FACILITATING ARCHITECT-CLIENT COMMUNICATION IN THE PRE-DESIGN PHASE

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Abstract. The process of architects exploring the program with clients often take place through face-to-face oral discussions and visual aids, such as photos and sketches. Our research focuses on two communication mediums: language and sketch. We employ machine learning techniques to assist architects and clients to improve their communication and reduce misunderstandings. We have trained a Naive Bayesian Classifier machine, the language assistant (LA), to classify architectural vocabularies with associations to design requirements. In addition, we have trained a Generative Adversarial Network, the sketch assistant (SA), to generate photo quality images based on architects' sketches. The language assistant and sketch assistant combined can facilitate architect-client communication during the pre-design stage.

Keywords. Architect-Client Communication; Pre-design; Architectural Programming; Machine Learning; Schematic Design.

1. Introduction

An architectural project begins from the pre-design phase, during which studies are done to analyze space requirements, opportunities and constraints of the proposed site, costs versus budgets. It is a critical phase for architects to explore the program with the clients to reach common agreement on an idea and direction. At this stage, the architect and the clients reached a consensus through a lot of communication to exchange the information (Taleb et al., 2017). Since architects and clients often do not share a common language about designs, their communication is slow and may result in misunderstandings. Past research has investigated architect-client communication issues and proposed models, strategies, and collaborative environments. While the efficiency of architect-client communication has improved for the design phase, in the pre-design phase, clients still encounter difficulties in articulating their needs or preferences. This seems to relate to a client's architectural knowledge, lacking of which makes it hard for the client to explain the needs and ideas well (Barrett, 1999).

To achieve mutual understanding, architects and clients employ various mediums to aid communications (Taleb et al., 2017). Clients often express their ideas with case pictures they like as a way to communicate with architects.

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Compared with using language alone, having pictures or images help both parties communicate more smoothly. Therefore, toolsto visualize information and support visual communication are indispensable (Shen, 2011; Shen et al., 2013). Visual information could be abstract or realistic (eg. 3D renderings), static or dynamic, (eg. animation) where each style may af ford communications of certain types of information (Sirikasem and Degelman, 1990). BIM models, as a communication medium, allow clients to provide timely feedback of designs through virtual reality, thus enable architects to understand and record clients' preferences and to make design corrections in time design (Lertlakkhanakul et al., 2008; Shen, 2011).

Subjects of architect-clients often concerns appearances, functions and budget.Appearances relate to visual attributes of architectural spaces and exterior. The appearance of a building can affect customers satisfactions, which is essential for architects and clients to reach consensus. (Tessema, 2008). Function is the easiest subjection to communication between architects and clients (Kiviniemi, 2005). Budget is the issue that customers concern the most, because it affect many design, as well as construction decisions, including size, configuration, material selection and other details and determine whether the required building can be built within a given budget.

2. Research Objectives

In recent years, tools by using machine learning have been continuously developed to help people integrate and analyze complex information. It even uses the collected information to make combined predictions to help people see new relationships, new information, and inspire people to change their ideas. We plan to use machine learning technology to help architects and clients improve communication and reduce misunderstandings. We look forward to using computers to help us sort out some of the information (language or photo medium) provided by the client, analyze the client's preference for which building types, and let the architects based on the relevant conditions and precautions of this type of building discuss with the client, and then design according to the required materials of this type, and quickly form a visual medium by sketching to provide the client's reference to make the communication process smoother (Figure.1).

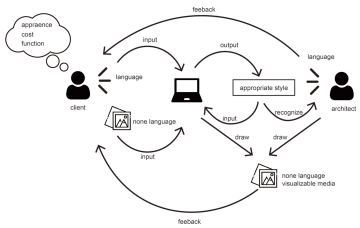

Figure 1. New communication flow.

3. Language Assistant (LA Model)

Clients often use their own experience to describe their requirement orally. They probably don't know what style of buildings are made of fair-faced concrete, but they tell the architect they want them house like some case was built by Tadao Ando. Or tell the architect, I want the Japanese style house. But the architect is not certain his thought the Japanese style is same or not with client thought. It's is easy to cause trouble for young architects with inexperience. Therefore, if we can help the architect to translate the blurred information in a clearer way, the architect can have a more accurate grasp of the needs of the client.

3.1. ABOUT THE TEXT

Because we lack the record of the dialogue between the architect and the client. Therefore, we use some record witch is the architectural magazine's editors interview to the client. Most of these interview records are narratives of the client's recollection of the process from selecting a site, interviewing with the architect, and completing the building. Although not actually participating in the discussion between the architect and the client, these interview records are based on the client's perspective and tone to discuss how they discussed with the architect and narrate their imagination and requirement for the space, which to some extent reflects the process of discussion.

3.2. MODEL

The NLP (Natural Language Processing, NLP) model is more accurate for semantic processing and is often used, but this model requires a large amount of sample data. Unfortunately, the dataset which related to architectural design is relatively scarce that we have to produce the dataset manually. In this experiment, all the data are classified through interviews and manual records, which cannot reach the amount required for deep learning. Therefore, we need to found an algorithm that can predict relatively accurately when the data is few. Finally, we use the Naive Bayesian Classifier which is commonly used in machine learning languages that still has a good learning effect when the data is not enough. The Naive Bayesian Classifier is based on the Bayesian theorem through the calculation of probability to allow the machine to determine which category a word should belong to. The important assumption of the Naive Bayesian classifier is conditional independence. Each feature is treated as an independent event, and the product of each feature's probability is used to obtain the maximum probability, and the maximum probability is the predicted value.

3.3. DATASET

In order to understand how the architect finds the conditions, limitations, and opportunities of the design in the massive dialogue messages with the client, and observe how the architect translates and classifies these clues into what kind of architectural professional words. And to observe whether different subjects face the same message, whether there are big differences in the labels of the key sentences and annotations. At this stage, we give different subjects the same text

for them to read. And ask them to mark the words and sentences that are helpful to the design according to their own architectural professional judgments, and write their associated architectural professional words to the words and sentences. After the samples were collected, it was found that the selected key sentences were roughly the same (Table 1), and nearly 74% of the key sentences were the same. According to the test results, each subject is concerned about the client's occupation and living conditions. It can be seen that the issues that the architects are concerned about are roughly the same, but the depth and depth of their attention to the same words and sentences due to the different positions or experiences of the subjects (architects, office employees or students) The breadth is also different, and the vocabulary of the label is also different (Table 2).

Table 1. Keywords count and percentage.

	Keywords Selected	Same Selected	Individual Selected
Count	43	32	11
Persentage	100%	74%	26%

Table 2. The example of keywords sentence have different labels due to diffrerent subject.

Keywords sentence	Label			
The house will like a ship. Looks fashion and intersting.	Shape	Appearance	Imagery	
The building was built in fair-faced concrete rectangular box.	Shape	Appearance	Material	
The house is built for retire live.	Purpose	Long-term care	Universal Design	Barrier Free

3.4. DATASET PRODUCTION

After the collection is completed, we organize the data according to some rules. Each word or sentence will be labeled an architectural word. Sometimes only part of a sentence is marked, then the other parts of the sentence will be deleted and only the marked part will be kept. Sentences that are not marked are marked as "none" in order to increase the number of samples. Some headlines in the text are not marked.

Finally, we import the data set for training, and put the trained model into the data that the model has not seen before to distinguish. The result is not ideal, and the accuracy is about 21.4%. We summarized the following reasons:

1. The training set has the most labels with "None": Therefore, the chance of occurrence of nothing is the greatest. If there are more "None" labels in the test set, the prediction accuracy will improve. If the test set has fewer words and sentences with "None", it is possible The forecast rate drops.
2. The labels of the training set are too complex, and the same sentence has different labels, which causes the data set to be too scattered during training and affects the machine's judgment.
3. Data is not enough

In response to these problems, we modified the labeled rules of the data set on some of the factors that caused the problems:

1. The problem of label complexity and insufficient sample size: label complexity and sample size will affect each other. The higher the label complexity, the relative number of samples also need to increase to improve the training effect, so that the computer can strengthen the learning impression. However, data sets related to architecture are currently very scarce. If you want to conduct research on related topics, you need to create a training set yourself. Making training often consumes a lot of time and effort. Therefore, when the number of samples cannot be effectively increased, only The set can be modified to reduce the complexity of the label. In the first experiment, it was found that the words and sentences concerned by each subject were roughly the same, and the words marked on them also had a certain degree of relevance. As far as the results are concerned, we can classify these labeled words, sort out and formulate several architectural professional vocabularies for testers to choose, so as to reduce the complexity of labeling. Therefore, we classify and define several architectural professional vocabularies according to the tags of the previous test (Table 3), and let the architectural professionals select and label the important words and sentences they think. In order to be objective, we also asked the subjects to judge whether there are insufficient vocabulary to be added, and put them in the label after discussion.

Table 3. Definition of Label.

NO.	Label	Definition
0	Traffic	Car Movement; Parking Space
1	Site& Other Conditior	Site Location; Area; Terrain
2	MicroClimate	Temperature; Humidity
3	Building Performance	Ventilation; Lighting
4	Material	Architectual Material
5	Client's Opinion	Client's Opinion
6	Client's Expect	Look forward something but not specified solution
7	Client's Requirement	Specific requirement
8	Historical Issue	In old street area; Historical building
9	Building Code	Building Code
10	Environment	Near by park or school which good for project
11	BulidingType	Residential; Commercial; Factory etc…
12	Function	Function
13	Landscape	Green Belt; River
14	View	Not block view; A good view poition
15	Cost	Cost; Money
16	Open Space	Outdoor Space; Public Space
17	Local Customs	About religon or culture

1. Will not label the unmarked information: In the entire dialogue process, there are very few words that are helpful to the design, so the words and sentences labeled as “no” are also the most. For designers, words and sentences are judged as “no” and have no meaning, and they cannot help designers to make classification judgments.
2. Annotate different texts: the purpose is to increase the number of samples. After reducing the complexity of the label, if the learning effect is to be better, the best way is to diversify the sample to achieve a better training effect. In the last experiment, it was found that the subjects concerned about the same words and sentences, it can be inferred that the words and sentences concerned by the architectural professionals are about the same, but according to their work experience and characteristics (architects, office employees, students, etc.) The depth and breadth of the same words and sentences are also different, and the vocabulary of their labels is also different. Therefore, in the second experiment, different texts of each subject were labeled to increase the number of samples to

improve the training effect of the model.

3.5. DISCUSSION

In addition to showing that the training was more successful(Figure 2), this comparison indirectly helped us sort out the themes that the owners and architects communicated most often. Among them, the top three labels with the largest number are: Client's Expectation (14), Function (11) and Site& Other Condition (10). It can be speculated that the communication between the owner and the architect is divided into two phases:

1. Functions and bases are the easiest building professional vocabulary to describe: The owner can clearly state what kind of space functions he needs, such as how many bedrooms are needed, where the toilet or kitchen is located. Since the owners need a lot of funds to purchase land and require rigorous evaluation, they have a good understanding of the information about the base.
2. The owners have many ideas but are not clear: The label is the most about the expectations of the owners, and it also proves that there are many less clear needs that the owners cannot clearly state. This result also indicates that it is necessary to classify these unclear requirements into several common processing methods in buildings, so that the architect can give the owner some clear suggestions. For example, if the owner wants a house that is different from the neighboring house, he can be advised to use different materials or shapes for design.

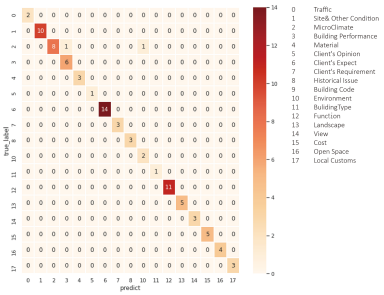

Figure 2. test data result.

Finally, the data that has not been read is put in for identification, and the accuracy is improved compared with the previous stage, about 57.1%. We observe the misjudged labels and find some associations(Figure3). Since the label is the owner's expectation during the training of the model, it is easy to distinguish this label when the model is looking at materials that have not been read. But we can observe that one of the correct labels is base and other conditions, but the machine judges it as microclimate. It seems that it can also correspond to the fact that although certain words are classified under one label, they are actually related to certain labels. The test example, such as building performance or function, may also be included in the scope of the label of the owner's expectation.

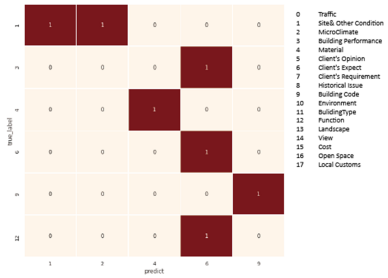

Figure 3. Table between true label and predict result.

4. Sketch Assistant (SA Model)

Why does the client like to take photos to communicate with the architect? Because the photos can directly show the owner's vision of the future of the project. The material and shape of the building itself can be presented in the photo. This is also an architectural professional vocabulary that the client can communicate with. Architects often use sketches for self-conversation, translating their thoughts into current drawings, and sometimes they must also use sketches to communicate with the owners, but they are often too abstract, requiring a lot of effort to explain and spend a lot of sketches. Let the clients understand.

4.1. MODEL

We use Generative Adversarial Network (GAN) to train the pixel-oriented PIX2PIX model. This model is composed of multiple layers of generators and discriminators(Figure4). The generator uses the color blocks we input to generate "fake" pictures and then uses the Discriminator to continuously discriminate the data until the discriminator knows that these pictures are "fake" pictures produced by the generator. The generator will also regenerate more realistic photos that are not judged by the discriminator as "fake" for the discriminator to recognize. The model is the result of the constant confrontation between the two. This model is based on this paper (Phillip Isola et al. 2017).

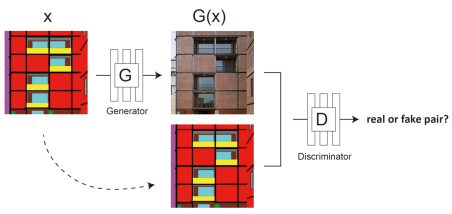

Figure 4. Principle of Pix2pix (Phillip Isola et al. 2017).

4.2. DATASET

We found 199 pictures on the Internet. Because the size of the input picture must be 64 times the length and width of the model, the picture was first cropped to 512*512 pixels. Then make the label color table corresponding to the material, the color is set according to the similar color of the real material. When choosing colors, try not to choose similar colors to avoid confusion. Objects other than buildings are classified as unrecognizable. Finally, we make a image set with a picture and a color block map according to the rules (Figure 5).

color/顏色	R	G	B	label/標籤名
	255	0	255	NA
	256	97	0	painting
	0	153	68	stone
	255	241	0	grille
	0	0	0	metale_plate
	0	0	255	curtain_wall
	0	255	255	window
	255	0	0	brick
	147	45	0	wood
	115	115	115	concrete
	146	7	131	tile

Figure 5. Material Label Rule and Image set.

In order to understand how the architect disassembled the materials on the classified photos, we invited several experienced designers to assist in the labeling. After the label was recovered, we found some interesting classifications. Among them, the classification of certain materials is different due to the judgment of the labeler. For example, because many grids are made by wood, some people label the denser grids to the wood material or classify the sparsely arranged grids on the grid (Figure 6). These classifications are finally reflected in the results of the model.

Figure 6. Some label easy to confuse.

4.3. TRAINING

After organized the image set, we input it to train the model. In the training results of 1200˜7200 epoch, the generated image has roughly the color of the architectural frame and material, but the texture of the material is not satisfactory. Finally, we trained the model to 14,400 epochs, and the generated photos were almost consistent with the original images. Finally, we used the model to generate (Figure 7) and observed:

1. In the material part, according to the number of samples in the training set, it can be generated according to the texture and color with the largest number (for example, the most color of the metal plate is black).
2. The details of the material are still not ideal: from the generated image Look, types with more material details such as bricks or grilles are less effective, which may also be caused by insufficient training samples.
3. The unrecognized part works well: Judging from the generated results, it is surprising that the sky and plants can be drawn.

Figure 7. Result of test data by using epoch 14400 model.

4.4. DISCUSSION

We later discussed the results with the professionals who helped label. When classifying labels, it is found that even the same material will have different colors and textures. Because this model allows the computer to recognize the color of pixels for training, it may affect the training effect. After the discussion, if you want to use this model as a tool for communication, the training model can be adjusted as follows: Several models can be classified according to the type of building, and the choice can be judged according to the owner's needs, such as using style or geographical distinction: the same area or The styles of the buildings are basically similar to the materials used. If you divide them into several training sets (such as Scandinavian style, Chinese style; urban or country), you can choose in use, so you can more accurately judge the effect of the material, The discussion with the owner can be smoother.

5. Conclusion

Our research employed two machine-learning models to help architects communicate with clients more smoothly. In addition, we experimented how architects can transform messages into elements that are helpful to design. Through the process of making training sets and observing training results, we explored the interrelationship of visual and verbal communication data, as well as how to classify relevant data to establish a more accurate model to assist architects and clients to communicate. These two machines are designed for the pre-design stage.

Whether it is creating a perspective video or a BIM model, relatively accurate information is needed to create it. If there is a misunderstanding with the client at the beginning, drawing with incorrect data will not only cause waste in operations, but also difficulty in subsequent communication. Use the machine- learning model to judge the client's uncertain requirement or preferences, and draw photos as an aid communication tool to obtain relatively only inquiries and speculation. The information gathered is much more reliable, especially for new contacts and For junior architects who have less experience in communication with the clients, it can help them grasp the key points. It is also because these two machines have to judge blurred information. Compared with the renderings and BIM models,

they cannot provide accurate architectural effects, nor can they allow the owner to experience the appearance of the house and the use of the interior. Simulation evaluation has been carried out.

The output media of the current LA and SA models are separate. The main purpose is to explore how the architect's operation of the verbal and nonverbal media can be transformed into information that he understands and communicate with the owner after translation. Since it is necessary to understand and confirm the relatively vague information of the owner, visualizing the information makes the communication between the two parties more smooth. In the follow-up research, we will focus on further transforming the information of the owner's language into a visual medium to reduce misunderstandings caused by speculation and make the information clearer for subsequent design.

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