# Exploration on Diversity Generation of Campus Layout Based on GAN

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**Abstract.** Previous studies have shown that GAN has made some progress in the generation of campus layout plan, but the result is single output for single input condition. This paper hopes to make some attempts and explorations on the diversity generation of campus planning layout design by machine learning. Based on Pix2Pix model, this paper proposes a method to divide image channels so that the campus function bubble diagram and the site boundary can both become the input conditions. There is a strong correspondence between the campus functional bubble diagram and the campus layout. The main idea of this study is to control the generated results by changing the input of the campus functional bubble diagram, so that we can have a diversity layout of campus according to the same site conditions. In the experiment, we train thirty samples of campus planning layout design, and finally evaluate the generated results in a qualitative and quantitative way, which proves that the generated results are relatively ideal. This research enables designers to participate in the process of machine learning generative design to control the generation results.

**Keywords:** GAN · Campus planning layout design · Campus function bubble diagram · Diverse generative design

## 1 Introduction

At present, the machine learning technology developed rapidly, brings new possibilities to the field of architectural design. Among the machine learning techniques, the generative against network (GAN) has certain potential in the architectural design layout generation research. GAN can generate a specific layout plan automatically according to the given site conditions by summarizing the potential composition rules of various elements in a large number of layout data. However, most of the current studies are focused on the apartment and block plan with relatively simple functions, and there are few studies on the more complex objects, and the generated results are unitary and uncontrollable.

Campus is large scale, with complex internal functions, clear zoning plan and has certain rules in element composition. It is a special community organization in the city,


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including not only educational buildings, but also business, entertainment, sports, and other functions, almost as a miniature society, so it has many possibilities of layout. The traditional campus planning and design is a major construction, which often needs a lot of manpower and material resources. The Architects need to spend a lot of time to repeatedly modify the design schemes and compare the multiple schemes to select the best one. Campus layout design is an important link in the early stage of campus planning. If multiple preliminary layout design can be proposed quickly in the early stage of design and multiple design options can be provided to designers, it will bring higher efficiency.

This research considered to apply machine learning technology in campus design layout generation. In this paper, we proposed a novel campus layout design method. According to the way of architect doing design by drawing the functional bubbles sketch, we took the campus site boundary and functional bubble diagram together as input. Different functional bubbles correspond to different functional zonings inside the campus. The machine can summarize the corresponding relationship between functional bubbles and campus building layout. Finally, by changing different functional bubble diagrams, we will have diverse campus layouts based on a single boundary. This research allows designers to control the generated design results, and they can adjust the results as needed.

## 2 Related Work in the Field of Architectural Layout

In recent years, machine learning technology has made some progress in the field of building layout generation [2, 4, 5, 7]. With more complex research objects and ever larger scales, some scholars begin to explore the possibility of combining machine learning with campus planning and layout design. Chang [1] proposed the use of reinforcement learning and parametric modeling for campus design generation. This method can provide many design choices based on different design parameters. However, it is based on artificial algorithms and limited optimization goals to guide the generation design, which cannot get a more organic layout form. Luo [3] used deep learning to discusses the idea and method of campus layout generation, and proposed a selecting rule and annotation method for small sample generation. With such a method, the computer can automatically generate the layout of the campus under the conditions of given campus boundaries and surrounding roads. This experiment demonstrates that machine learning techniques can generate more complex layouts like campus. However, this research is limited to the single output, and can only output a single result according to the condition of a site, which cannot meet the needs of comparing multiple schemes in campus design at the early conceptual stage. Therefore, the designer cannot control the final output result and adjust the generated results.

In terms of research on diversity generation of layouts. Pan [6] obtained the results of diverse generation by using GauGAN model to generate the layout of the neighborhood community in north of China. This study showed us the possibility of deep learning for diverse layout output, which affected the output results by changing the images of the input. But the final diverse output results did not change much, and it is difficult to see the direct influence of the input elements on the results. So far, the research on diversified output is not mature enough.

In conclusion, there has been few researches on the generation of campus planning and design combined with machine learning. This paper hopes to further explore the application of deep learning technology for diverse output of campus layout, and study how to establish a more direct connection between input elements and output elements, so that designers can control the direction of the generated results.

## 3 Methodology

The main process of diversified generation of campus layouts based on deep learning is as follows:

1. Database establishment. The main collection date is the central loop type campus planning and design plan.
2. Data labelling and extraction of campus functional bubble diagrams. Establish a data labeling method based on architectural knowledge.
3. Training and testing. Pix2Pix model is adopted for training and testing.
4. Evaluation and analysis. The results are evaluated and analyzed to verify the possibility of diversity generation.

### 3.1 Model Architecture

The Pix2Pix model is one of the conditional generative adversarial network models (cGAN). It can be used in image processing tasks to map the input image to the output image, and it can achieve the supervised image-to-image translation. The network structure of Pix2Pix contains a generator and a discriminator. The generator used the U-Net structure to encode the input image, and then decodes it into a fake image that resembles the real one. The discriminator used the conditional discriminator PatchGAN.

### 3.2 Training Method

The input and output of the original Pix2Pix model are three-channel images, which can only support single image input and output. In order to achieve multiple input, we modified the input image channel based on the original Pix2Pix model, changing the three channels to six channels, and finally the model can realize the simultaneous input of two images.

This research was based on the original experiment (Fig. 1) and then put forward a new training method (Fig. 2). Input the campus site boundary and campus functional bubble diagrams into the generator at the same time and it generated a layout plan of campus approaching the real sample. Then we put this plan and the corresponding real campus plan together into the discriminator. The discriminator evaluated both, and gamed with the generator until the model converged. Finally, we input different functional bubble diagrams to generate diversity campus layouts based on the same site conditions, so we can achieve the goal of controlling the result by inputting different bubble diagrams.

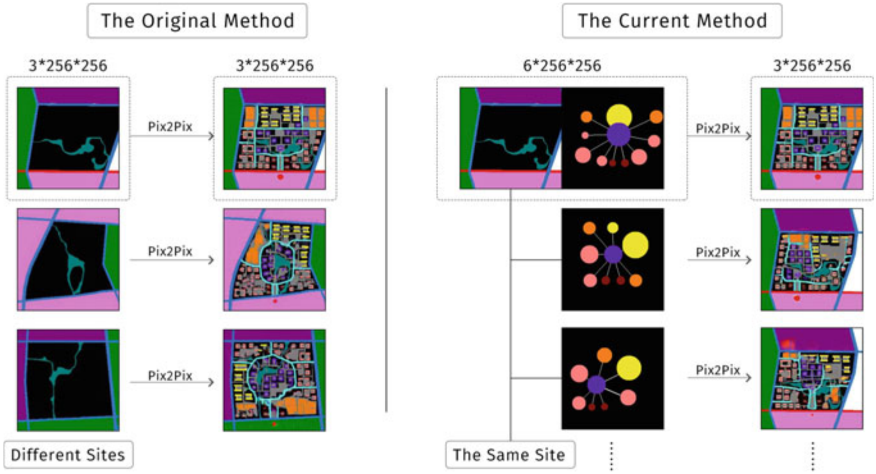


**Fig. 1.** The original method and the current method

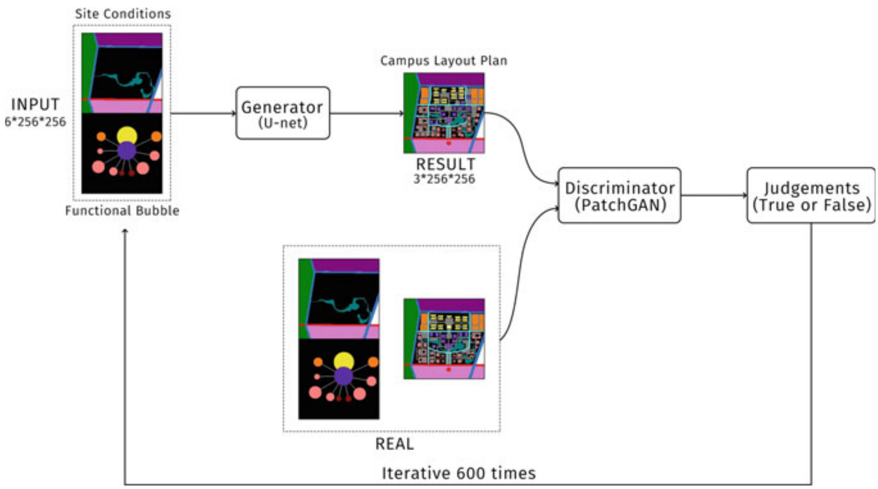


**Fig. 2.** Training method

## 3.3 Dataset

We have collected campus cases through portfolios of major design institutes, and papers, books and websites related to campus planning.

### 3.3.1 Selecting Rules

Considering the impact of samples on the generated results, we conducted the following selecting method for the data:

1. Appropriate Scale. Select the sites with scale between 50–100 hectares.
2. Square boundary. The boundary of the campus' site should be relatively square.
3. Consistent planning style. The layout plan used in this experiment is the central loop type.
4. Complete and clear functional zoning.

Finally, thirty campus samples (Fig. 3) were selected, four of which were used as test samples.

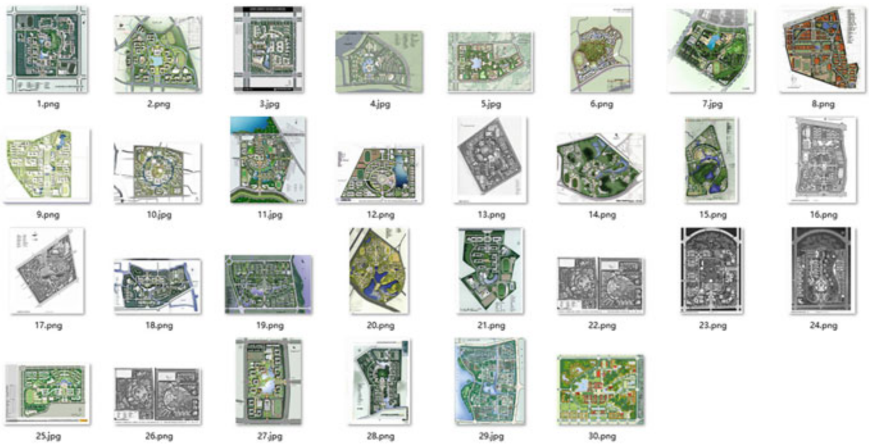


**Fig. 3.** Selected samples

### 3.3.2 Sample Labelling

We labelled the data of the campus plan with uniform form, proportion, and color block. By summarizing the main layout features of different campus building, such as teaching buildings and dormitories, we extracted the common forms and simplify some special building layouts.

We convert these functional zonings into the form of functional bubble diagrams (Fig. 4). Firstly, the color blocks of functional zoning are divided according to the original functions and roads. And then the size of the color blocks determines the size of the bubble. The larger the color block is, the larger the function bubble is. In addition, the functional bubble diagram can also reflect the proximity of different zonings and the total number of functional zonings.

### 3.3.3 Data Augmentation

In this experiment, a total of 120 data were obtained by expanding the data set through horizontal mirroring and vertical mirroring to improve the learning effect of the machine on the samples. Considering that rotation would affect the orientation of teaching buildings, dormitories, and other buildings, we did not rotate data in this experiment.

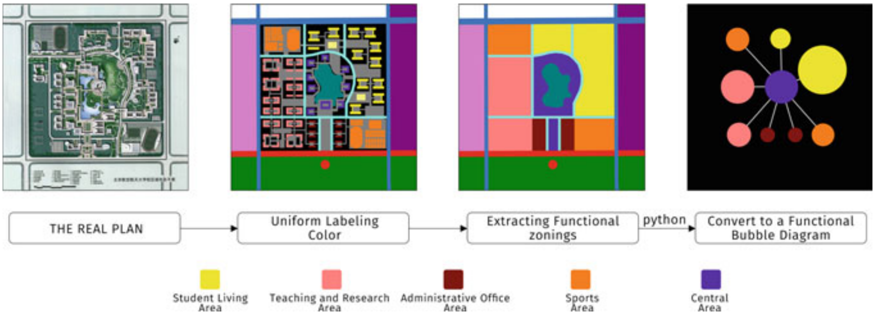


**Fig. 4.** Process of extracting campus functional bubble diagram

# 4 Training and Testing

## 4.1 Previous Experiment

Our research team has done an experiment of generating campus plan based on machine learning. The method of step-by-step training is adopted. The first training inputs site boundary and outputs functional zoning plan. The second training inputs functional zoning plan, and outputs campus layout plan. Through step-by-step training, the campus plans are generated (Fig. 5).

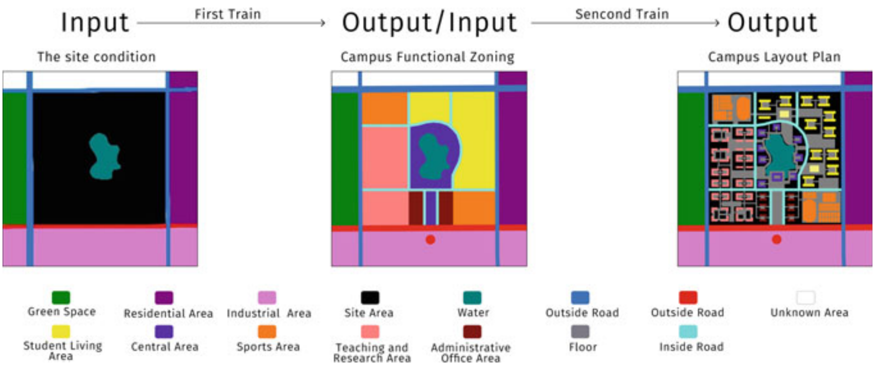


**Fig. 5.** Step by step training method

The experiment could generate a single result for each site, which cannot be changed and adjusted to the needs of designers to achieve diverse results. Therefore, we carried out the subsequent improved experiments.

## 4.2 Improved Experiments

In order to solve above problems, we make some adjustments and improvements in the following experiment:

1. Extract function bubble diagrams according to the original function layout.
2. The functional bubble diagram was proposed to be involved in the experiment. The site boundary condition and the functional bubble diagrams thus become the input together in order to realize the joint influence of multiple images on the generated results.
3. In the pre-experiment, the functional zoning plans of campus were generated.
4. In the final experiment, the layout plans of campus were generated.

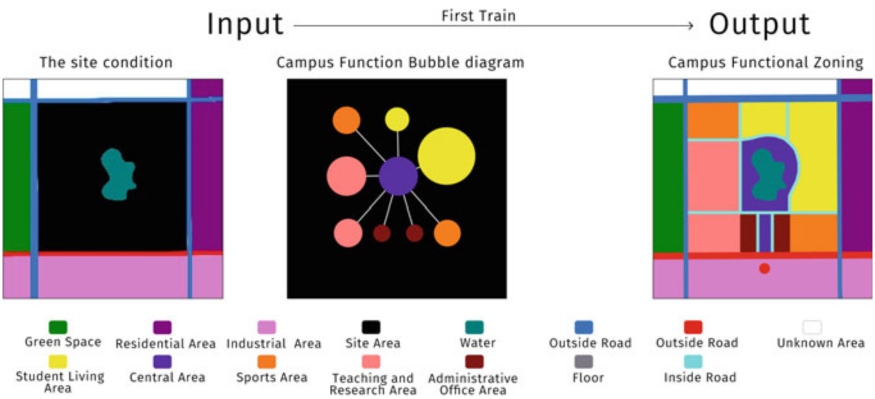


**Fig. 6.** Pre-experiment training data: input and output, labeling rules

In the pre-experiment (Fig. 6), we took the campus site boundary condition and the campus function bubble diagram as input, and the corresponding real campus function zoning plan as output. We input them into the machine for learning at the same time. The learning rate was adjusted to 0.002 and the number of iterations was 600.

The results of the above experiments (Fig. 7) were relatively good, and the generated functional zoning plans could change according to the change of functional bubbles diagrams. In order to explore the ability of the Pix2Pix model to generate complex plans, we tried to generate the layout of campus planning in one step in the following experiment (Fig. 8). The campus site condition and the campus function bubble diagrams were taken as input, and the corresponding real campus planning layout plan was taken as the output. The learning rate was adjusted to 0.002, and the number of iterations is 600 times, which could generate ideal effects.

Through the two experiments, the machine can directly learn the internal rules of the campus layout plans. Therefore, we will directly test the model of the final experiment and then analyze it.

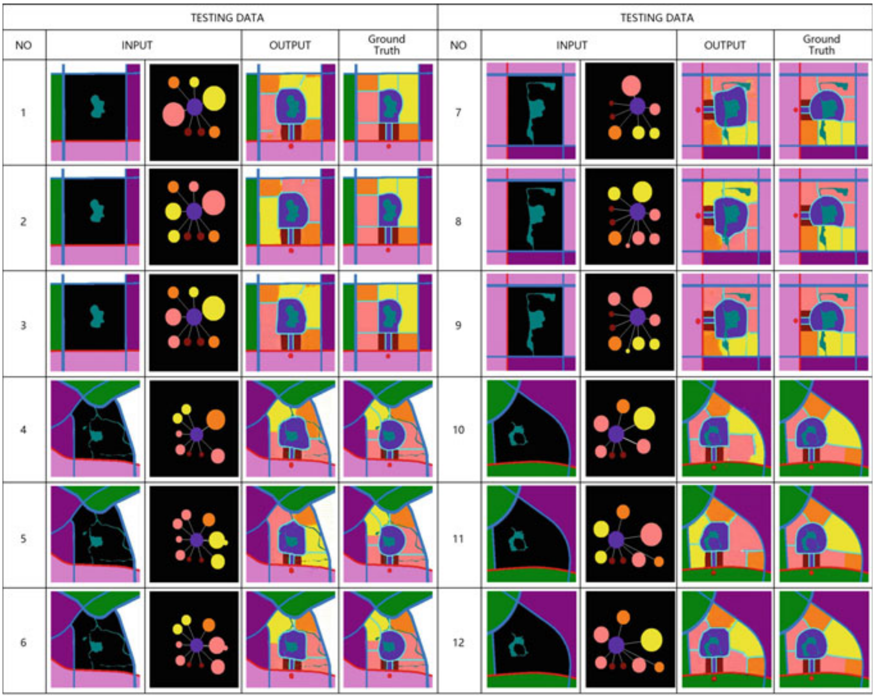


**Fig. 7.** Pre-experiment testing results

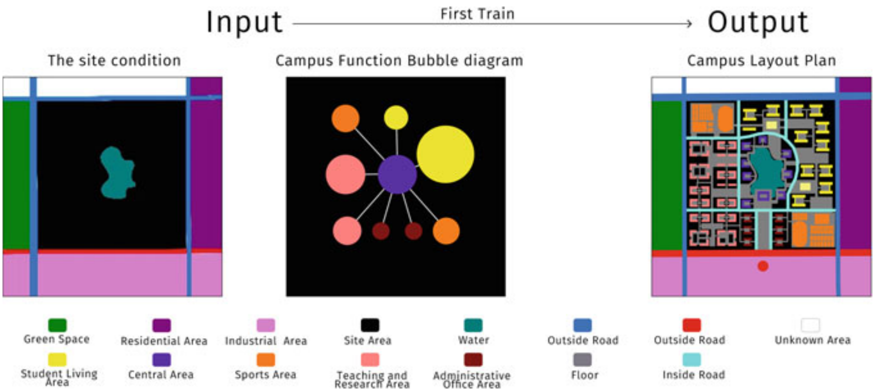


**Fig. 8.** The final experiment training data: input and output, labeling rules

## 4.3 Result Analysis

### 4.3.1 Qualitative Evaluation Criteria:

1. Adjust the position, size, and quantity of the functional bubble diagrams, to see if the results can show a variety of changes.

1.1. Modify the color of the bubble.
1.2 Modify the position of the bubble.
1.3. Add or subtract a bubble.
1.4. Modify the size of a bubble.
1.5. Customize a completely new layout.

2. Compared the result of the original functional layout with the real plan to see if it follows the common sense of architectural design, and observe whether the results of layout are reasonable. For example, it is advisable to have a north–south layout and a building distribution.
3. Observe whether it made some adjustments according to the surrounding environment, such as adjusting the overall direction of the building layout according to the inclined angle of the road, responding to the main landscape, and whether the changes of the surrounding site function will have an impact on the result.
4. Observe the sharpness of the generated images, including whether image pixels and building boundary are clear, and whether it can generate continuity of road.

### 4.3.2 Analysis

In this step, we used the method of controlling the variable (Fig. 9) to discuss the effect of functional bubble diagrams on the Generating effect and found the implicit correspondence relationship between functional bubbles and the site layout.

Through qualitative analysis, it can be found that changing the bubble diagram can affect the functional layout of the campus to a certain extent. The NO. 3–5 and NO. 4–5 illustrated that the arbitrarily placed bubble diagram can generate a new building layout, and can follow the campus layout rules well. The machine has learned the relationship between the administrative district and the main entrance, which shows the controllability of this approach. In terms of learning the layout rules of campus, the machine could basically master the layout of buildings in the central area around the central landscape, and the buildings are oriented towards the landscape, which can be a reasonable layout form. The buildings were able to give way to the road and some of them can be distributed along the trend of the road. But in the formation of image clarity, the architectural boundary is vague and the continuity of the road is poor.

Through quantitative analysis, functional elements in the generated images were relatively complete, and the machine basically learned the correspondence relationship between the building layout and the functional bubbles. In conclusion, this experiment demonstrates the ability of machine learning to learn complex objects.

## 5 Discussion

This paper showed a new idea of the diverse layout generation that users can control the results of campus layout by inputting different bubble diagrams. The results of the experiment reached our expected results. At the same time, the experiment showed that samples of common patterns can improve the efficiency of the machine learning complex building layouts, and demonstrated the huge potential of the machine to learn

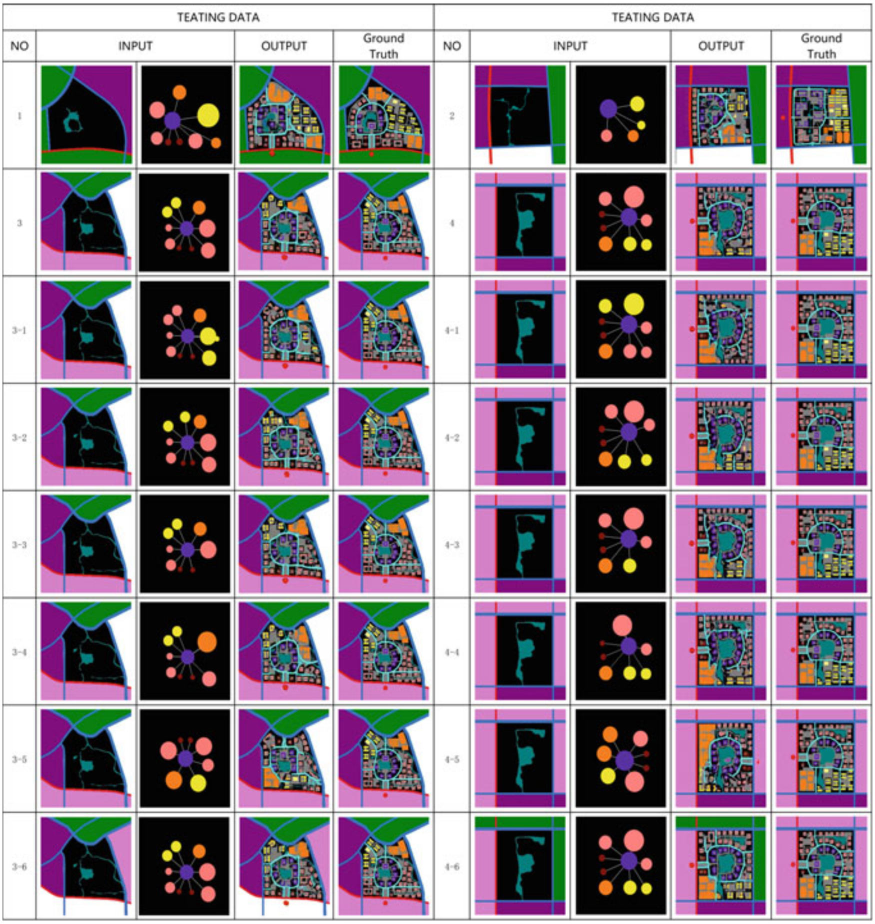


**Fig. 9.** The final experiment testing results

the complex layouts. In the future, on discussing the diverse generation, we hope to study different influencing factors: the impact of axis relationships on campus layout generation and another machine learning model which will generate diverse results of campus.

This study is only limited to the plan generation, without too much consideration of 3D generation. In the future research, we will build a three-dimensional model based on the generated results, and achieve a visual 3D model effect.

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