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A review of design intelligence: progress, problems, and challenges

Key words: Design intelligence; Creativity; Personas; Ideation; AI-generated content; Computational aesthetics

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Motivation

1. With the advent of AI 2.0, especially the emergence and evolution of the generative adversarial networks (GANs), computers began to have a new creative ability. Design intelligence becomes a powerful force driving the development of design and creative fields.

2. The concept and framework of design intelligence have not been proposed, and the state-of-the-art techniques of related topics have not been well summarized. Several problems and challenges that hamper the further application of design intelligence remain open to address.

Main idea

1. Framework of design intelligence

(1) It refers to AI technology that addresses issues in the design and creative process and generates creative solutions;

(2) It includes a data module and a creative module, and the creative module has four main components, i.e., user need analysis, ideation, content generation, and design evaluation.

2. Progress in design intelligence research

(1) AI-based user need analysis; (2) AI-based ideation;

(3) AI-based content generation; (4) AI-based design evaluation.

3. Open problems and challenges

(1) Creativity, novelty, and diversity; (2) Large variance in the data;

(3) High cost in collecting data; (4) Limited number of samples;

(5) Interpretability of models and results; (6) Human-computer collaboration.

Introduction

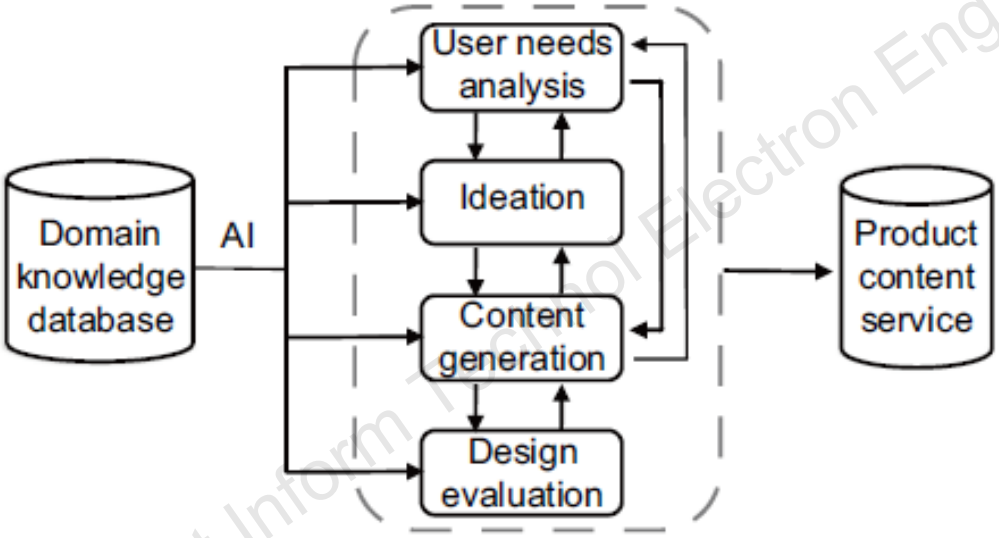


Fig. 2 Framework of design intelligence. The four main data-driven analytic components are in the center. Arrows indicate the main information flows among components

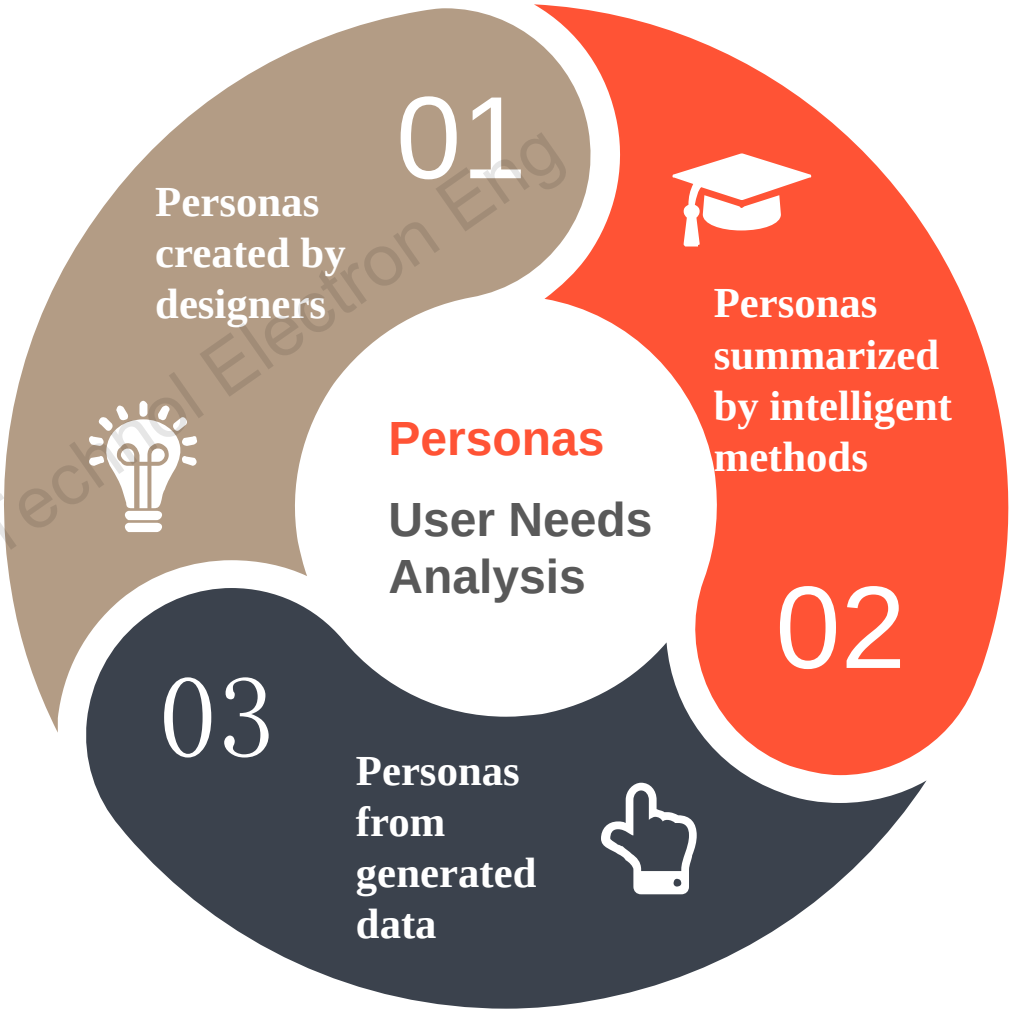
AI-based user need analysis

Criticisms

Taking considerable time and effort, being expensive, lacking credibility, inheriting organizational tensions and individual biases, being inconsistent, and so on.

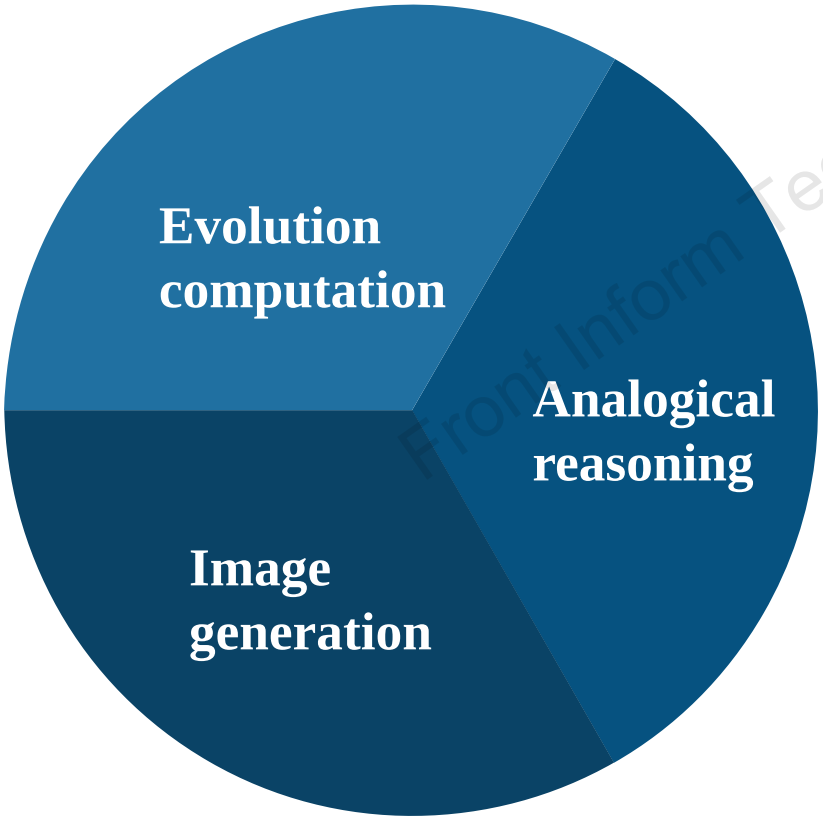
Open problems

Large amount of behavioral data; text, visual, auditory, body movement, and even VR or AR data; lacking persona assessment.

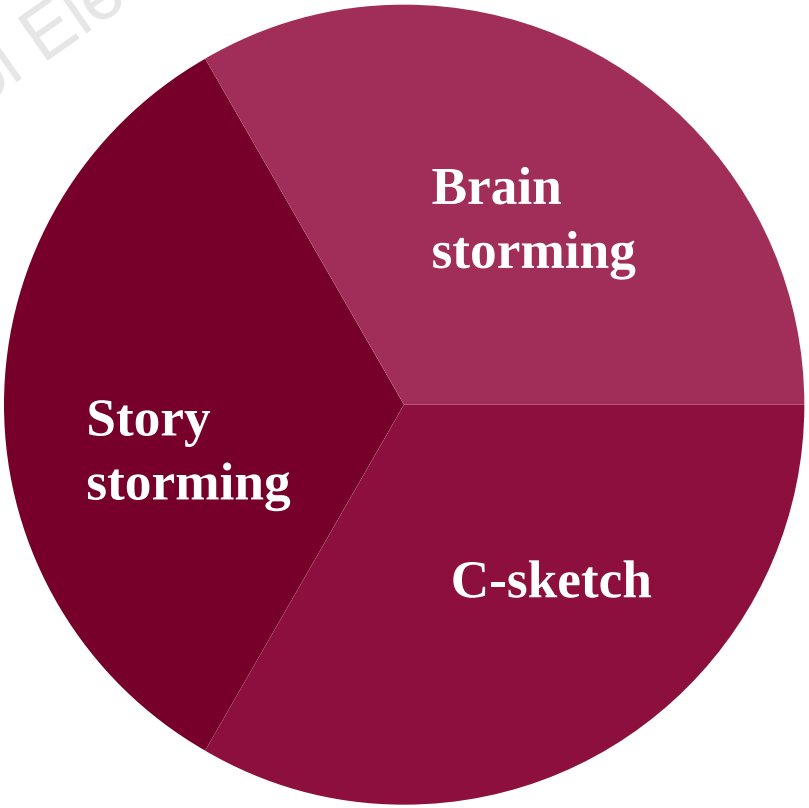


AI-based ideation

Stimuli-based ideation



Interaction-based ideation



AI-based content generation

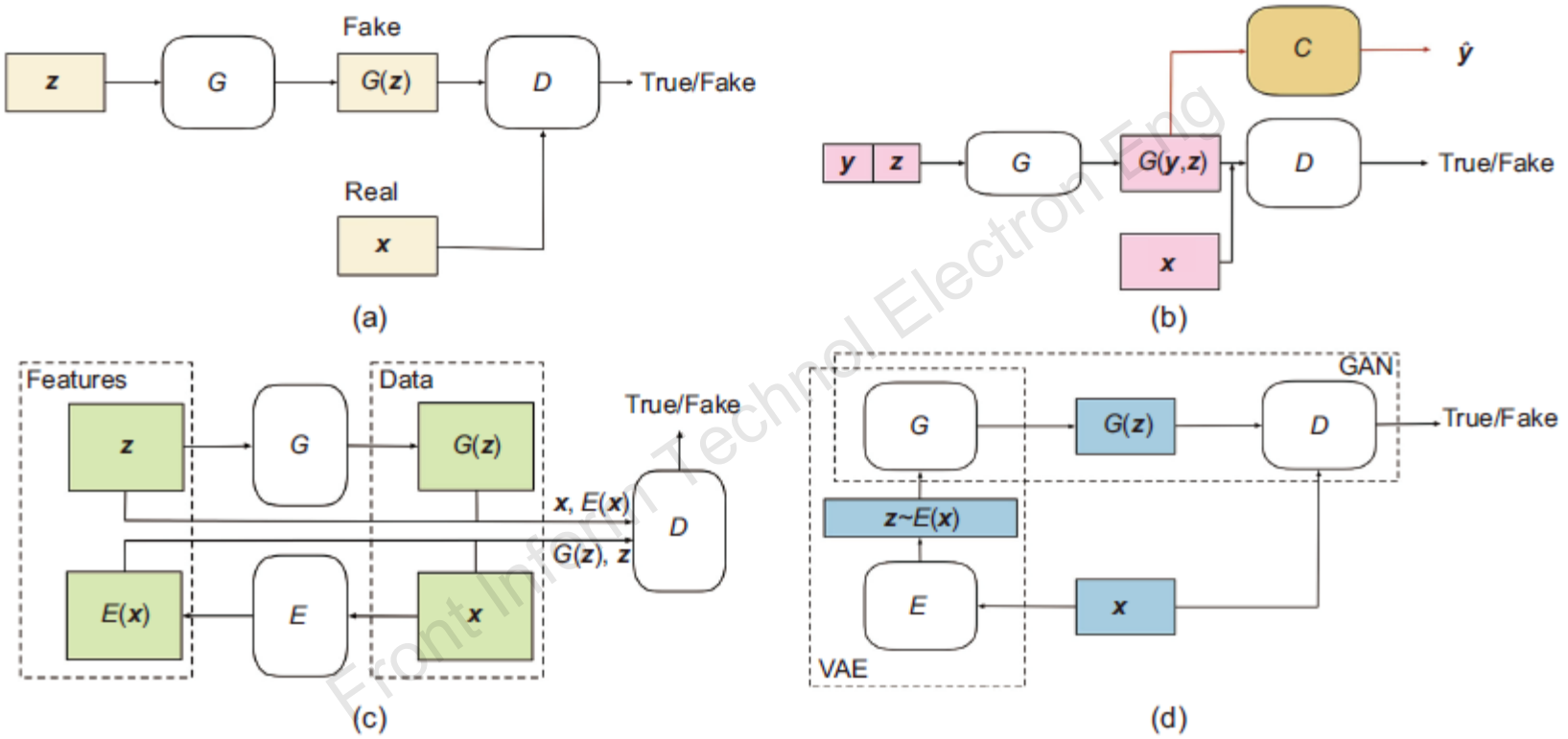
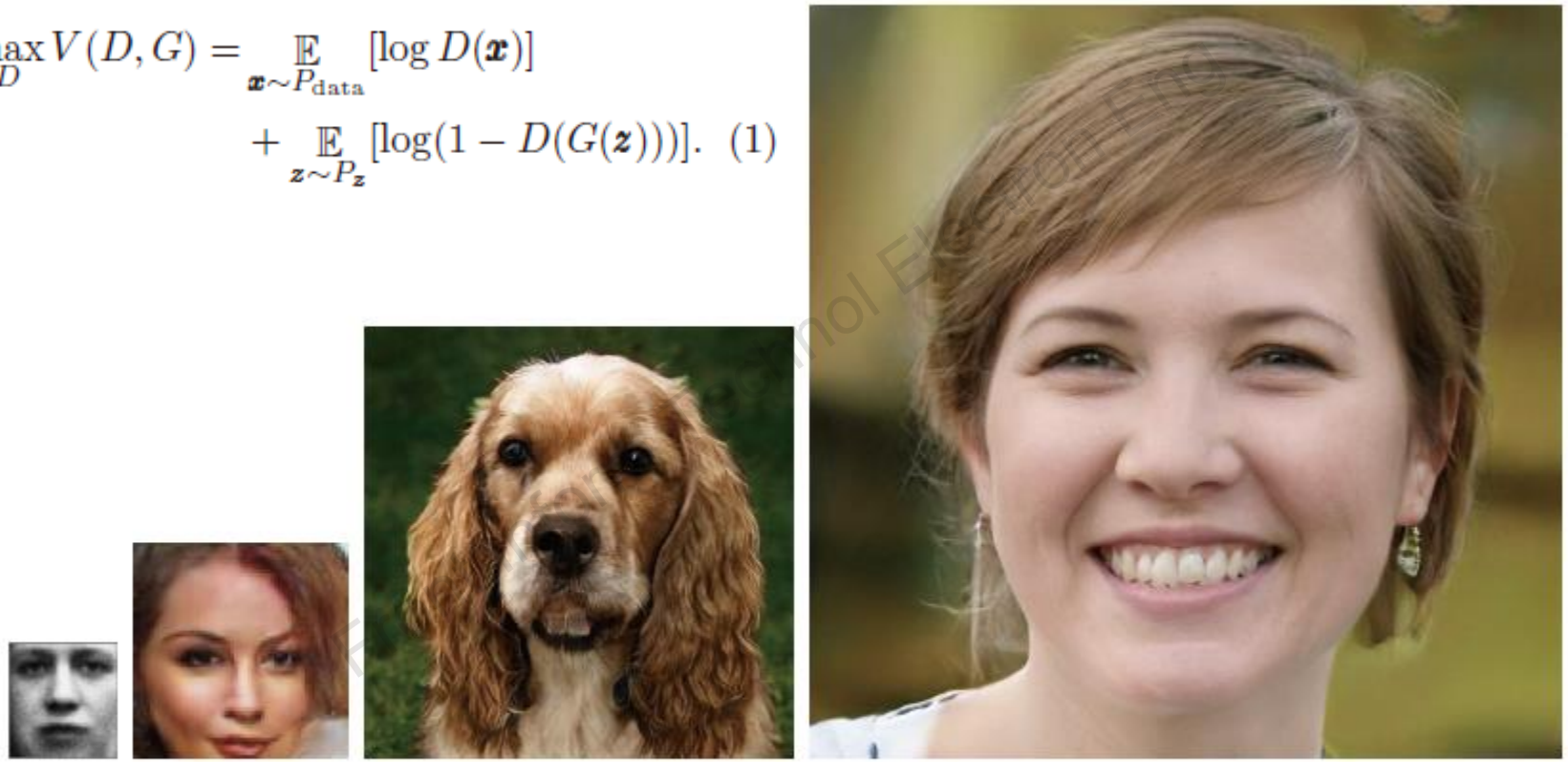


Fig. 4 Architectures of various GANs: (a) general structure of vanilla GAN, where the generator G takes a noise vector z as input and outputs a generated sample $G(z)$, while the discriminator D takes both the real and generated samples as inputs and predicts whether they are real or fake; (b) architecture of GAN with a conditional input/an auxiliary classifier, where y is the conditional input label and C is the classifier to predict the label $\hat{y}$ of generated sample $G(y, z)$; (c) architecture of GAN with auto-encoder (AE) structure, where the encoder E takes real sample x as input and produces a feature vector $E(x)$ as output; (d) architecture of GAN with variational auto-encoder (VAE) to exploit both of their benefits

Generative models

$$\min_G \max_D V(D,G) = \mathop{\mathbb{E}}_{\boldsymbol{x}\sim P_{\text{data}}} [\log D(\boldsymbol{x})] + \mathop{\mathbb{E}}_{\boldsymbol{z}\sim P_{\boldsymbol{z}}} [\log(1 - D(G(\boldsymbol{z})))]. \quad (1)$$



(a) (b) (c) (d)

Fig. 5 Development of GANs from 2014 to 2019: (a) GAN (Goodfellow et al., 2014); (b) DCGAN (Radford et al., 2016); (c) BigGAN (Brock et al., 2018); (d) StyleGAN (Karras et al., 2019). Their resolutions are 32×32, 128×128, 512×512, and 1024×1024, respectively. In addition to the improvement in resolution, the details of the generated images are more abundant and realistic

Approaches for intelligence-generated content

Text-to-image synthesis

Fig. 6 Examples of text-to-image results. All pictures were generated from a text description using GANs. References to color refer to the online version of this figure. Reprinted from Xu et al. (2018), Copyright 2018, with permission from IEEE

Approaches for intelligence-generated content (Cont'd)

Image-to-image translation

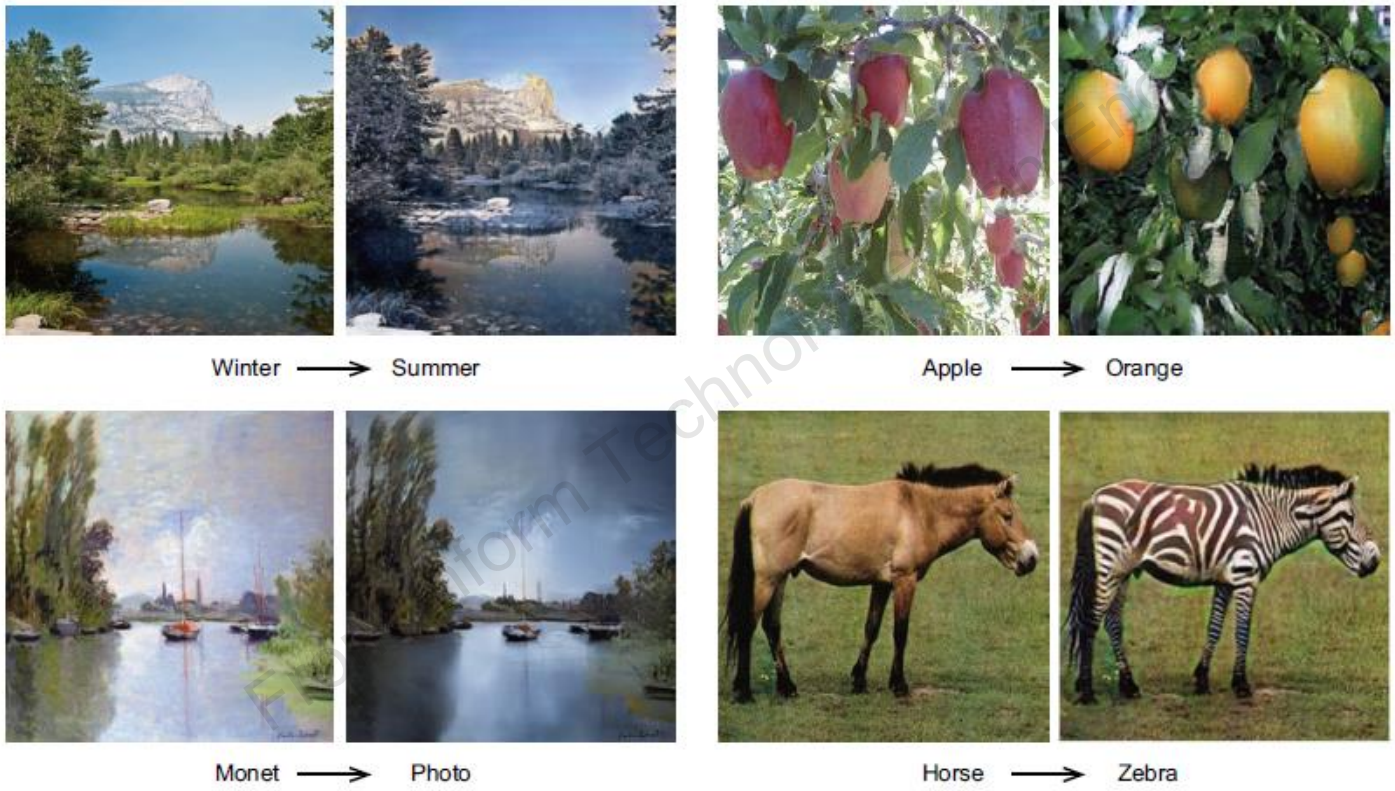


Fig. 7 Image-to-image translation examples

Supervised translation:

$$L_{\text{cGAN}}(G,D) = \mathop{\mathbb{E}}_{\boldsymbol{x},\boldsymbol{y}}\left[\log D(x,y)\right] + \mathop{\mathbb{E}}_{\boldsymbol{z},\boldsymbol{y}}\left[1-\log D(G(z,y),y)\right]. \quad (2)$$

Unsupervised general translation:

$$L_{\text{cyc}}(G,F) = \mathop{\mathbb{E}}_{\boldsymbol{x}\sim P_{\text{data}}(\boldsymbol{x})}\left[\|F(G(x))-x\|_1\right] + \mathop{\mathbb{E}}_{\boldsymbol{y}\sim P_{\text{data}}(\boldsymbol{y})}\left[\|G(F(y))-y\|_1\right]. \quad (3)$$

Approaches for intelligence-generated content (Cont'd)

Image enhancement

Fig. 8 Visual results of image inpainting. The masked area is shown in white

(a) (b) (c)

Fig. 9 Visual comparisons between different methods for super-resolution: (a) high-resolution original image; (b) super-resolution result by Keys (1981) (bicubic); (c) super-resolution result by Wang XT et al. (2018) (ESRGAN)

Approaches for intelligence-generated content (Cont'd)

Content-style transfer

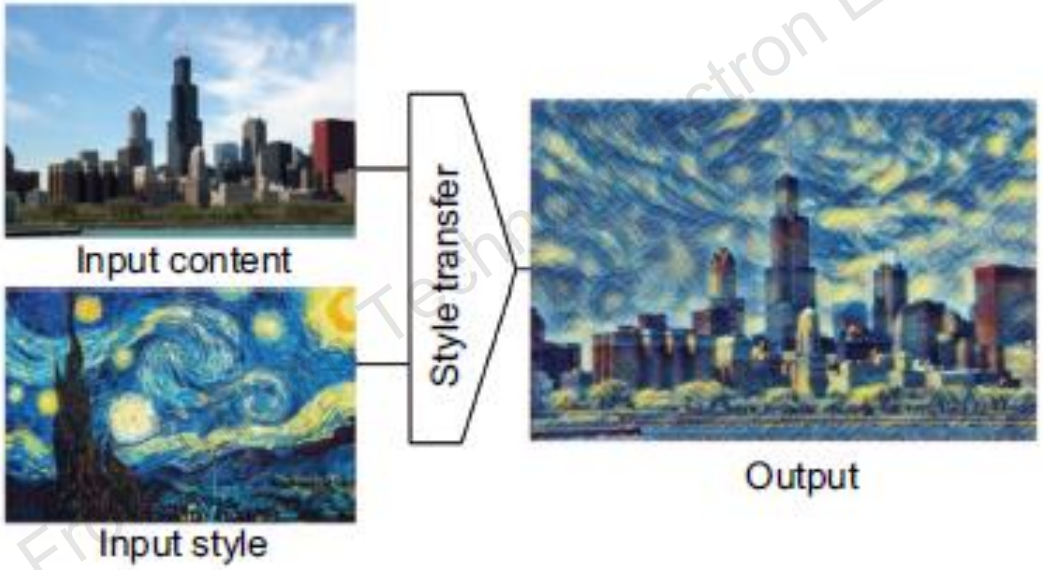


Fig. 10 An example of content-style transfer algorithm to transfer the style of a painting onto a given photograph. The style image is "Starry night" by Vincent van Gogh

AI-based design evaluation

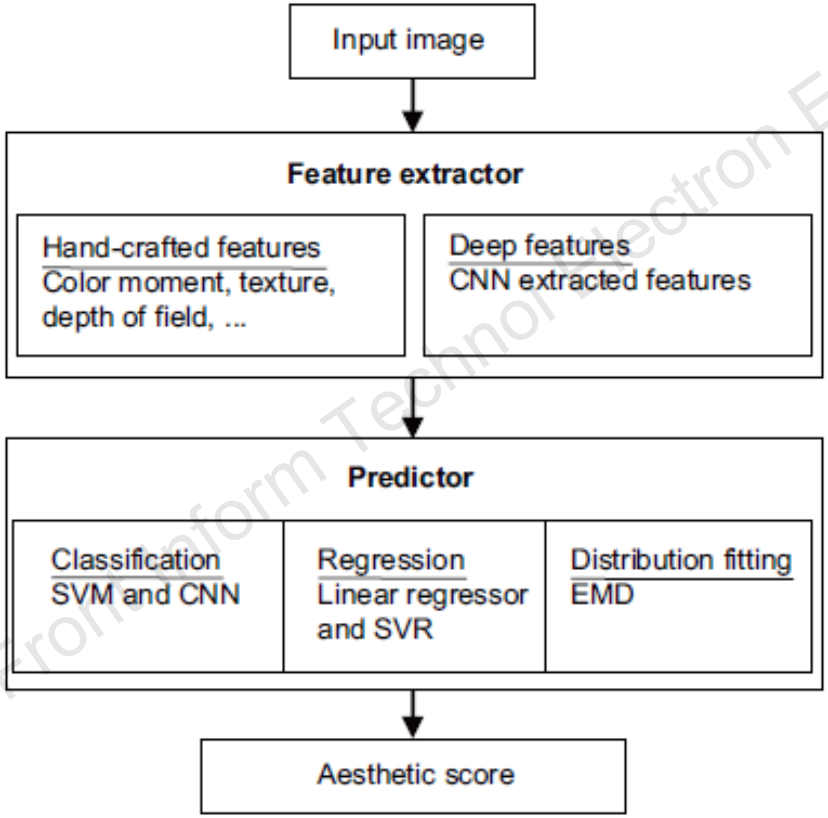


Fig. 11 A typical pipeline of a computational aesthetics system

AI-based design evaluation (Cont'd)

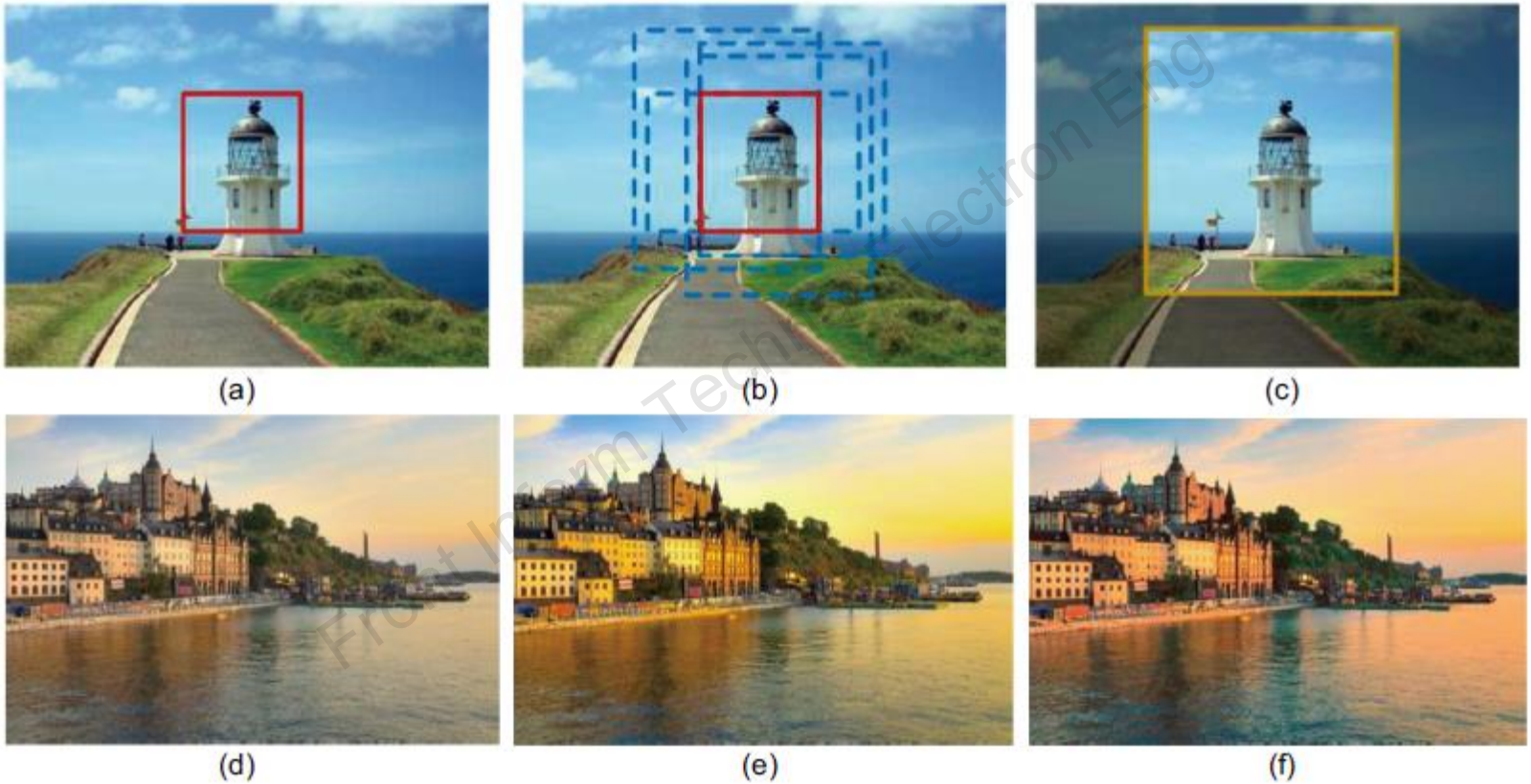


Fig. 12 Initial crop (the red rectangle) (a), cropping candidates (blue rectangles) (b), best candidate selected by the aesthetic assessment network (c), input image (d), output by the piecewise color enhancer (e), and output by the deep filtering based enhancer (f). References to color refer to the online version of this figure. (a)–(c) are reprinted from Wang and Shen (2017), Copyright 2017, with permission from IEEE, and (d)–(f) are reprinted from Deng et al. (2018), Copyright 2018, with permission from ACM

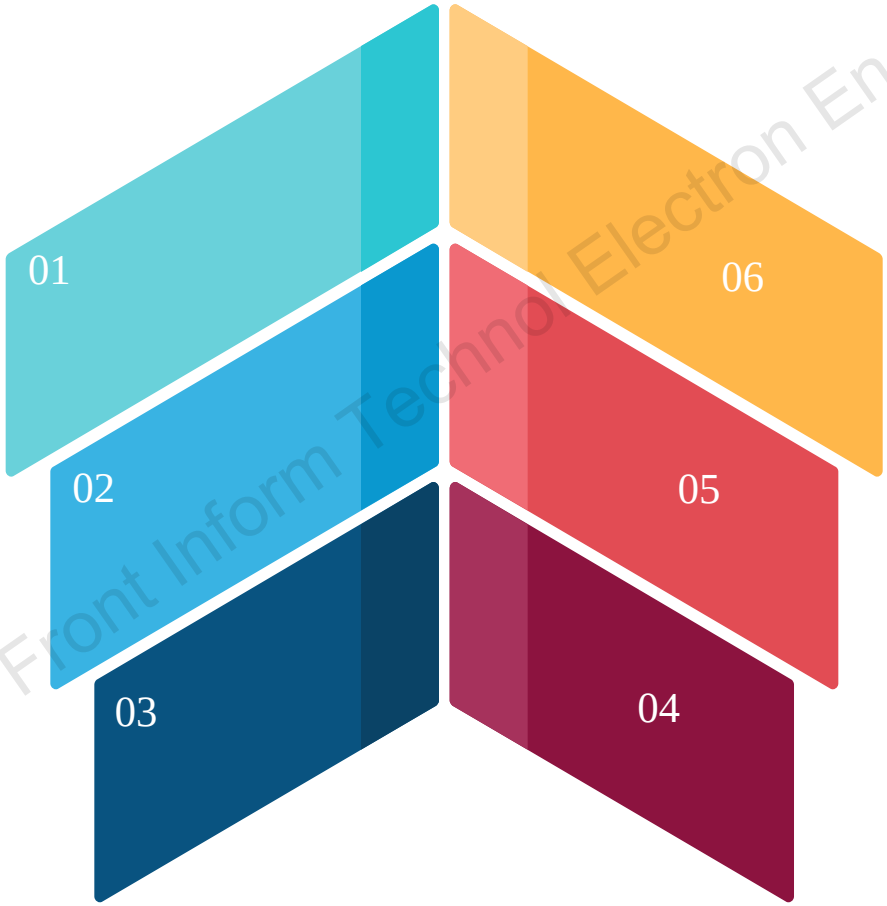
Open problems and challenges

Open problems

Creativity, novelty, and diversity

Large variance in the data

High cost in collecting data



Challenges

Limited number of samples

Interpretability of models and results

Human-computer collaboration

Conclusions

1. The concept and framework of design intelligence have been proposed.

2. Progress in the four components of design intelligence, i.e., AI-based user need analysis, AI-based ideation, AI-based content generation, and AI-based design evaluation, has been reviewed in detail.

3. Open problems and challenges for design intelligence have been discussed.