

## (TUE-PM-181)

## **PosterLayout:** A New Benchmark and Approach for Content-aware Visual-Textual Presentation Layout

**HsiaoYuan Hsu**<sup>1,2</sup>, Xiangteng He<sup>1,2</sup>, Yuxin Peng<sup>1,2</sup>, Hao Kong<sup>3</sup> and Qing Zhang<sup>3</sup> <sup>1</sup>Wangxuan Institute of Computer Technology, Peking University <sup>2</sup>National Key Laboratory for Multimedia Information Processing, Peking University <sup>3</sup>Meituan

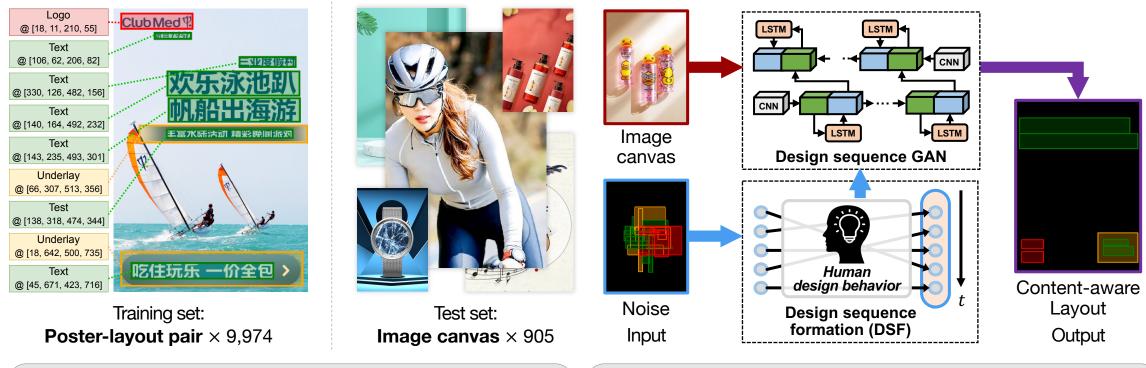


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PKU PosterLayout Dataset

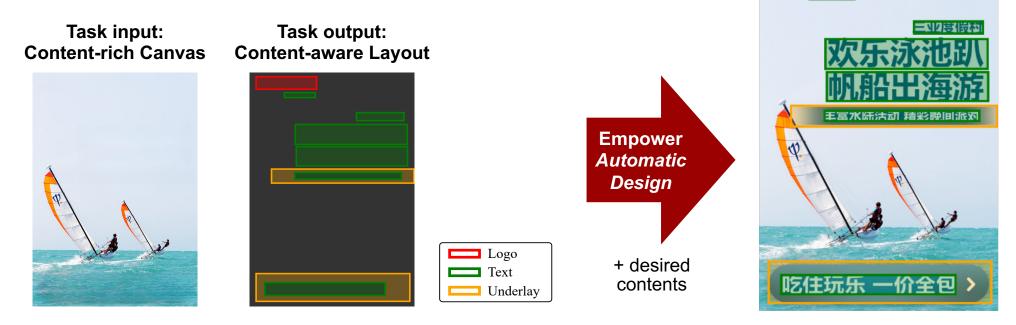
#### **Design Sequence GAN (DS-GAN)**

### Outline

- Introduction
- A New Benchmark: PKU PosterLayout
- A New Approach: Design Sequence GAN (DS-GAN)
- Experiments
- Conclusion

### **Background & Application Scenario**

- Content-aware Visual-Textual Presentation Layout
  - Given an **image canvas**, arrange spatial space for *informative or* <u>decorative elements</u>, such as text, logo, and underlay
  - Useful in template-free poster designs





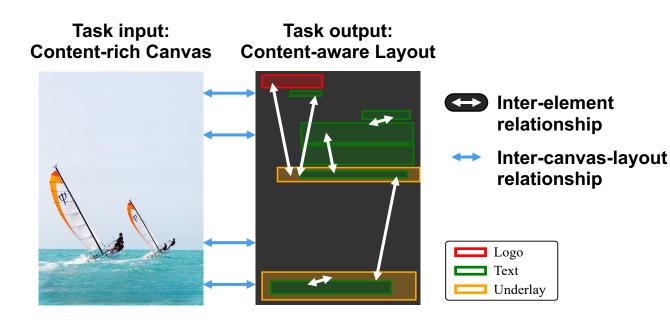
Club Med 4

## Challenges & Motivations (1/2)



#### • Complex inter-element and inter-canvas-layout relationships modeling

- Considering the two relationships in a balanced manner is critical
- Human design behavior can provide a naturally balanced heuristics
- Lack of a **public benchmark** dedicated to this novel task

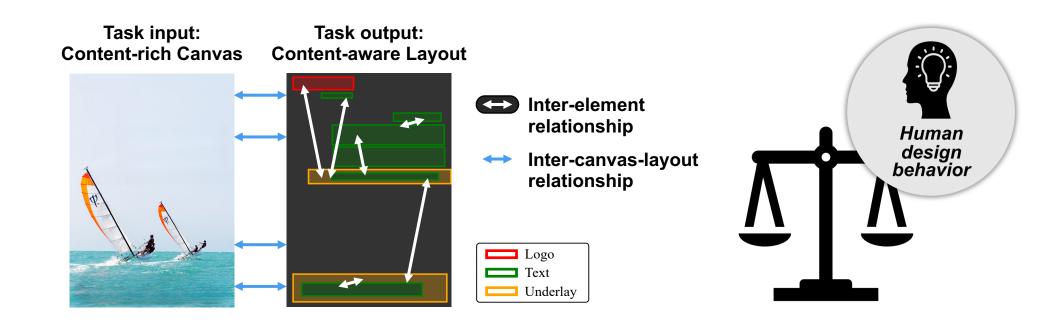


## Challenges & Motivations (2/2)



Complex inter-element and inter-canvas-layout relationships modeling

- Considering the two relationships in a balanced manner is critical
- Human design behavior can provide a naturally balanced heuristics
- Lack of a public benchmark dedicated to this novel task



## Outline



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#### A New Benchmark: PKU PosterLayout





# Training set: **Poster-layout pair** × 9,974

Test set: Image canvas × 905

## Specialties of PKU PosterLayout (1/3)

#### i. Domain diversity

- Data were collected from multiple sources, varying in domain, quality, and resolution
  - Shifts in distributions can make the dataset more general

#### Image sources

(1) https://www.taobao.com/ [1] (2) https://unsplash.com/ (3) https://www.freepik.com/
(4) https://pixabay.com/ (5) https://pngimg.com/ (6) https://www.stickpng.com/



Natural images



E-commerce product images



Blended images

### Specialties of PKU PosterLayout (2/3)

#### ii. Content diversity

• Objects in images are broadly distributed in 9 coarse-grained categories covering most e-commerce products



Food / drinks



Sports / transportation



Fresh produce

Cosmetics / accessories



#### Clothing







Electronics / office supplies



Groceries



Appliances / decor



### Specialties of PKU PosterLayout (3/3)

#### iii. Layout complexity and variety

- It is the *first* public dataset containing **complex layouts** with >10 elements
  - Providing more difficulties in modeling the inter-element relationship
  - Capable of supporting extended tasks requiring complex layouts



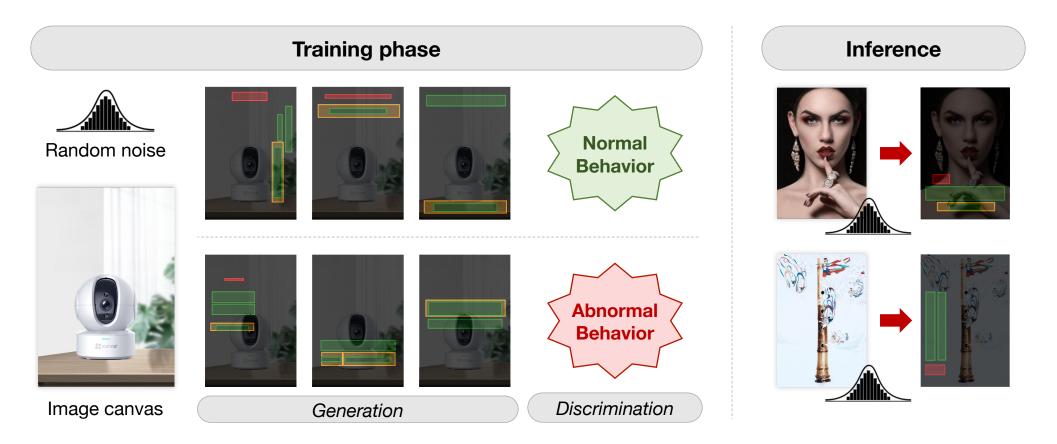
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## A New Approach: Design Sequence GAN (DS-GAN)

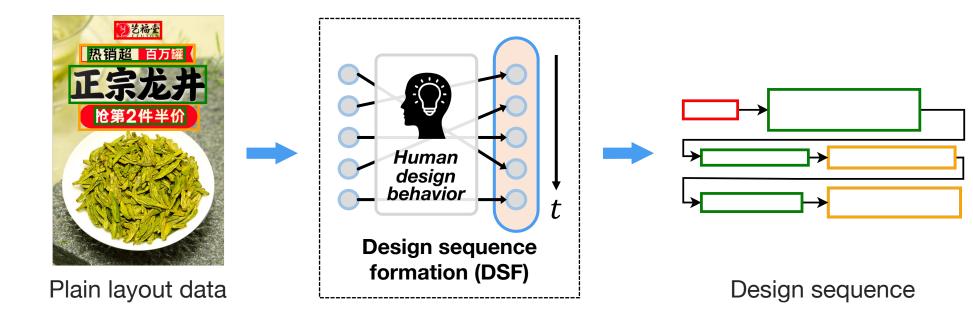
- Abstract design behavior into the order in which the designer places elements on the canvas, named as **design sequence**



### Design Sequence GAN (1/3)

#### i. Design sequence formation (DSF)

- Inspired by Human design behavior
- Converting plain layout data into temporal design sequences
  - Considering (1) category, (2) area, and (3) grouping of elements



#### Design Sequence GAN (2/3)



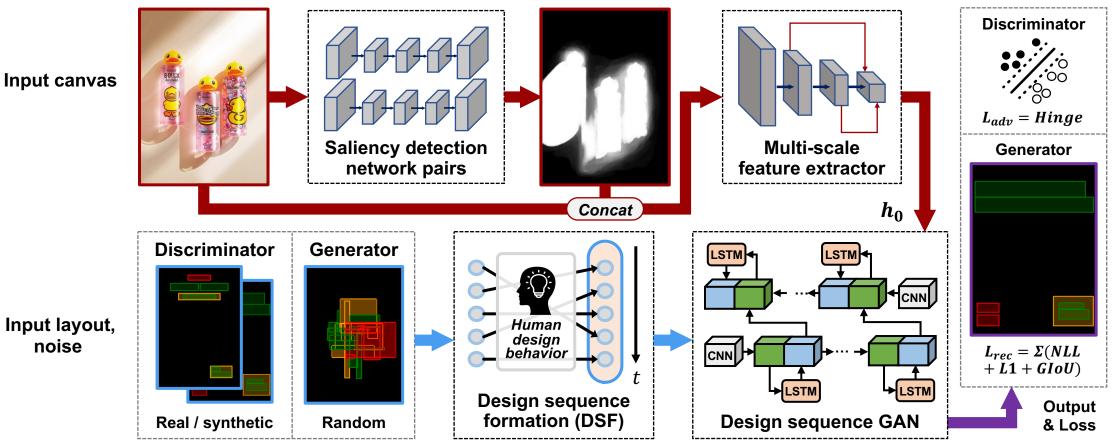
#### ii. Design sequence GAN (DS-GAN)

- Implemented by CNN-LSTM models, triggered by visual features of the canvas to generate image content-aware layouts
- Acting like a human who first observes the image and then starts the design

#### Design Sequence GAN (3/3)

#### ii. Design sequence GAN (DS-GAN)





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#### • Experiments

Conclusion

#### Comparisons with State-of-the-art Methods

- Compare our DS-GAN with SOTA methods on PKU PosterLayout and report metrics, including:
  - Graphic metrics: evaluating inter-element relationship

{<u>Val</u>idity of size, <u>Ove</u>rlay, <u>Alignment</u>, <u>Und</u>erlay effectiveness (loose, strict)</u>}

- Content-aware metrics: evaluating inter-canvas-layout relationship

{<u>Uti</u>lization rate of non-salient region, <u>Occ</u>lusion, <u>Rea</u>dability}

	Target	Val ↑	Ove ↓	Ali ↓	Und⊢↑	Und <sub>s</sub> ↑	Uti ↑	Occ ↓	Rea ↓
SmartText [2]	Т	-	-	-	-	-	0.0849	0.0912	0.1528
CGL-GAN [3]	V-T	0.7066	0.0605	0.0062	0.8624	0.4043	0.2257	0.1546	0.1715
DS-GAN (Ours)	V-T	0.8788	0.0220	0.0046	0.8315	0.4320	0.2541	0.2088	0.1874

Almost **dominate** graphic metrics

Get a good trade-off between two aspects of metrics

### Ablation Study (1/2)

- Gain insight into the effects of
  - CNN-LSTM models: remaining only the last fully connected layers

	Val ↑	Ove ↓	Ali ↓	Und₁ ↑	Und₅ ↑	Uti ↑	Occ ↓	Rea ↓
Without CNN-LSTM	0.6765	0.0888	0.0112	0.0106	0.0000	0.2155	0.2804	0.2015
With CNN-LSTM (DS-GAN)	0.8788	0.0220	0.0046	0.8315	0.4320	0.2541	0.2088	0.1874

Removing the **behavior pattern model** destroys the methodology

### Ablation Study (2/2)



- Gain insight into the effects of
  - CNN-LSTM models: remaining only the last fully connected layers
  - DSF: limiting the maximum sequence length and adopting different formation strategies

	Val ↑	Ove ↓	Ali ↓	Und₁ ↑	Und₅ ↑	<i>Uti</i> ↑	Occ ↓	Rea ↓	$AE\downarrow$
Random	<b>1.000</b> (+0.1454)	0.0881 (+0.0666)	0.0062 (+0.0007)	0.7417 (-0.1380)	0.3243 (-0.1499)	0.2240 (-0.0328)	0.2475 (+0.0361)	<b>0.1909</b> (+0.0035)	0.5730
Geometric	0.9667 (+0.1215)	<b>0.0261</b> (+0.0026)	0.005 (+0.0004)	0.7849 (-0.0824)	0.4433 (-0.0757)	0.2439 (-0.0170)	0.2482 (+0.0438)	0.1937 (+0.0052)	0.3486
DSF-based (DS-GAN- <b>8</b> )	0.9572 (+0.0784)	0.0362 (+0.0142)	<b>0.0043</b> (-0.0003)	<b>0.8850</b> (+0.0535)	<b>0.5824</b> (+0.1504)	<b>0.2526</b> (-0.0015)	<b>0.2341</b> (+0.0253)	0.1910 (+0.0036)	0.3272

#### Visualized Results (1/3)

- Our DS-GAN generates more appealing layouts for diverse canvases
  - Actively **utilize** all suitable spaces, retaining some *visually natural* **occlusion**



SmartText [2]





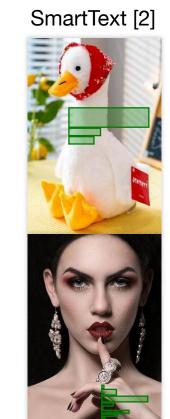
CGL-GAN [3] DS-GAN (Ours)

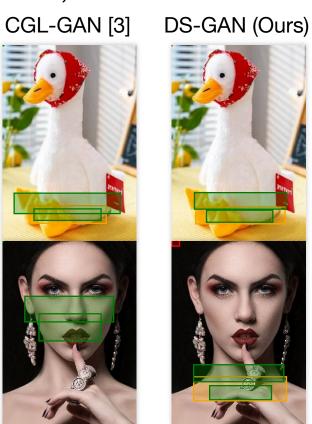


#### Visualized Results (2/3)

- Our DS-GAN generates more appealing layouts for diverse canvases
  - Avoid unpleasant overlay, non-alignment, or occlusion



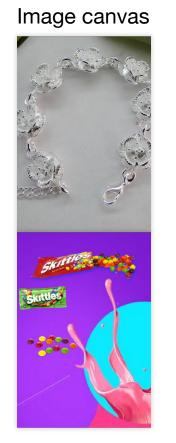




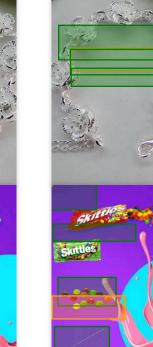


#### Visualized Results (3/3)

- E K I
- Our DS-GAN generates more appealing layouts for diverse canvases
  - Capable of handling canvases with special-shaped, complex objects











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#### Conclusion

- This paper devoted to content-aware visual-textual presentation layouts by
  - Construct a new benchmark, *PKU PosterLayout*
  - Propose a new generative approach, **DS-GAN**, inspired by human behavior
    - Composed of DSF and CNN-LSTM-based GAN, both of which are critical
- Several experiments were conducted and verified *PKU PosterLayout*'s usefulness and *DS-GAN*'s effectiveness
- The dataset and code are open-sourced (visit the project page!), hopefully encouraging further research

#### Reference



- [1] Gangwei Jiang, Shiyao Wang, Tiezheng Ge, Yuning Jiang, Ying Wei, and Defu Lian. Self-supervised text erasing with controllable image synthesis. In Proceedings of the ACM International Conference on Multimedia (ACM MM), pages 1973–1983, 2022.
- [2] Chenhui Li, Peiying Zhang, and Changbo Wang. Harmonious textual layout generation over natural images via deep aesthetics learning. IEEE Transactions on Multimedia (TMM), 2021.
- [3] Min Zhou, Chenchen Xu, Ye Ma, Tiezheng Ge, Yuning Jiang, and Weiwei Xu. Composition-aware graphic layout GAN for visual-textual presentation designs. In Proceedings of the International Joint Conference on Artificial Intelligence (IJCAI), pages 4995–5001, 2022.

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# Thank you!

& Feel free to contact us!!

