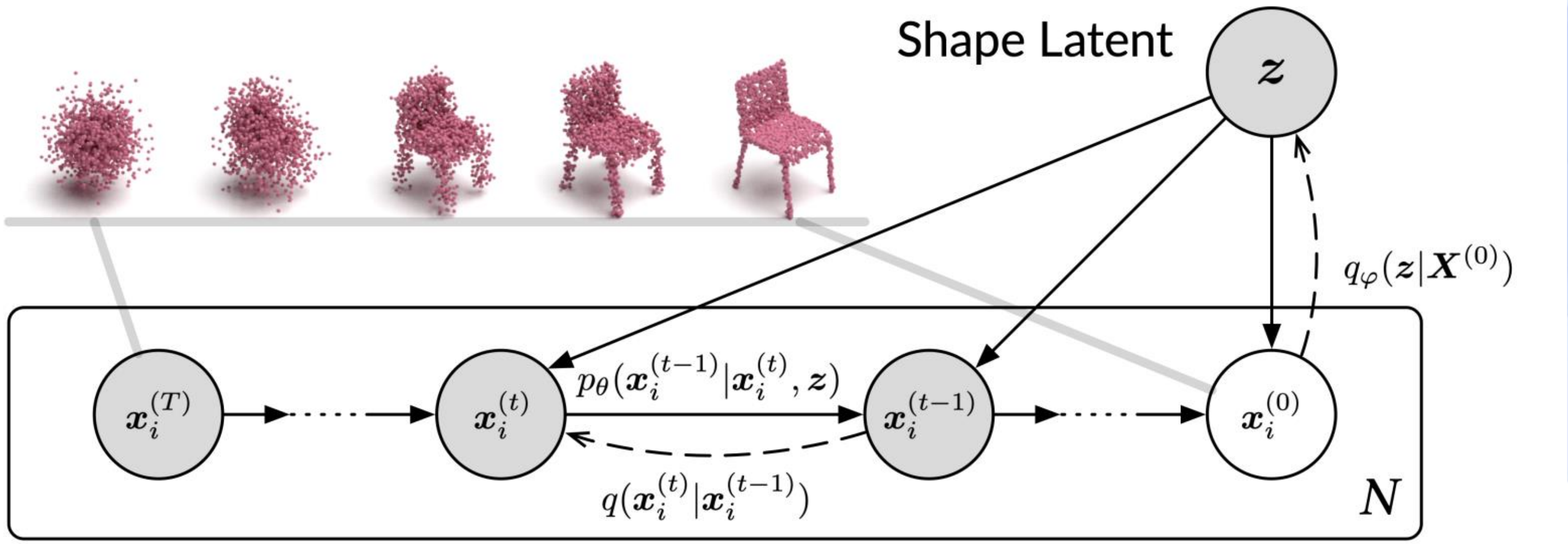
Computer Vision – inpainting



Applications

Computer vision – point cloud generation

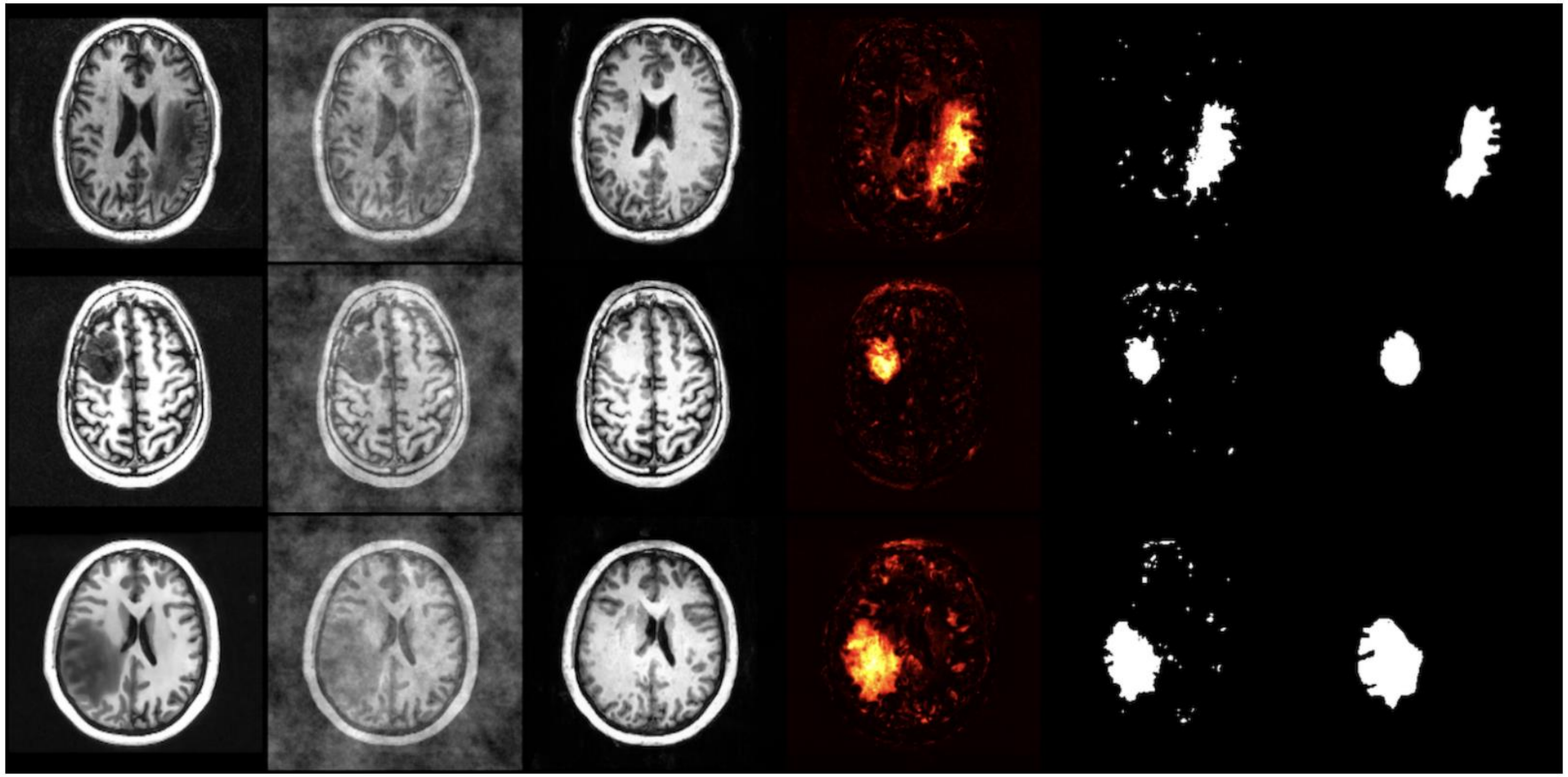
- Scans often miss information due to partial observation or occlusion.
- Use diffusion models to infer missing parts.
- Treat the points in a cloud as a set of particles in an evolving thermodynamic system.



Applications

Computer vision – anomaly detection

- AnoDDPM – attempt to "repair" patient data:
- Instead of adding Gaussian noise, add power law noise



Applications

Natural language generation

- Due to the success of ChatGPT, we tend to forget that Stable Diffusion 2 was released BEFORE GPT-4.
- It is reasonable to think that there might be some good diffusion-based language models…

…but LLMs are still king in this arena

- For a detailed exploration of why see:

https://sander.ai/2023/01/09/diffusion-language.html

Applications

Multimodal generation – text-to-image

- We already covered SD, but there are numerous other models:
  - DALL-E 1,2 and 3
  - Imagen
  - GLIDE
  - VQ-Diffusion
- There are also models which build upon latent diffusion models:
  - DreamBooth – a method of fine tuning pretrained models

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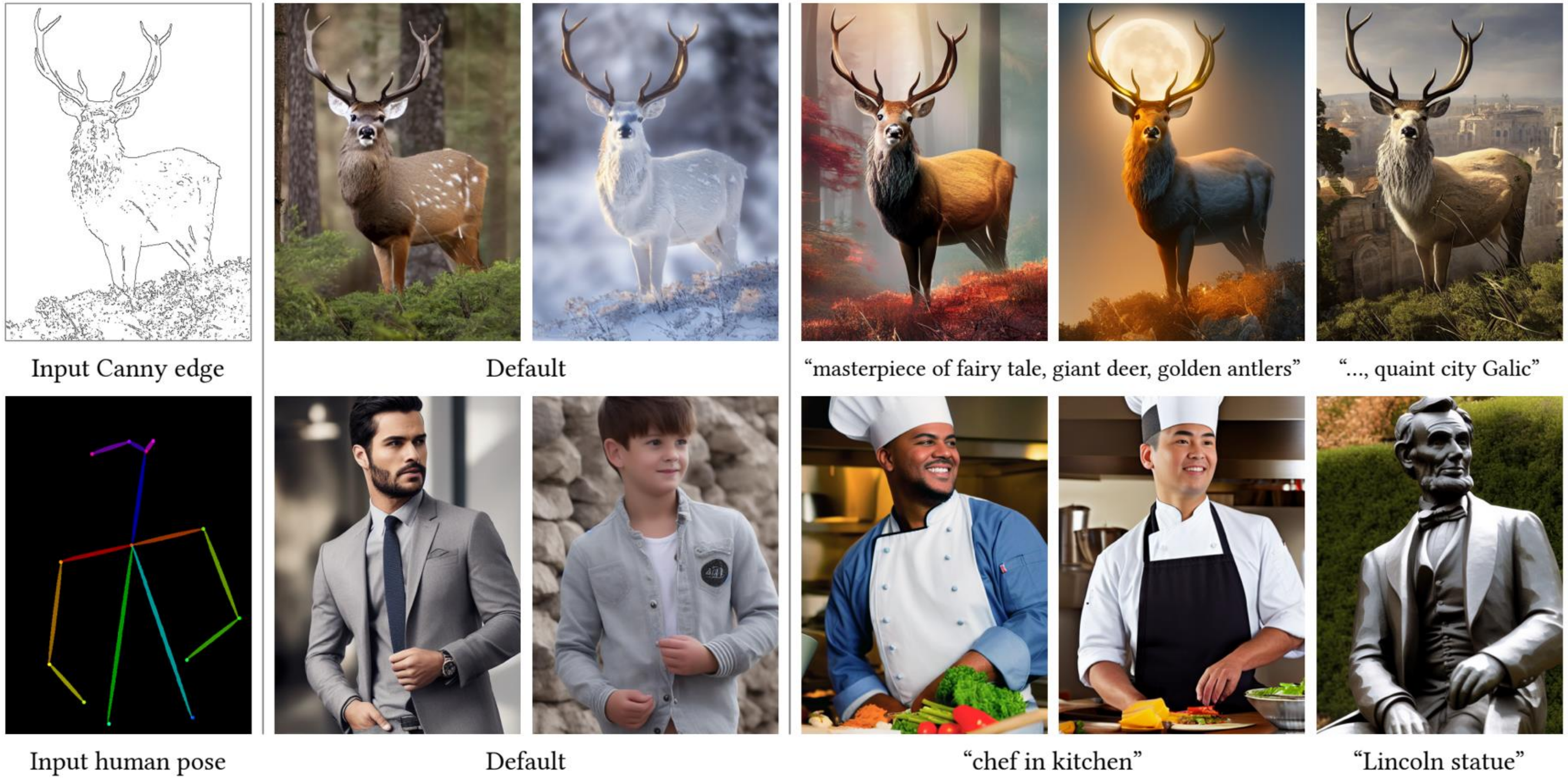
Applications

Multimodal generation – text-to-image

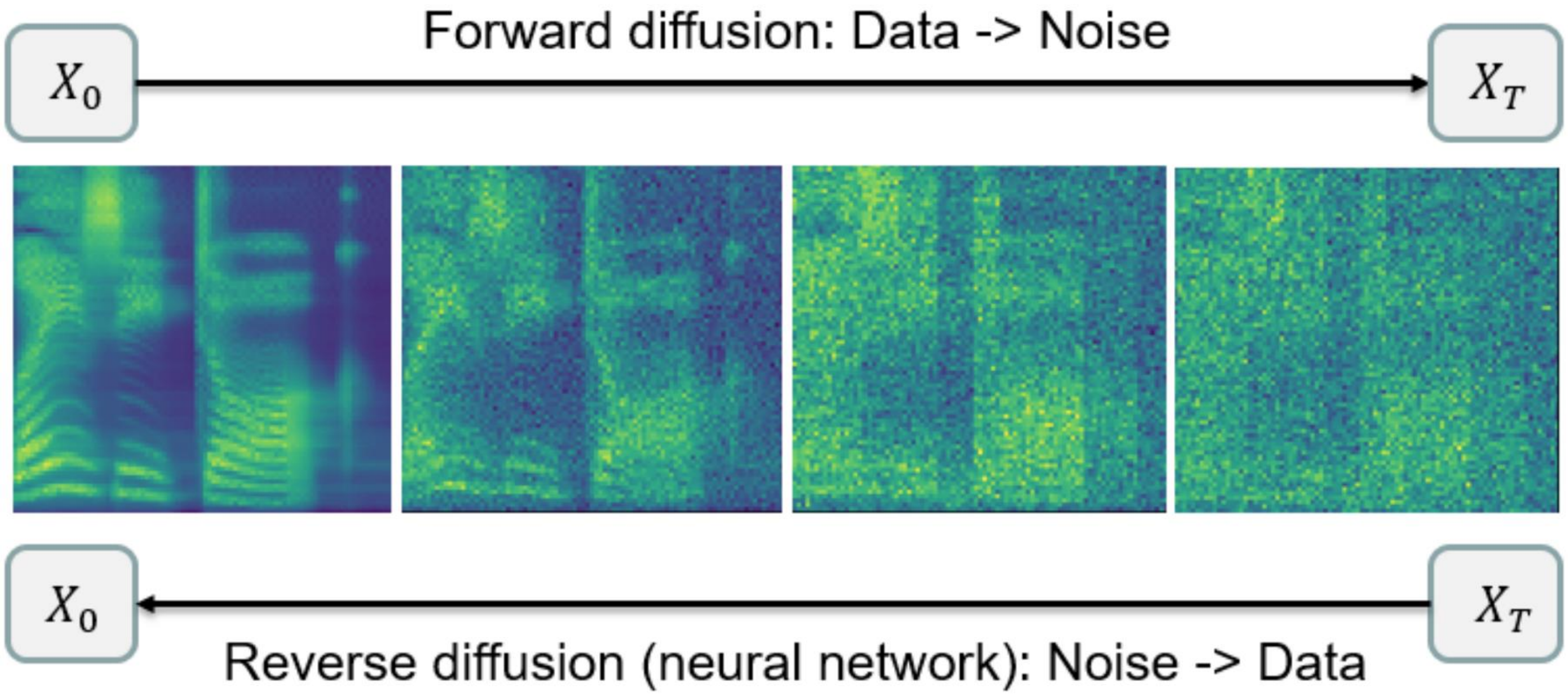
- ControlNet – additional spatial conditioning controls:



Applications

Multimodal generation – text-to-audio

- Grad-TTS – text-to-speech:



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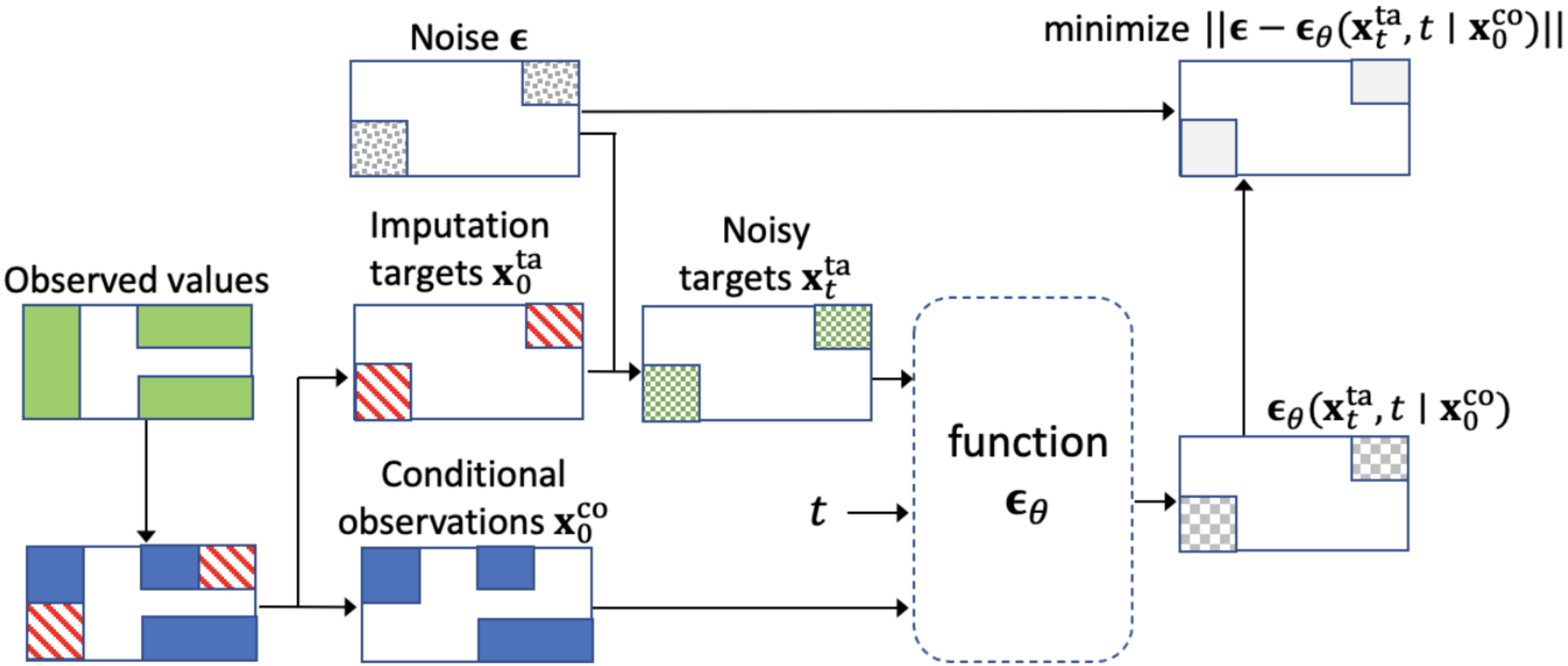
Temporal data modeling – imputation

- Real world time series data often contains missing information
- Imputation is the process of filling in that missing data:



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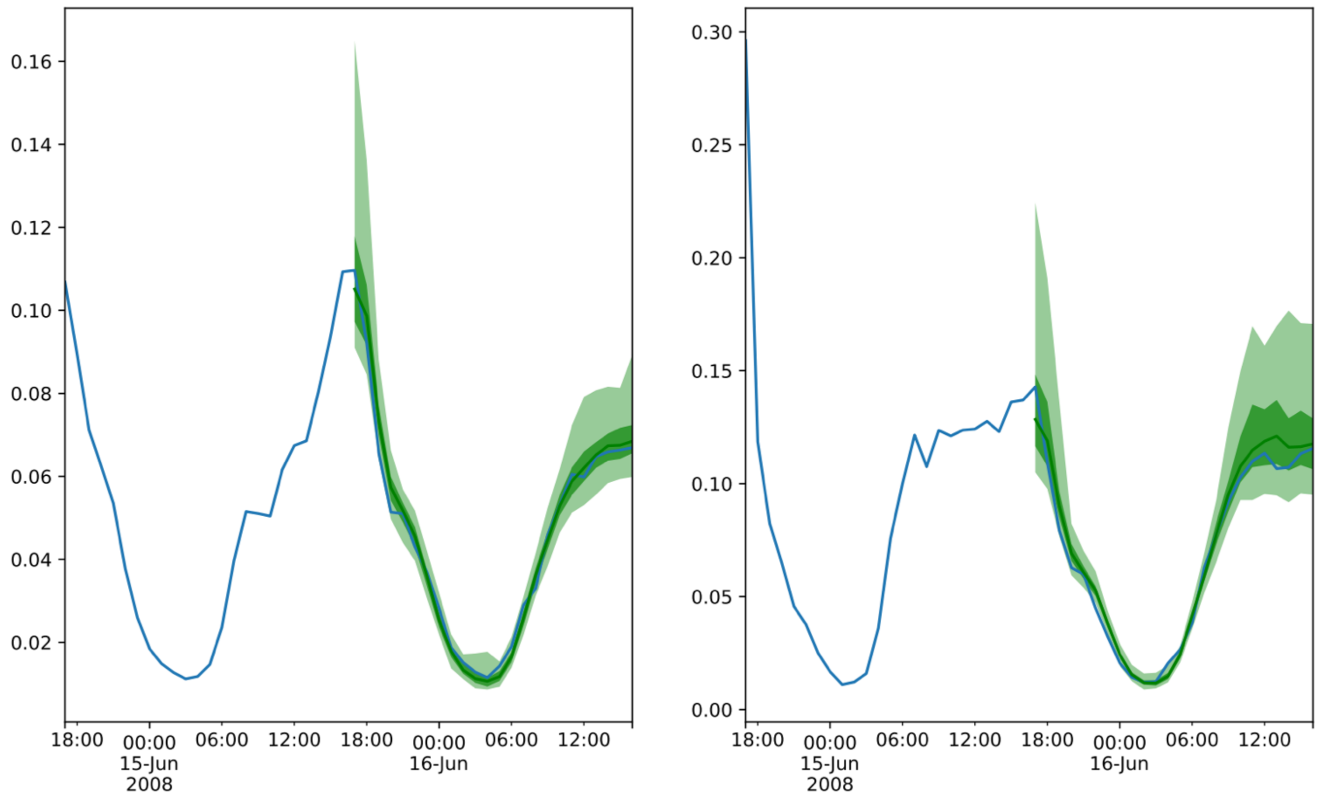
Temporal data modeling – forecasting

- TimeGrad – multivariate probabilistic time series forecasting
- Uses a RNN to predict traffic data…



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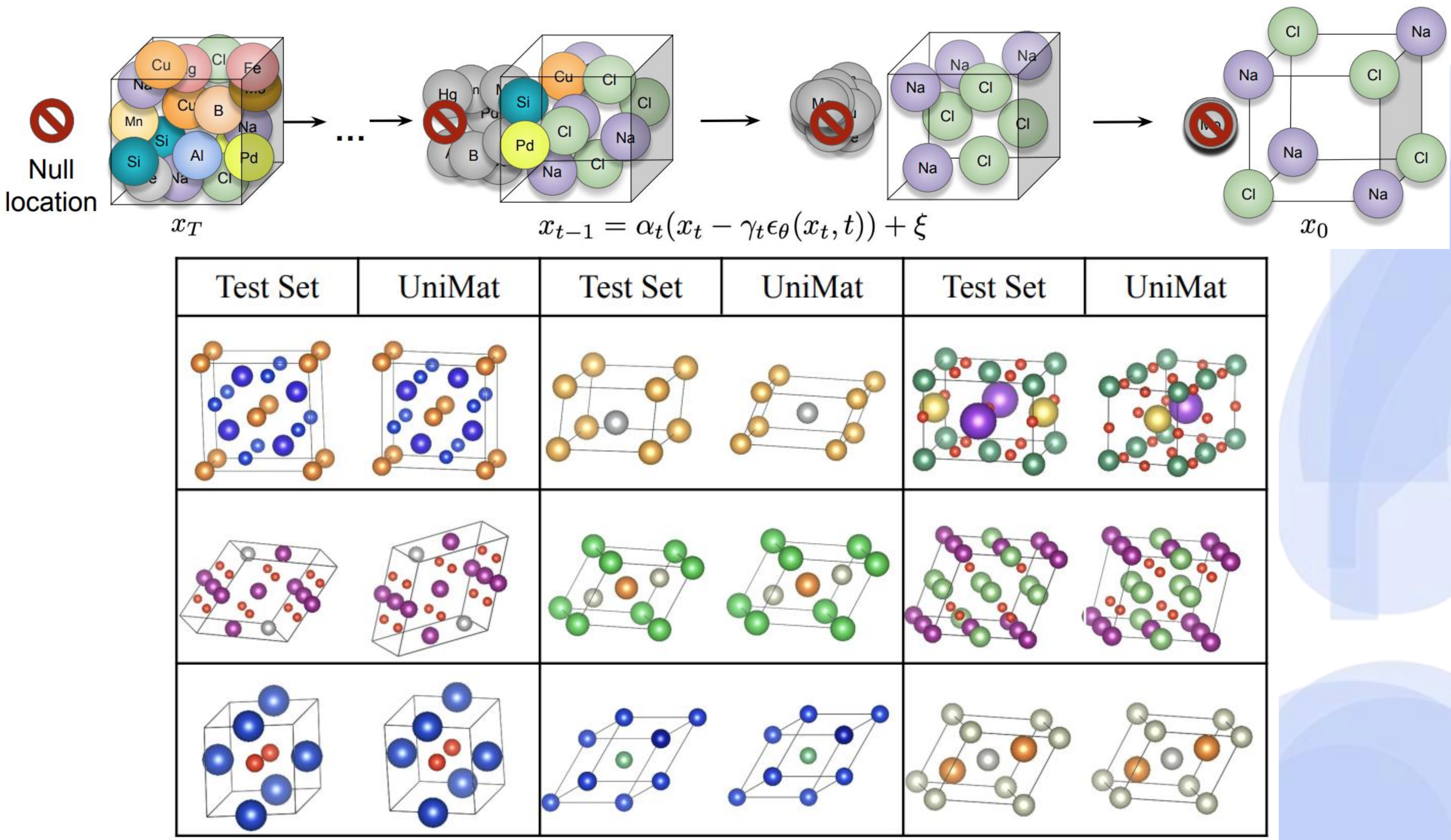
Materials

- Scalable diffusion for Materials Generation, DeepMind



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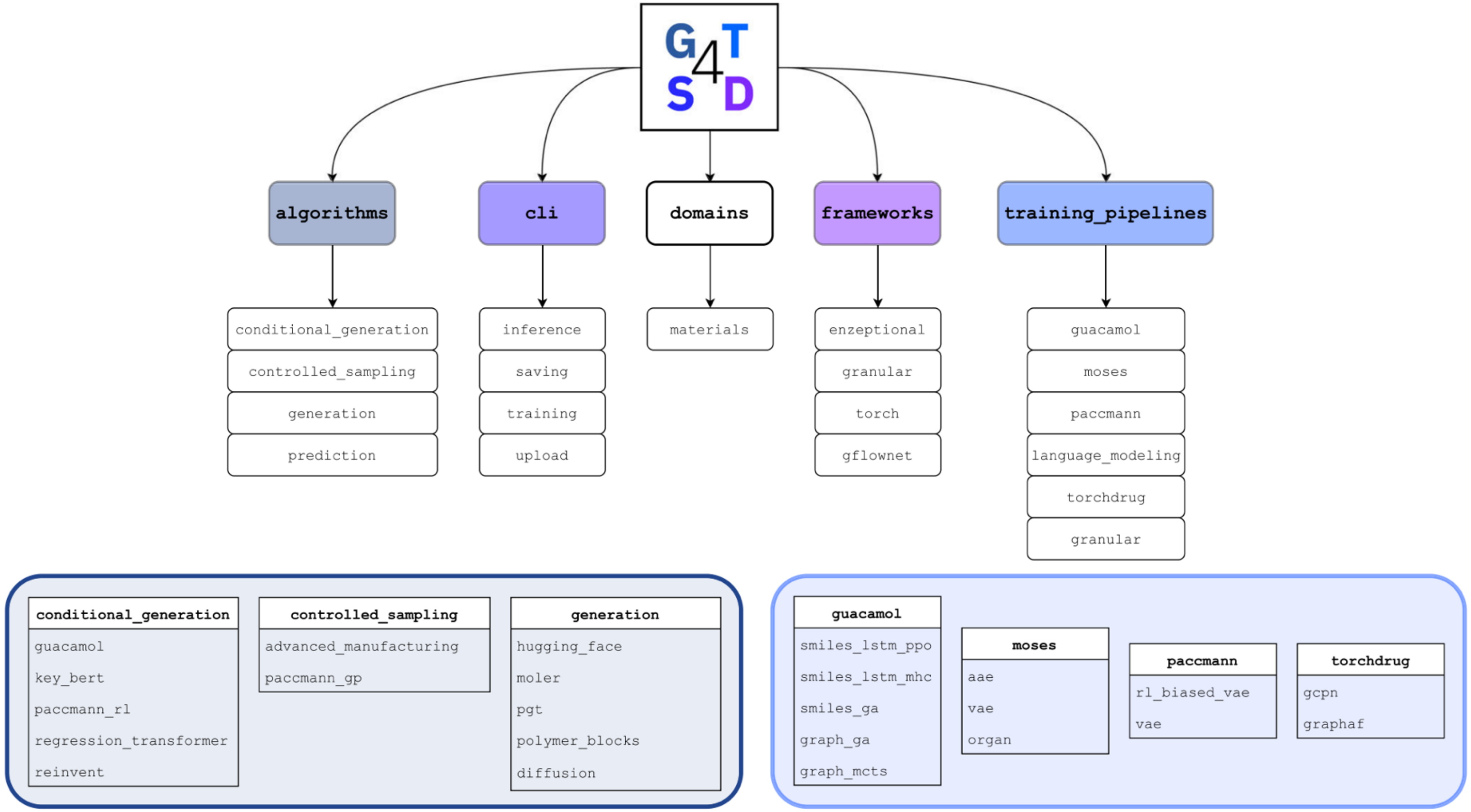
Materials

- Generative toolkit for scientific discovery



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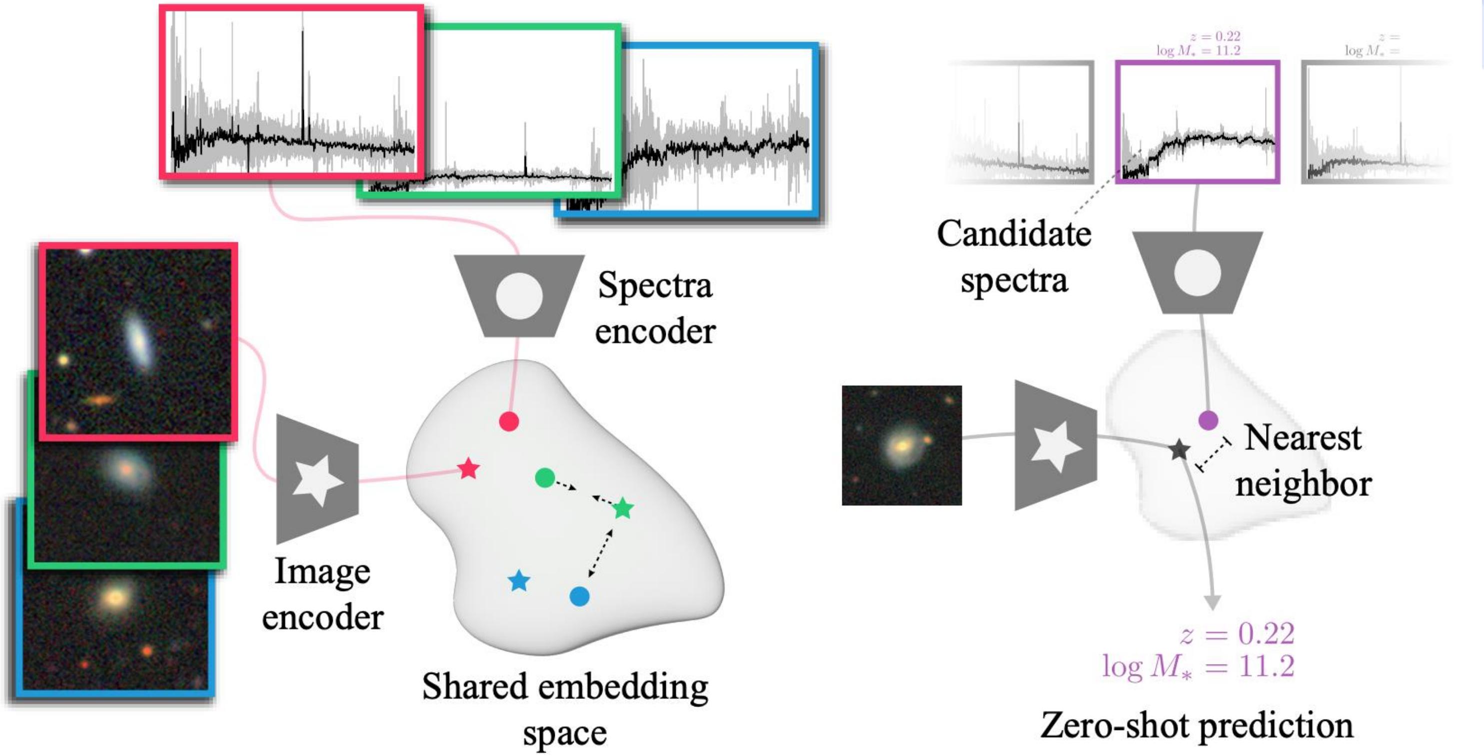
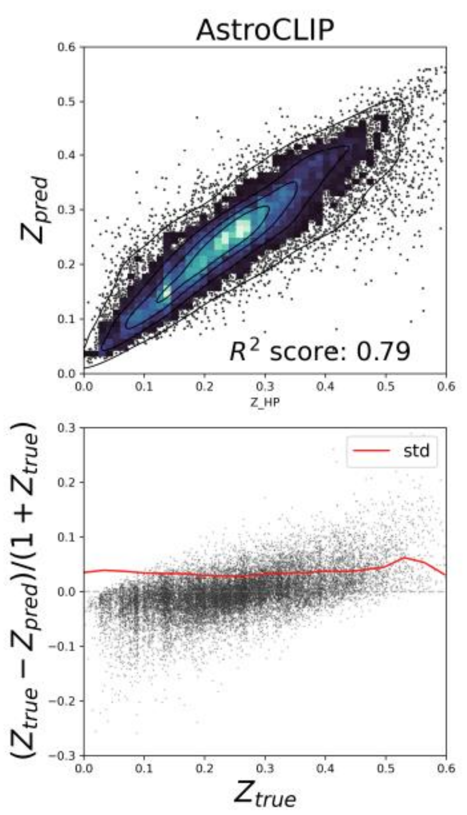
Astrophysics

- AstroCLIP: A Cross-Modal Foundation Model for Galaxies, Parker et al, 2023





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Evaluating Diffusion Models

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Evaluation

How can we effectively evaluate diffusion models?

- How you choose to evaluate will be heavily dependent upon the task
- The maturity of the metrics will also depend on the task
- Evaluation for stable diffusion models will be significantly more advanced than for almost all other fields.
- For many tasks, evaluation metrics will be whatever you are familiar with
  - E.g. for segmentation intersection over union
  - For imputation RMSE

Evaluation

Stable Diffusion Models – qualitative methods

- Involves human assessment of generated images
- Quality is measured across a range of aspects:
  - Compositionality
  - Image-text alignment
  - Spatial relations
- Outputs are measured for common prompts of varying degrees of difficulty:
  - DrawBench
  - PartiPrompts

Evaluation

Stable Diffusion Models – quantitative methods

- Text-guided
  - CLIP score – measures the compatibility of image-caption pairs
  - Semantic similarity between image and caption
  - Higher CLIP score is better
  - CLIP score is highly correlated with human judgement
- Image-conditioned
  - Generate an image with a prompt (e.g. “A picture of a majestic Tonkinese cat.”)
  - Feed image into the model with a prompt (e.g. “Make the cat into a samurai.”) to produce image A.
  - Feed image into the model with a second prompt (e.g. “Make the cat into a businesscat.”) to produce image B
  - We then look at the change in the CLIP score between image A and B and between the change in the two captions
  - The higher the better
  - We can also measure the similarity between the original image, and the changed image

Evaluation

Stable Diffusion Models – quantitative methods

- Class-conditioned models are pretrained on a class-labeled dataset.
  - Frechet Inception Distance (FID)
  - Kernel Inception Distance
  - Inception Score
- FID
  - Find the Frechet distance between Gaussians fitted to feature representations of Inception.
  - Use the Inception v3 model and cut off the final classification layer
  - Get the ImageNet dataset (or a subset of it)
  - Generate a bunch of images
  - Stuff both generated and ImageNet images into Inception and get the feature representations
  - Fit two Gaussians to the representations
  - Compute the Frechet Distance.