

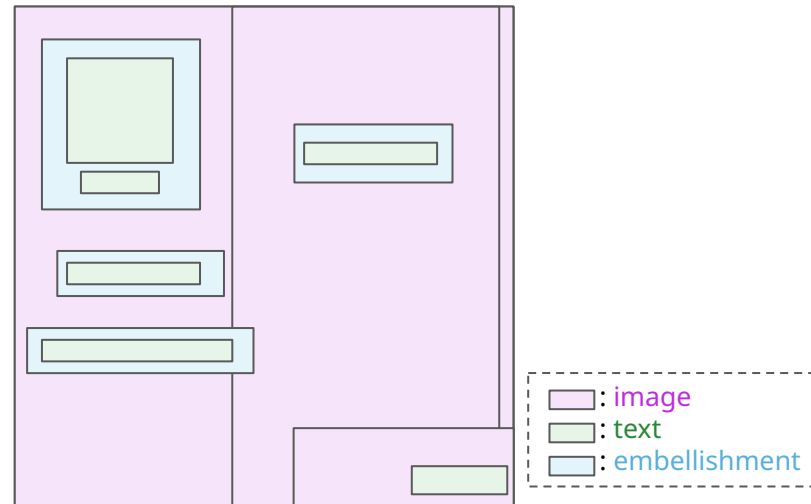
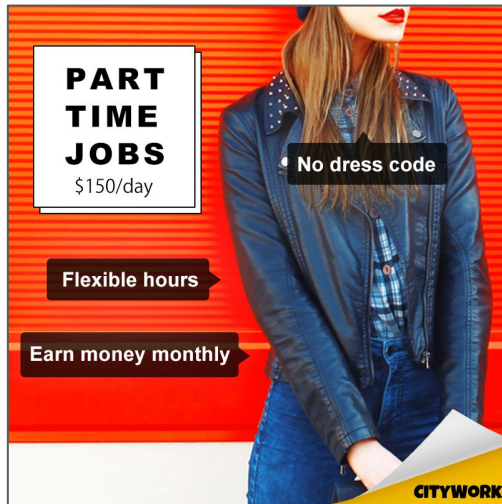
# LayoutDM: Discrete Diffusion Model for Controllable Layout Generation

Naoto Inoue   Kotaro Kikuchi   Mayu Otani  
Edgar Simo-Serra   Kota Yamaguchi



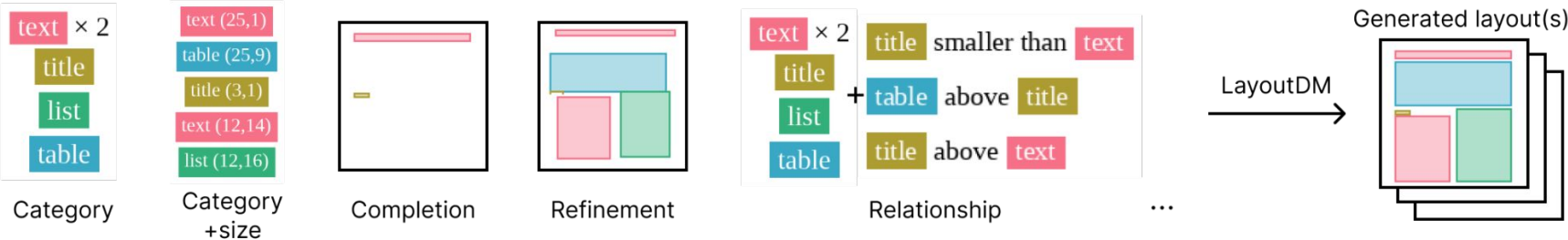
# Layout

= Simple yet essential interface to understand & control visual design



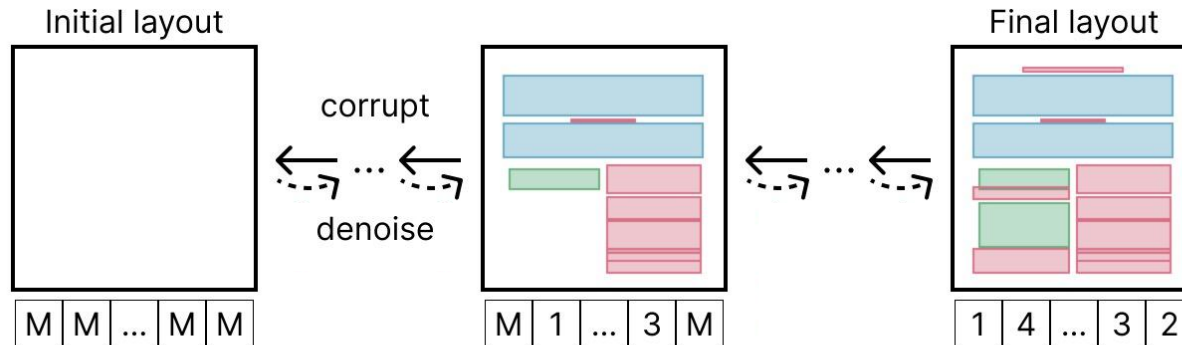
# Controllable Layout Generation

Our work: solve a broad range of tasks in a **single** model



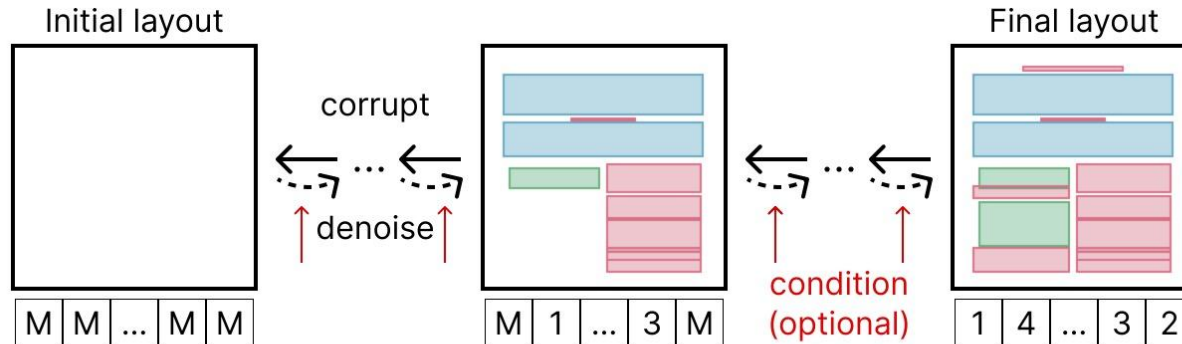
# LayoutDM

- A discrete diffusion model tamed for layout generation

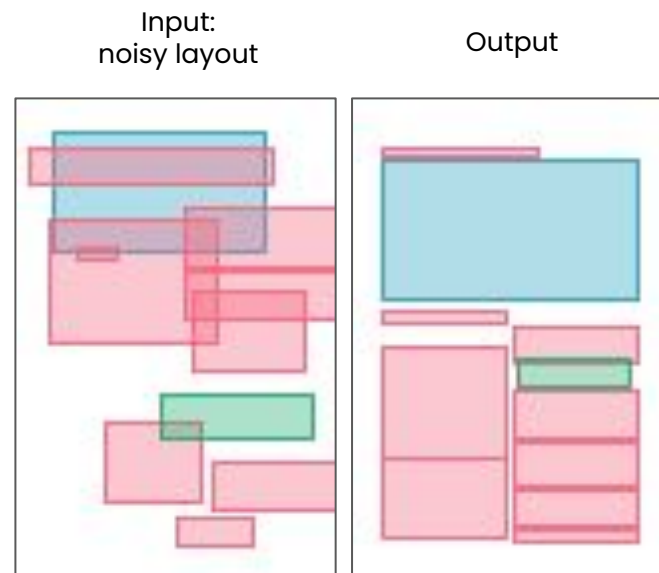
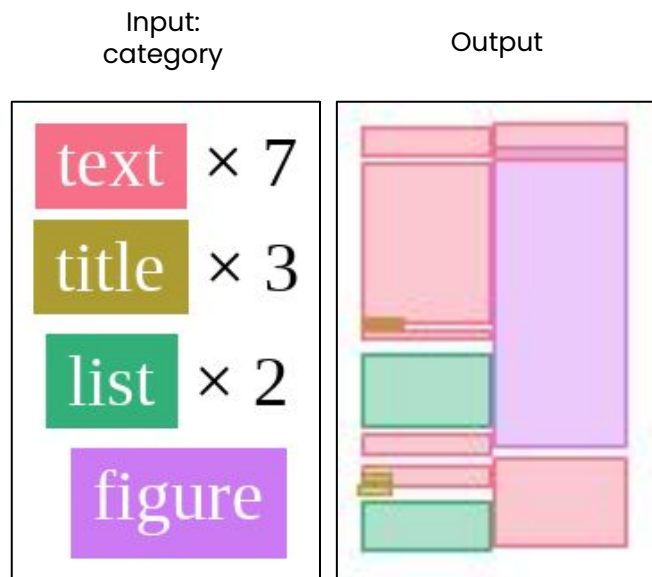


# LayoutDM

- A discrete diffusion model tamed for layout generation
- Training-free algorithm to inject various conditions during inference



## LayoutDM Results

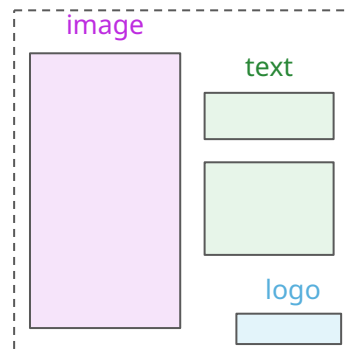


## What is Layout?

- A set of category (1-dim.) + positional info. (4-dim. e.g., xywh)
- Recent trend: layout as a sequence of discrete variables (c.f., text)

```
[  
  ["image", 0.3, 0.5, 0.25, 0.9],  
  ["text", 0.7, 0.35, 0.25, 0.15],  
  ["text", 0.7, 0.6, 0.25, 0.4],  
  ["logo", 0.85, 0.95, 0.2, 0.04],  
]
```

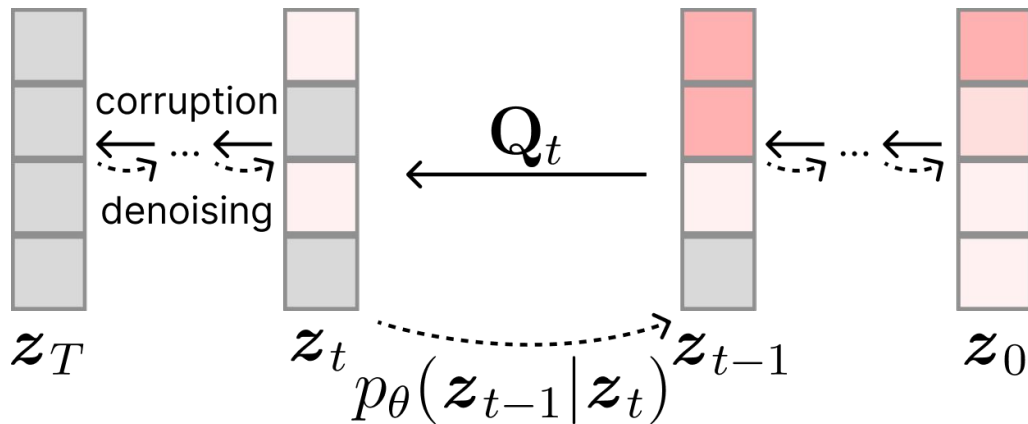
Data



Visualization

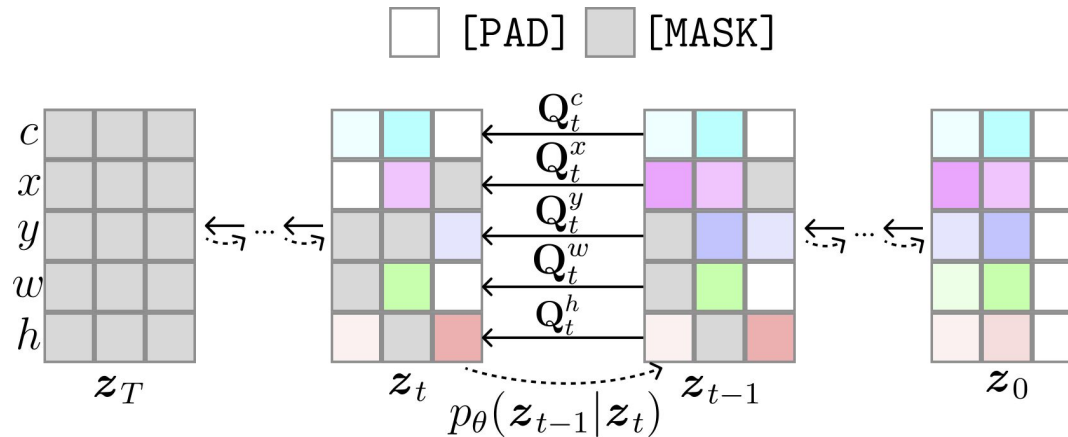
## Discrete Diffusion Models [[Austin+, NeurIPS'21](#)]

- = diffusion models for modeling categorical variables (e.g., text)
- Corruption: a token is stochastically replaced with another in vocabulary



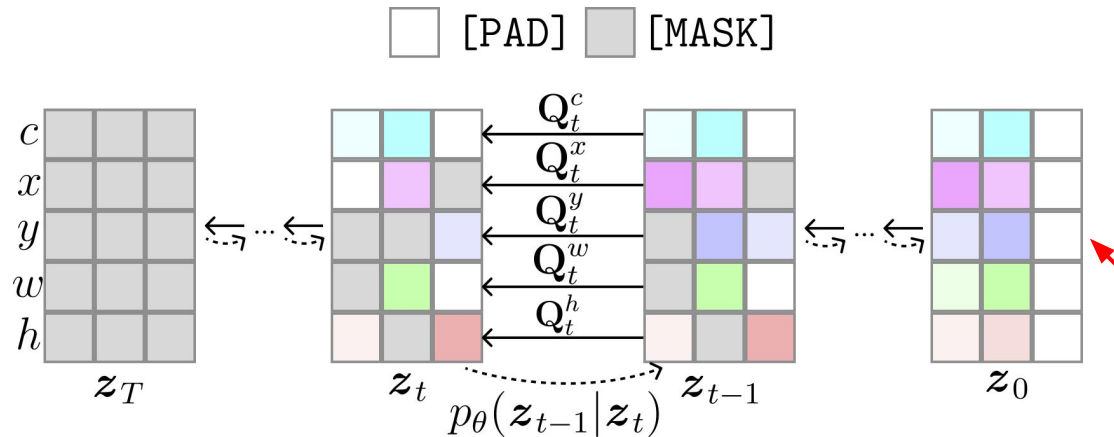


# Adapting Discrete Diffusion Models for Layout



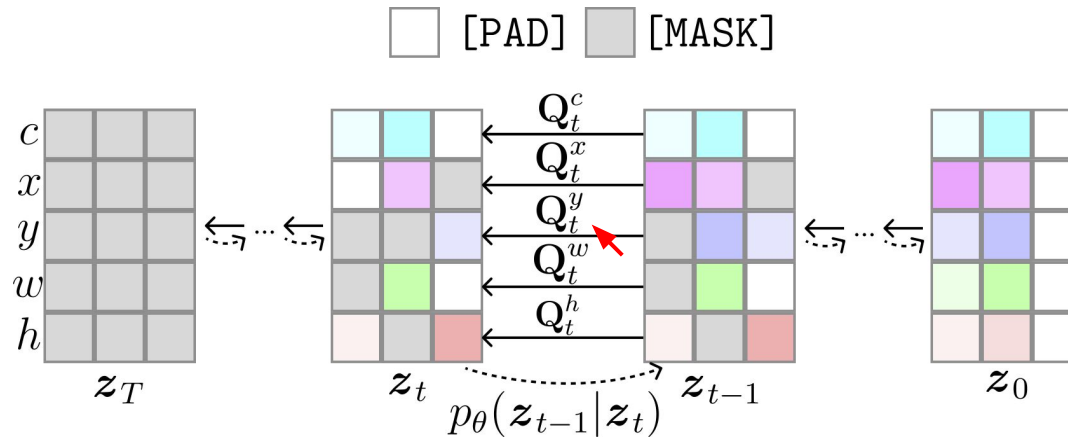
# Adapting Discrete Diffusion Models for Layout

- [PAD] token to enable variable length generation

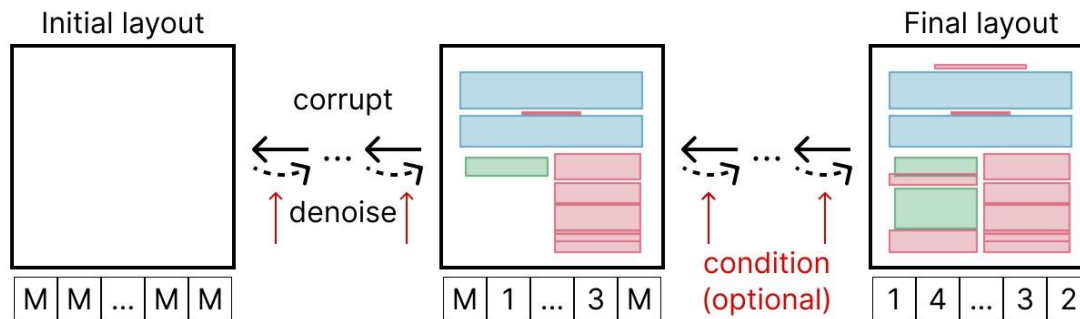


# Adapting Discrete Diffusion Models for Layout

- [PAD] token to enable variable length generation
- Modality-wise corruption process

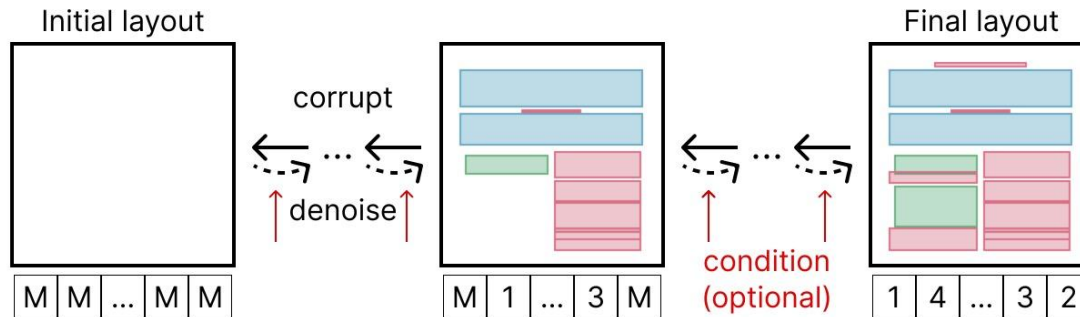


## How to Feed Conditions during Inference?



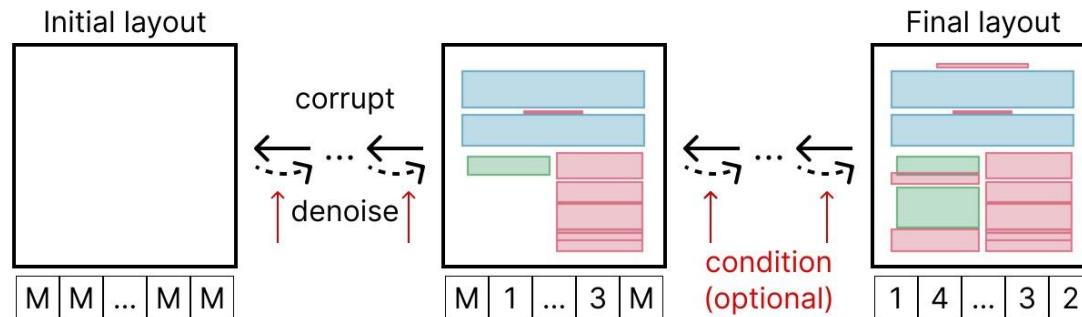
## How to Feed Conditions during Inference?

- **Hard condition: masking**
  - e.g., “i-th element’s category is C”



## How to Feed Conditions during Inference?

- **Hard condition: masking**
  - e.g., “i-th element’s category is C”
- **Soft condition: logit adjustment**
  - e.g., “an element at the top”, “an element bigger than another”

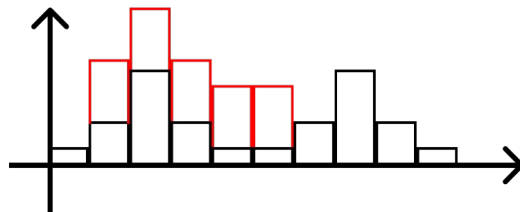


## Logit Adjustment

Inject soft condition as a **prior term**

$$\begin{aligned}\log \hat{p}_\theta(\mathbf{z}_{t-1}|\mathbf{z}_t) &= \log p_\theta(\mathbf{z}_{t-1}|\mathbf{z}_t) + \lambda_\pi \pi \\ \mathbf{z}_{t-1} &\sim \hat{p}_\theta(\mathbf{z}_{t-1}|\mathbf{z}_t)\end{aligned}$$

Prior term

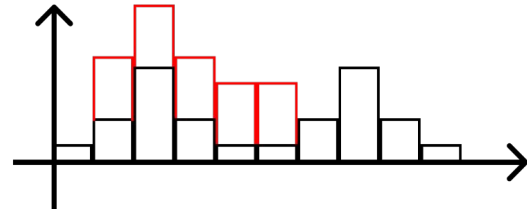


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Prior term



How to implement a prior?

- Hard coding (e.g., refinement task)
- Gradients from loss functions w.r.t. the prediction (e.g., relationship task)

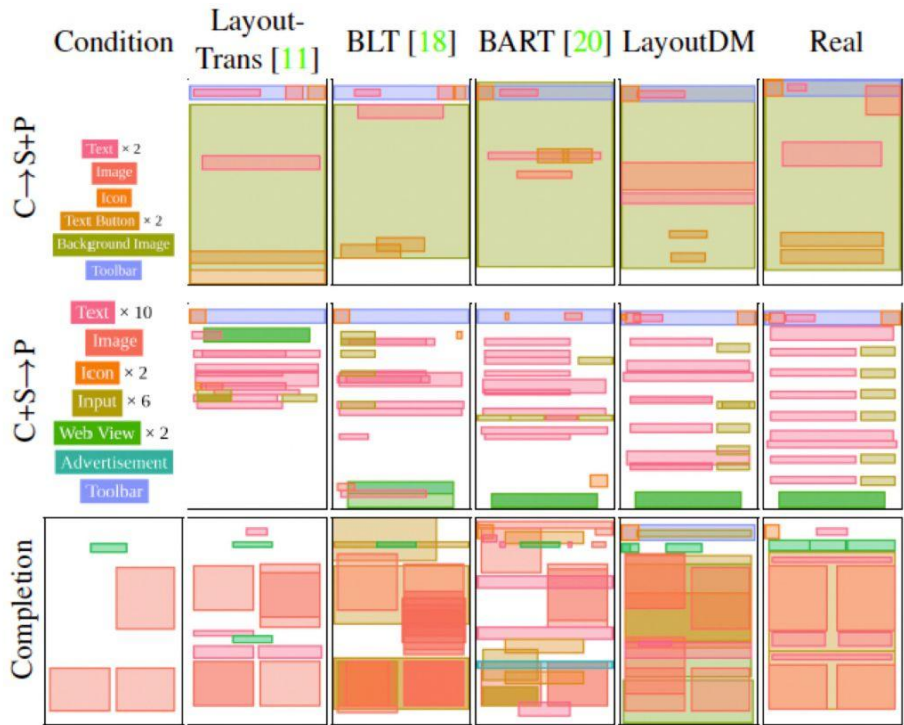


## Advantages over Existing Methods

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- **No fixed generation order unlike auto-regressive models**
  - c.f., LayoutTransformer [[Gupta+, ICCV'21](#)]
- **Flexibly changing the number of elements to be generated**
  - c.f., BLT [[Kong+, ECCV'22](#)]
- **Incorporating both hard and soft conditions**
  - c.f., NDN [[Lee+, ECCV'20](#)]

# Results in Rico [Deka+, UIST'17]

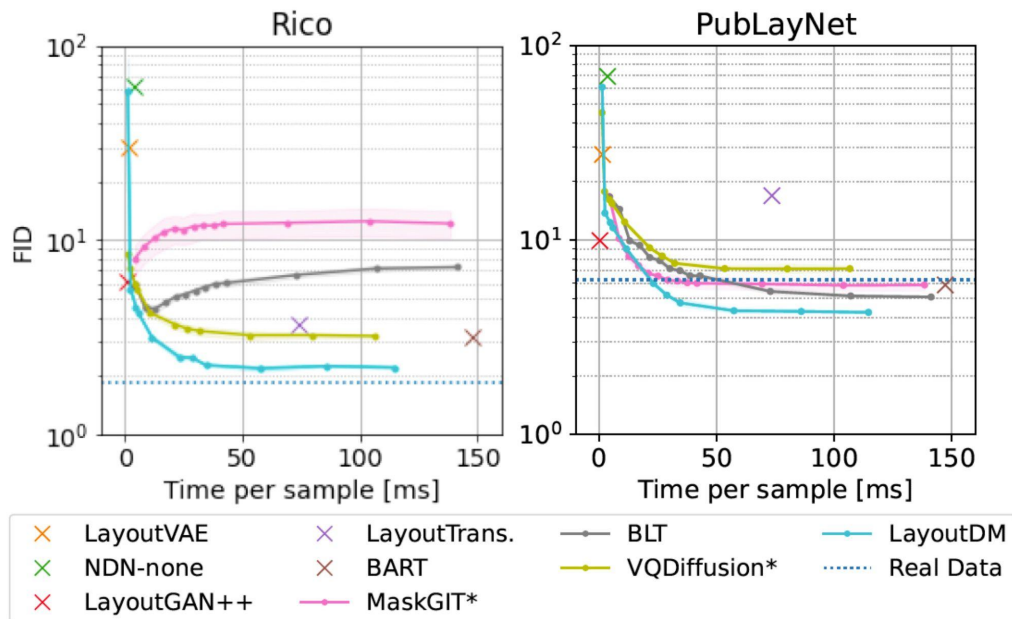


# Results in PubLayNet [Zhong+, ICDAR'19]



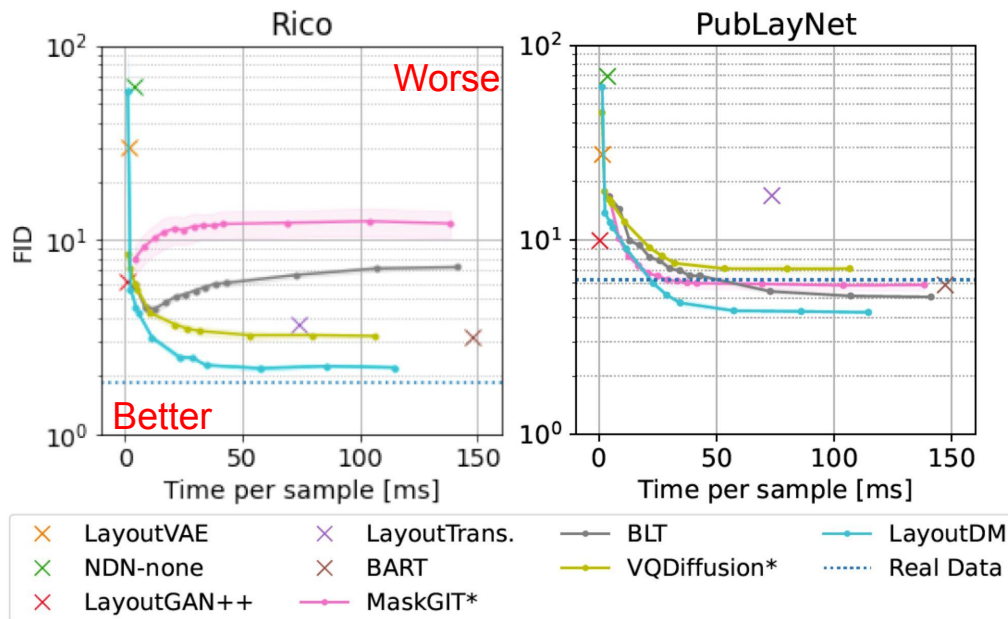
## Quantitative Evaluation (in category + size $\rightarrow$ position)

LayoutDM achieves the best speed-quality tradeoff



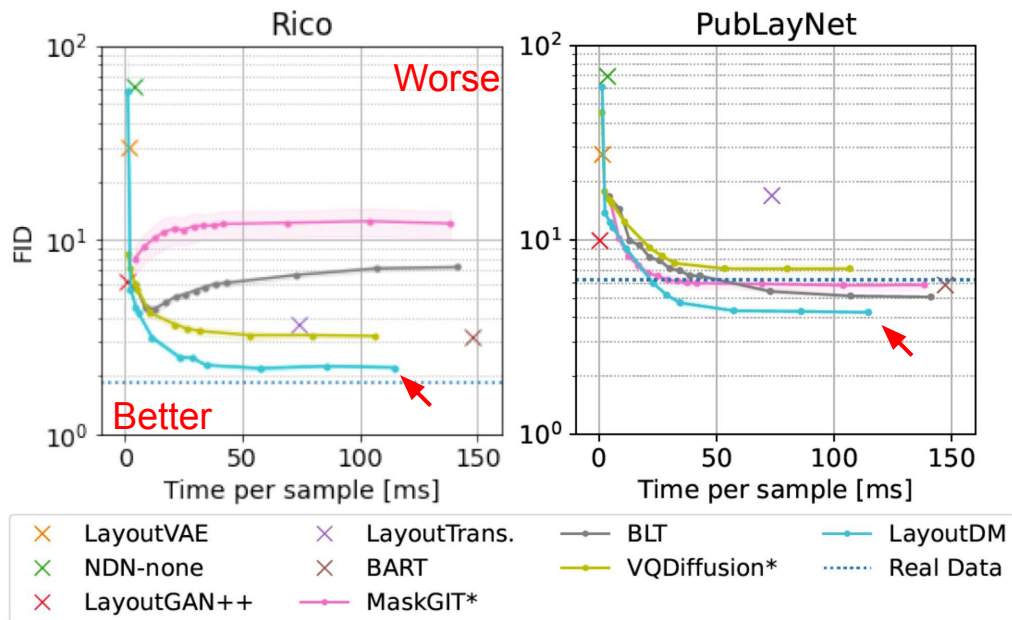
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## Summary

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- A discrete diffusion model tamed for layout generation
- Training-free algorithm to inject various conditions during inference
- Favorable performance against task-specific/agnostic baselines

Check codes and more results at

<https://cyberagentailab.github.io/layout-dm/>

