Reinforcement Learning finetuned Vision-Code Transformer for UI-to-Code Generation

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Generating code from screenshots

- Labor-intensive and time-consuming process
- Automation prone to errors
- Text similarity ≠ visual similarity

Related

- Pix2code
- Sketch2code
- Pix2Struct

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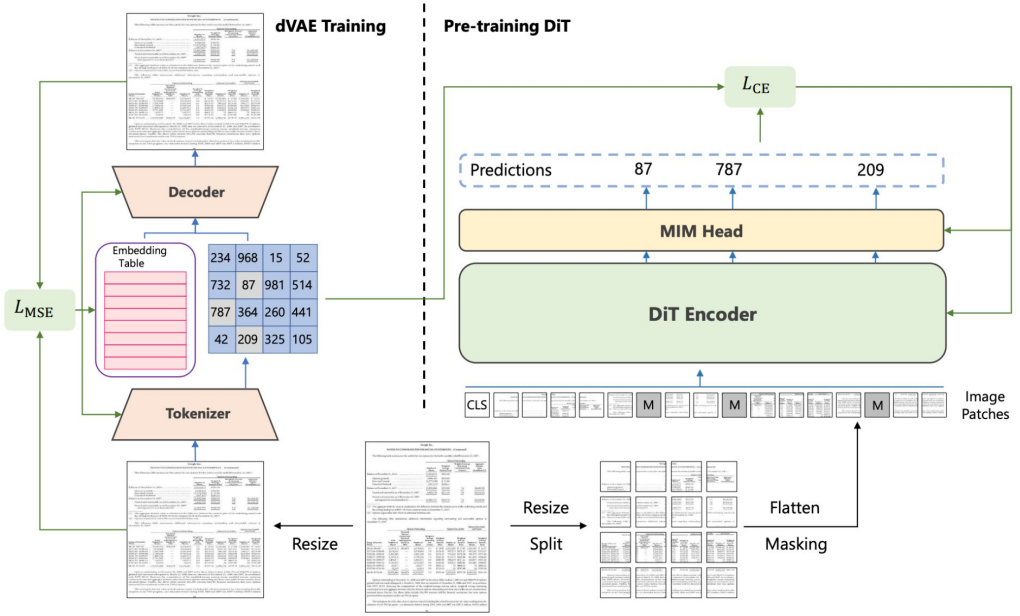
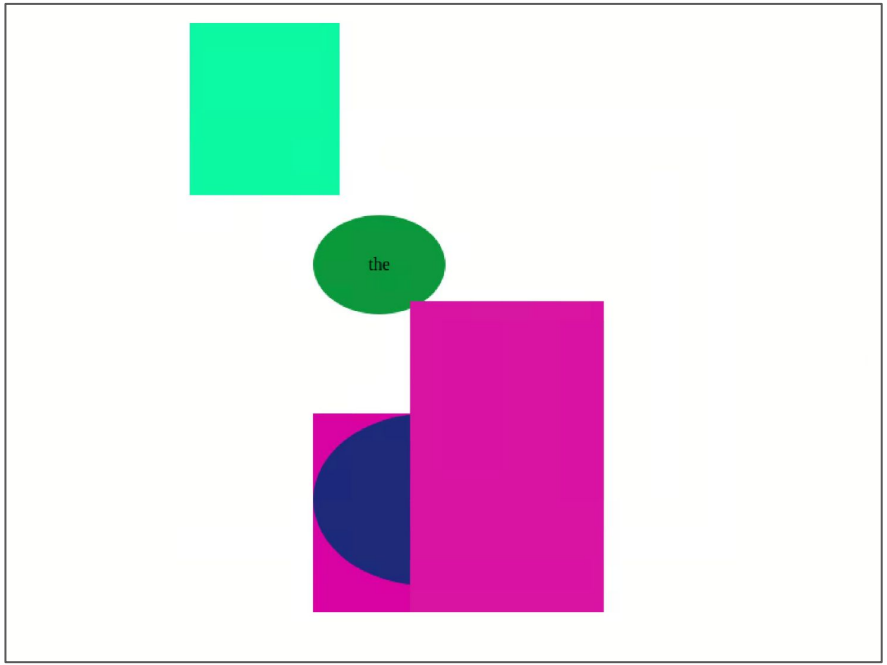


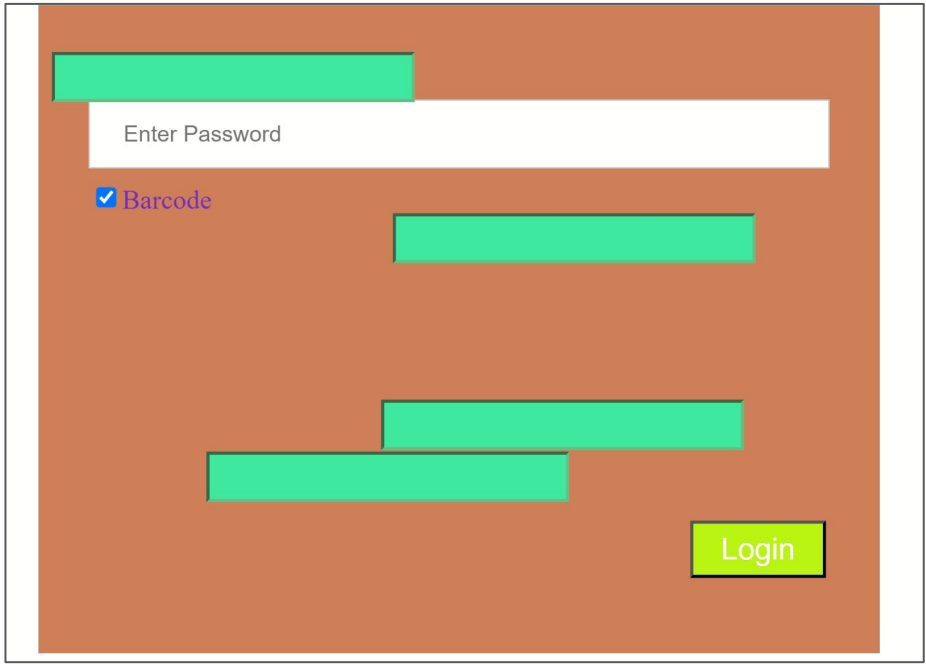
Figure 2: The model architecture of DiT with MIM pre-training.

Datasets

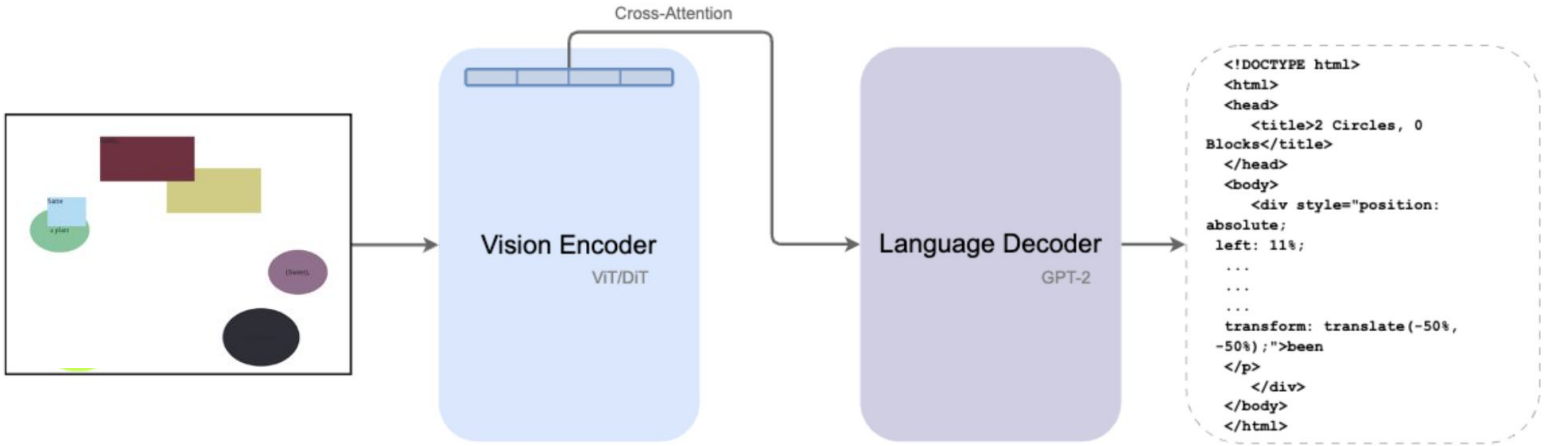
Dataset	N Samples	Element Types	Colors	Max N Objects	Max Text Length
RUID	25000	Rectangle, Eclipse, Button a, button, img, div, span, p, input (text, radio, checkbox, submit), select, textarea	Arbitrary	6	1
RUID-Large	50000		Arbitrary	12	5

Samples



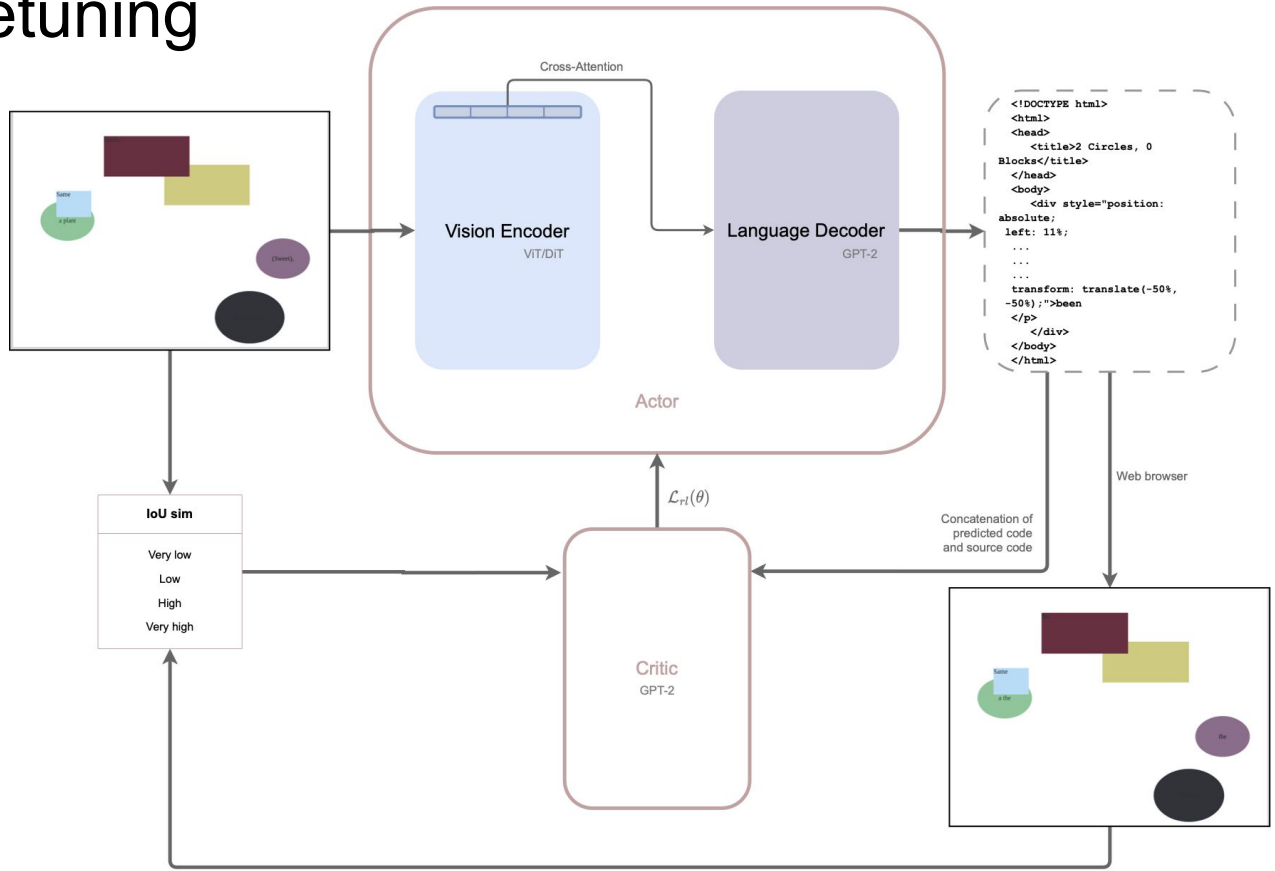


Baseline

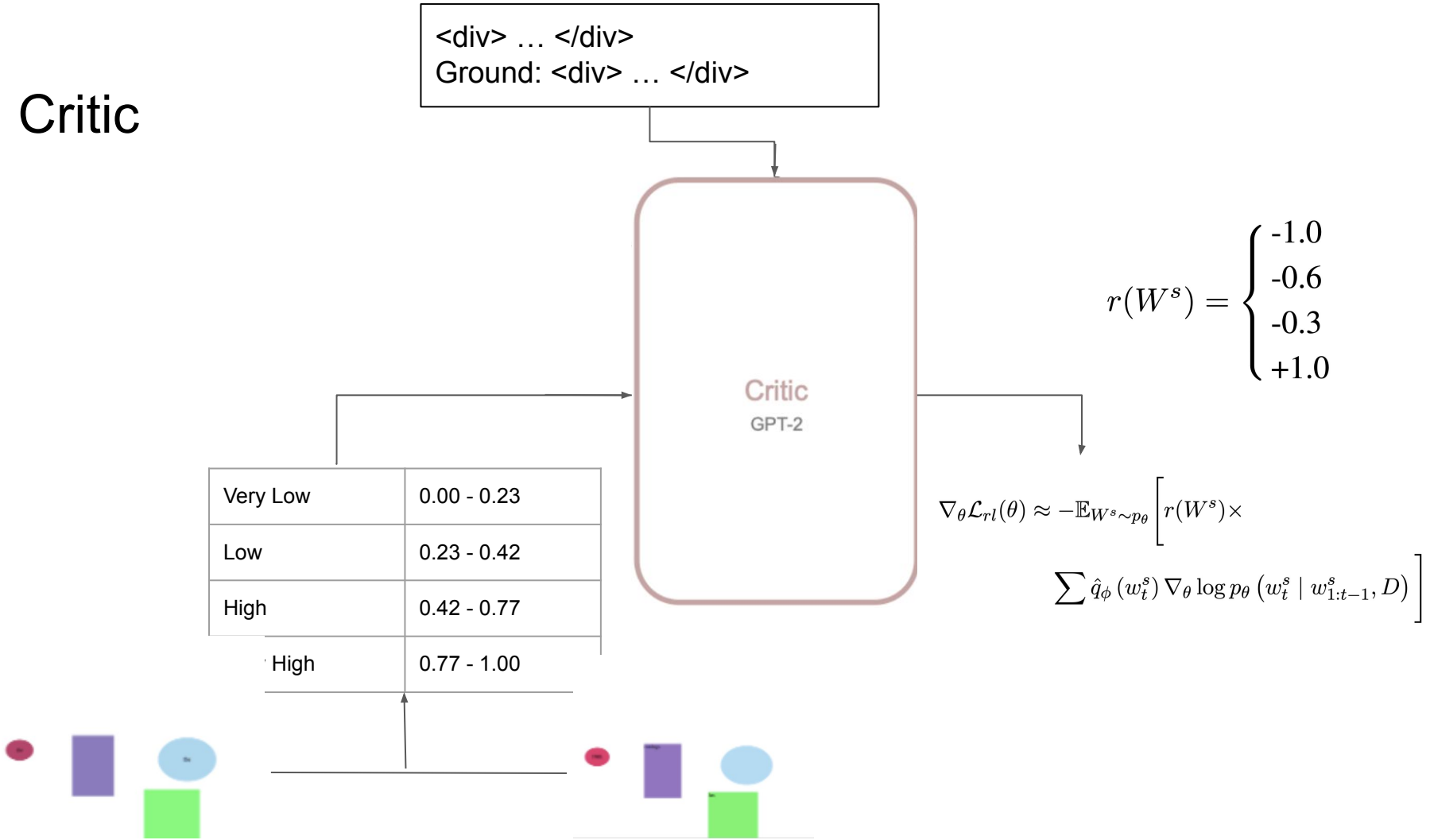

Cross-Attention
Vision Encoder
ViT/DiT
Language Decoder
GPT-2
<!DOCTYPE html>
<html>
<head>
<title>2 Circles, 0 Blocks</title>
</head>
<body>
<div style="position: absolute;
left: 11%;
...
...
...
transform: translate(-50%, -50%);">been
</p>

</body>
</html>

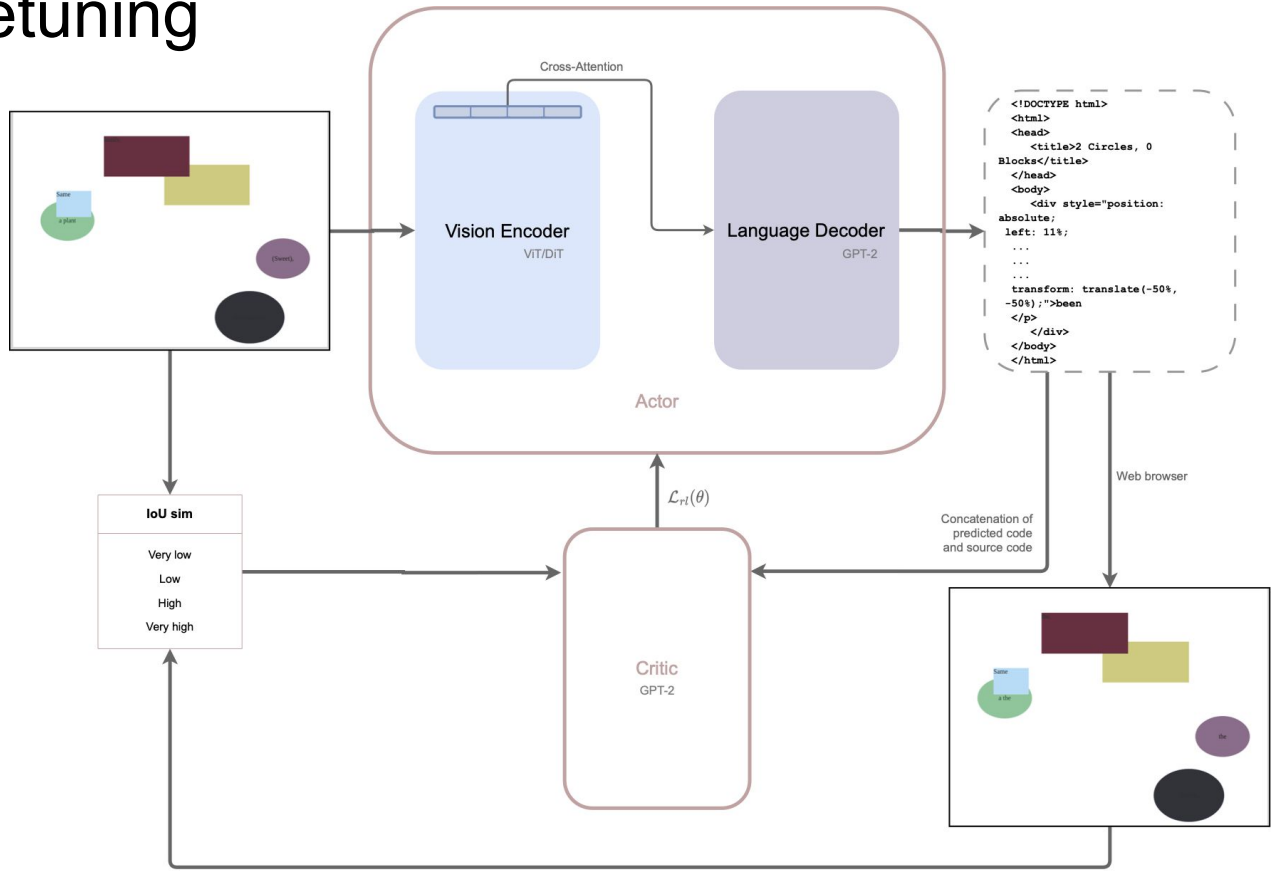
RL Finetuning



Critic


 …
Ground: …
Critic
GPT-2
Very Low
0.00 - 0.23
Low
0.23 - 0.42
High
0.42 - 0.77
High
0.77 - 1.00
$r(W^s) = \begin{cases} -1.0 \\ -0.6 \\ -0.3 \\ +1.0 \end{cases}$
$\nabla_\theta \mathcal{L}_{rl}(\theta) \approx -\mathbb{E}_{W^s \sim p_\theta} \Big[r(W^s) \times \sum \hat{q}_\phi \left(w_t^s\right) \nabla_\theta \log p_\theta \left(w_t^s \mid w_{1:t-1}^s, D\right) \Big]$

RL Finetuning



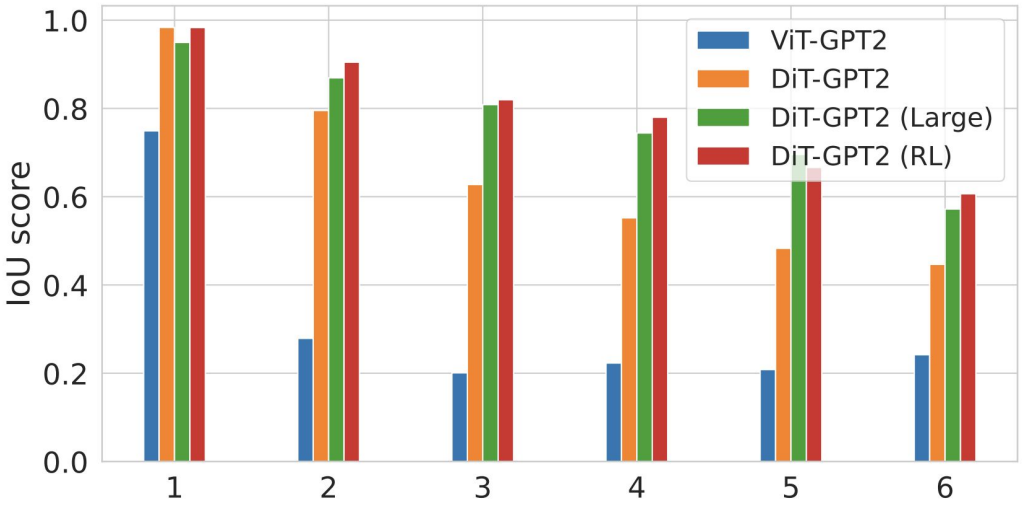
CodeBLEU → htmlBLEU

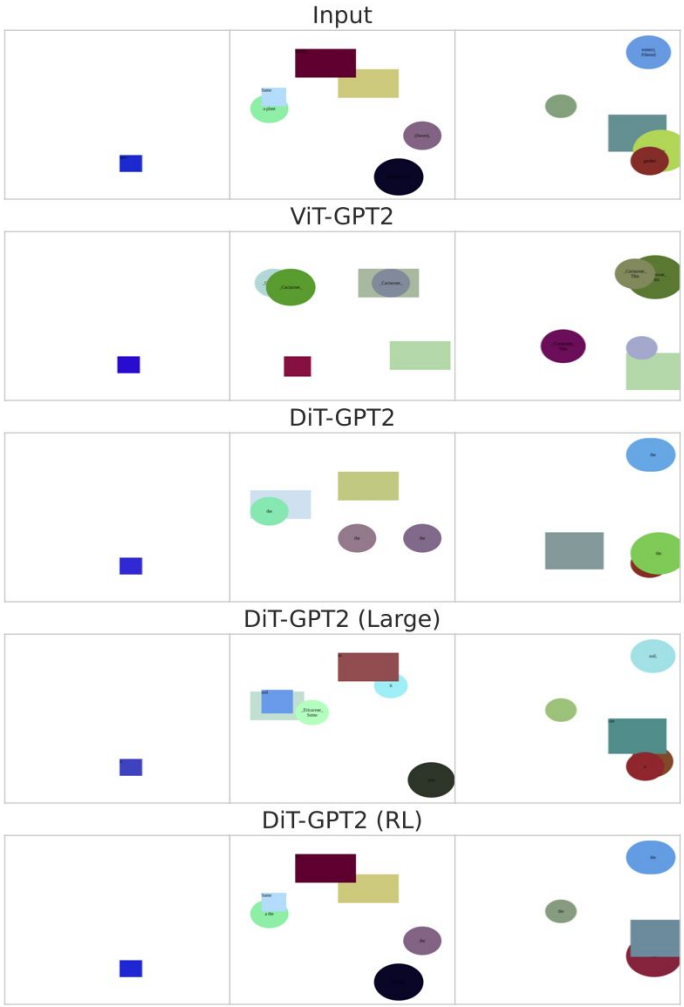
- Syntactic AST match - > Syntactic DOM Tree Match
- Semantic data-flow match -> Semantic Attribute Match
- Weighted tag matching - Calculated by seeing effect of tag error on MSE

Results - Baselines

Model	ViT-GPT2	DiT-GPT2
Metrics		
BLEU ↑	0.65 ± 0.08	**0.74** ± 0.09
htmlBLEU ↑	0.62 ± 0.13	**0.69** ± 0.14
IoU ↑	0.31 ± 0.25	**0.64** ± 0.27
MSE ↓	19.63 ± 11.59	**12.25** ± 8.83
MSE (Single Channel) ↓	0.15 ± 0.09	**0.07** ± 0.06
Element Counts ↑	**0.97** ± 0.16	**0.97** ± 0.18
Human Evaluation (Normalized)		
Color Fidelity ↑	0.26 ± 0.26	0.61 ± 0.32
Structural Similarity ↑	0.44 ± 0.35	0.62 ± 0.35

Results


1.0
0.8
0.6
0.4
0.2
0.0
IoU score
1
2
3
4
5
6
ViT-GPT2
DiT-GPT2
DiT-GPT2 (Large)
DiT-GPT2 (RL)


Input
ViT-GPT2
DiT-GPT2
DiT-GPT2 (Large)
DiT-GPT2 (RL)

Results

Model	ViT-GPT2	DiT-GPT2	DiT-GPT2 (L.)	DIT-GPT2 (RL)
Metrics				
BLEU ↑	0.65 ± 0.08	0.74 ± 0.09	0.68 ± 0.11	**0.76** ± 0.08
htmlBLEU ↑	0.62 ± 0.13	0.69 ± 0.14	0.67 ± 0.12	**0.70** ± 0.13
IoU ↑	0.31 ± 0.25	0.64 ± 0.27	**0.81** ± 0.19	0.79 ± 0.23
MSE ↓	19.63 ± 11.59	12.25 ± 8.83	11.34 ± 8.17	**9.02** ± 6.96
MSE (Single Channel) ↓	0.15 ± 0.09	0.07 ± 0.06	**0.03** ± 0.05	**0.03** ± 0.04
Element Counts ↑	0.97 ± 0.16	0.97 ± 0.18	0.86 ± 0.36	0.96 ± 0.20
Human Evaluation (Normalized)				
Color Fidelity ↑	0.41 ± 0.29	0.66 ± 0.28	0.51 ± 0.27	**0.83** ± 0.21
Structural Similarity ↑	0.49 ± 0.33	0.67 ± 0.27	**0.85** ± 0.18	0.83 ± 0.25

Open Questions

- RL methodology choice
- Human Feedback
- Complex datasets
- Model Selection

Thank you!
Any Questions?