

My Color:

Finding Your Optimal Color Style through ML

Sooji Kim

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Sang-gyeun Ahn

James Pierce

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Abstract

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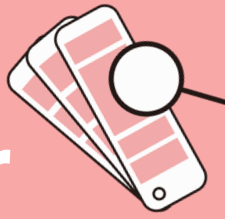
Sooji Kim

Chair of the Supervisory Committee: Sang-gyeun Ahn

School of Art + Art History + Design

During the Fourth Industrial Revolution, Machine Learning (ML) has become one of the most critical technologies in various industries around the world. However, designers tend to view ML as challenging to understand in the design field because they are not familiar with using ML in their actual work. In this paper, I focus on exploring a method that can design a better user experience (UX) in shopping using ML. I present the app My Color, which can analyze people's interior color style and offer recommended colors based on their style preferences. Through this project, I suggest what specifically ML applied design projects can be, and I discuss methodology about how designers can use it positively without being overwhelmed.

My Color



Finding Your Optimal Color Style through ML

Sooji Kim

ML plays an increasingly important role in how new products and services deliver an improved user experience.

Today, **UX designers face challenges in understanding ML capabilities**, in envisioning new products and services, and in collaborating effectively with data scientists.

(Yang et al., 2018)

Introduction

In the era of the Fourth Industrial Revolution, the importance of big data and Artificial Intelligence (AI) technology came to the fore. Artificial Intelligence is a compound word: “artificial” and “intelligence.” It literally means “intelligence created by human.” According to the Merriam-Webster definition, AI refers to a branch of computer science dealing with the simulation of intelligent behavior in computers. Technologies help us in many ways, however, the voice of concern regarding them is also not small. Especially in terms of automation, experts are expecting AI to take over many jobs in the future.

According to the World Economic Forum’s “The Future of Jobs Report 2020”, AI is expected to replace 85 million jobs worldwide by 2025. Though that sounds scary the report goes on to say that it will also create 97 million new jobs in the same timeframe [1].

Also, in an essay posted on Medium, AI guru Kai-Fu Lee — CEO of Sinovation Ventures and author of the 2018 book “AI Superpowers: China, Silicon Valley, and the New World Order” — posits that 50% of all jobs will be automated by AI inside of 15 years. Accountants, factory workers, truckers, paralegals, and radiologists — just to name a few — will be confronted by a disruption akin to that faced by farmers during the Industrial Revolution [2]. AI is expected to supplant designers as well. As many people know, certain design tasks are already being replaced by AI. For example, there are many websites that generate logo designs, many webpage building platforms offer proper design templates and many image editing software (like Photoshop) can automatically detect the boundary of backgrounds and remove them.

Considering this trend in the design field, working with AI technologies is an inevitable future for designers. Designers should understand AI and use it as a convenient tool, instead of being overwhelmed by it.

However, certain designers are not familiar with AI and some of them have a vague fear of it. According to the survey of UX designers conducted by Dove et al, participants uniformly described difficulties in understanding what ML was and how it worked. One respondent noted, “We designers do not understand the limits of machine learning and what it can/can’t do. Machine learning experts often complain to me that designers act like you can just sprinkle some data science onto a design and it will become automatically magical.”(Dove et al., 2017)

Yang et al. also interviewed 13 UX designers and found that almost all of the participants stated that they “know very little” about how ML works. They characterized their ML literacy as “understanding at a very high level... [at the level of] knowing what a classifier is and what a label is.” Only one participant (P6) had taken any ML course; an online course taken well after graduation (Yang et al., 2018).

My initial idea for the paper started from here. I became curious of what could be possible if designers understood ML operations and how to apply them to their work.

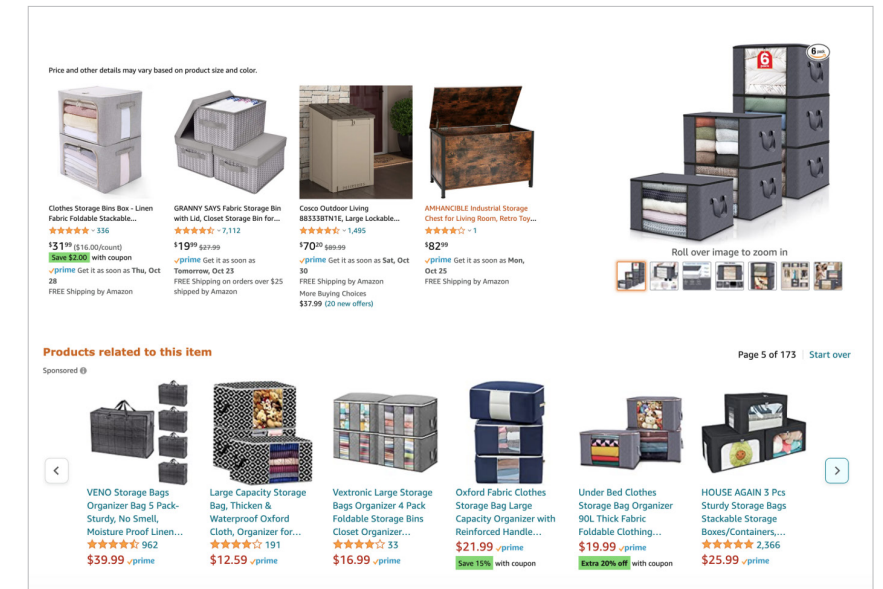


Figure 1. Amazon Shopping Offer

This idea also developed from my moving experience to Seattle in September 2021. During the pandemic, I took my first graduate school year online in Korea, which has a completely different time zone. Moving was tough and a big deal for me. I brought 6 suitcases from my home country and soon my Seattle apartment was full of my stuff.

I wanted to buy something to organize my things, so I went to the online Amazon app and searched for storage boxes. At this point, I realized that the recommendation system was not that helpful for my situation. Since I brought some stuff (such as a mattress and knockdown drawer) from Korea, there was a certain color that I was looking for. However, Amazon’s shopping offer system showed me random shapes, materials, and colors of storage boxes.

It seems the system only considered the category, not which design the user wants. This problem made me more distracted. As a result, I couldn’t decide what I wanted to buy. Based on this personal experience, I started to think about how we could get reinforced recommendation results which considered people’s actual visual preferences — especially focused on color combination — such that it can provide more satisfactory results.

I conducted my project with three hypotheses. First, we can find users’ color style preference with ML technology. Second, we can help users’ decision-making by defining their color style. Third, users can make more satisfying decisions through color recommendation.

Background

Paradox of Choice

We live a more bountiful life than ever before. With money, we can easily get the stuff that we need anytime, anywhere. There are many kinds of items on display in many stores and we can choose what we want from them. We are surrounded by plenty of choices.

“Nonetheless, though modern Americans have more choice than any group of people ever has before, and thus, presumably, more freedom and autonomy, we don’t seem to be benefiting from it psychologically (Schwartz, 2016).”

This phenomenon is called the Paradox of Choice (Figure 2). The Paradox of Choice stipulates that while we might believe that being presented with multiple options makes it easier to choose one that we are happy with, and thus increases consumer satisfaction, having an abundance of options requires more effort to decide and can leave us feeling unsatisfied with our choice [3].

According to Schwartz in his book *The Paradox of Choice, - Why More Is Less*, this is induced by people’s regret about the opportunity cost they couldn’t experience. To prevent this phenomenon and induce consumers’ quick decision-making, many companies introduced recommendation algorithms to provide personalized recommended items. For example, Netflix and Spotify recommend new content based on the user’s play history, and Amazon provides recommended item results through a similar process. Nowadays, these recommendation algorithms have become a core technology in various industries.

Decision Fatigue

Decision Fatigue refers to the decline in the quality of decisions made by an individual after a long session of decision making.

According to the graph (Figure 3), decision satisfaction and decision times are inversely proportional. This phenomenon, called Decision Fatigue, describes the impaired ability to make decisions and control behavior due to repeated acts of decision-making. Evidence suggests that individuals experiencing Decision Fatigue demonstrate an impaired ability to make trade-offs, prefer a passive role in the decision-making process, and often make choices that seem impulsive or irrational (Pignatiello et al., 2020).

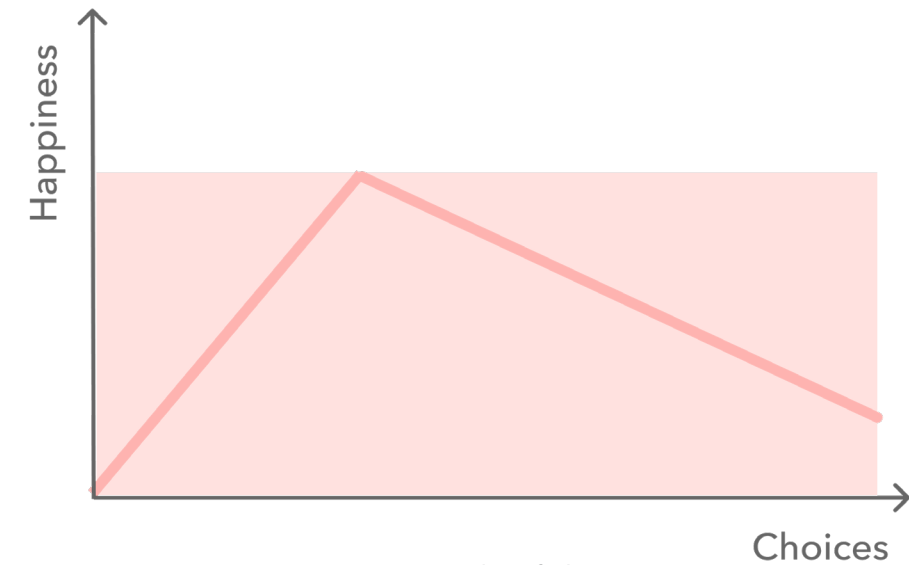


Figure 2. Paradox of Choice

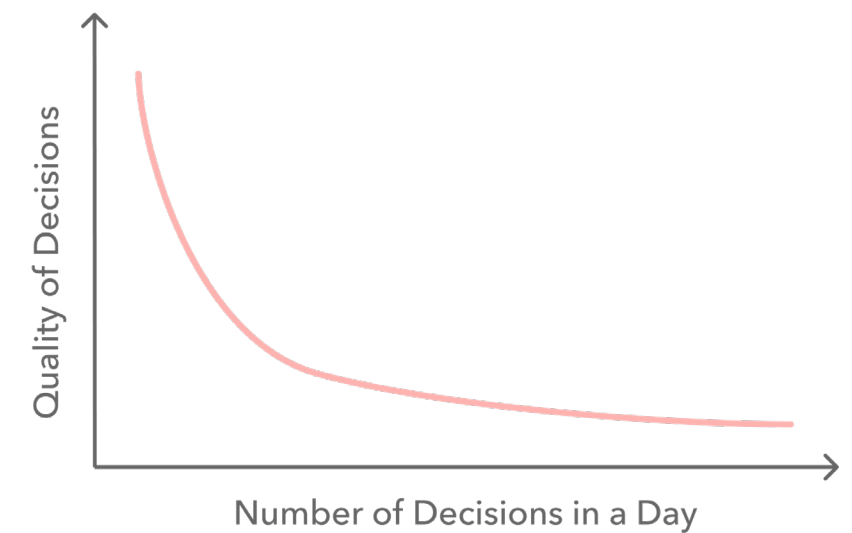


Figure 3. Decision Fatigue

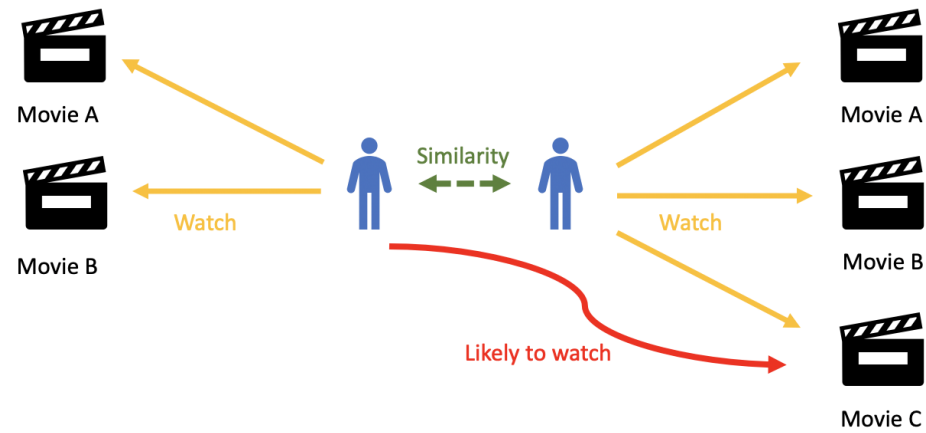


Figure 4. Collaborative Filtering (Leban, 2020)

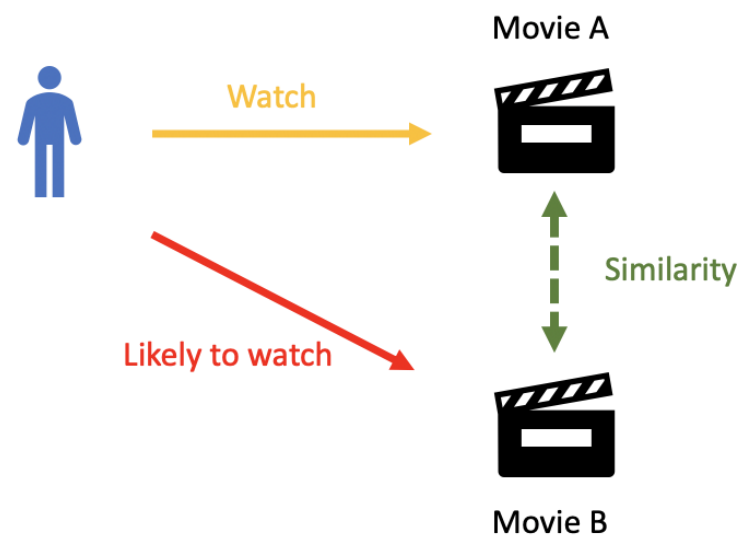


Figure 5. Content-Based Filtering (Leban, 2020)

Recommendation Algorithms

Based on the physiological phenomenon of decision making, to help consumers choose, various recommendation system has emerged. Many companies introduced artificial intelligence algorithms to provide personalized product offers. Recommendation systems predict a user's preference and suggest items by analyzing the past preference information of users. The data used for recommendations can be stored as a preference matrix that represents each user's preference for each item.(Choonho Kim & Juntae Kim, 2003).

There are two main filtering methods for this recommendation system. One is content-based filtering, and the other one is collaborative filtering.

First, Collaborative Filtering (Figure 4) is a popular recommendation algorithm that bases its predictions and recommendations on the rating or behavior of users in the system. This operates based on the user's taste or liking information from their online history and predicts their future choice.

Second, as the name suggests, Content-Based Filtering (Figure 5) operates based on content similarity. In contrast, Collaborative Filtering is based on the similarity of opinions on documents read in the past. It recommends items in the same categories that users previously purchased or liked.

These two ways need user and product information based on their online history. The more online-based data a company has, the more sophisticated recommendations the offer system can make. These system results are reliant on the consumer's online data; they cannot consider the user's actual preference in real life. Although publicly available consumer search engines have become the most effective to search the Internet, these tools fail to satisfy all user demands and preferences.(Hu et al., 2014)

Artificial Intelligence, Machine Learning, and Deep Learning

Today, as the range of artificial intelligence uses is gradually expanding, its implicated technologies keep changing. In general, within AI are the subtopics Machine Learning and Deep Learning. (Figure 6)

Machine learning is the subfield of computer science that, according to Arthur Samuel in 1959, gives "computers the ability to learn without being explicitly programmed." (Ongsulee, 2017). ML is the steps that the machine learns on its own based on provided data. In machine learning there are two main method that generally use for ML. "Supervised Learning" and "Unsupervised Learning." Most machine learning – about 70 percent – is supervised learning. Unsupervised learning accounts for 10 to 20 percent. Semi supervised and reinforcement learning are two other technologies that are sometimes used (Ongsulee, 2017).

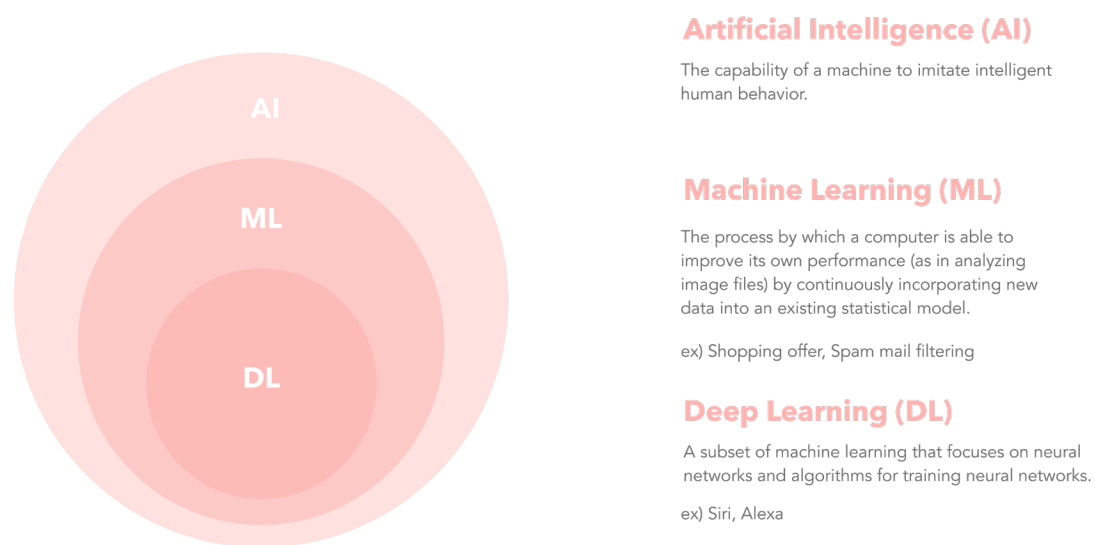


Figure 6. AI, ML, and DL

Clustering

I also interviewed an AI expert who is a former professor in computer engineering, and currently teaching employees at Samsung. We discussed how the recommendation systems in the current day work and is there anything we can reinforce. What I learned from this interview is that current machine learning systems are almost always based on the visual part of the object. For example, one of the unsupervised machine learning techniques is called Clustering.

Data clustering (also called clustering, cluster analysis, segmentation analysis, taxonomy analysis, or unsupervised classification) is a method of creating groups of objects, or clusters, in such a way that objects in one cluster are very similar and objects in different clusters are quite distinct. (Ongsulee, 2017)

Given a data set and some measure of similarity between data objects, the goal in most clustering algorithms is maximizing both the homogeneity within each cluster and the heterogeneity between different clusters (Bouhmala, 2016). Clustering is the process of dividing given objects into several individual clusters, and the number of clusters depends on the capability of the machine and engineer. There are no criteria to classify this process, so the systems must figure out the similarities based on the object value themselves. Therefore, the system determines the similarity based on the object's visual values.

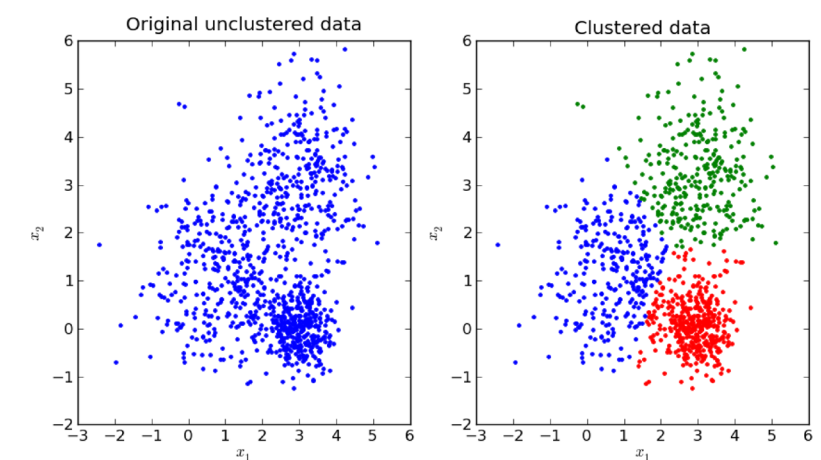


Figure 7. Clustering

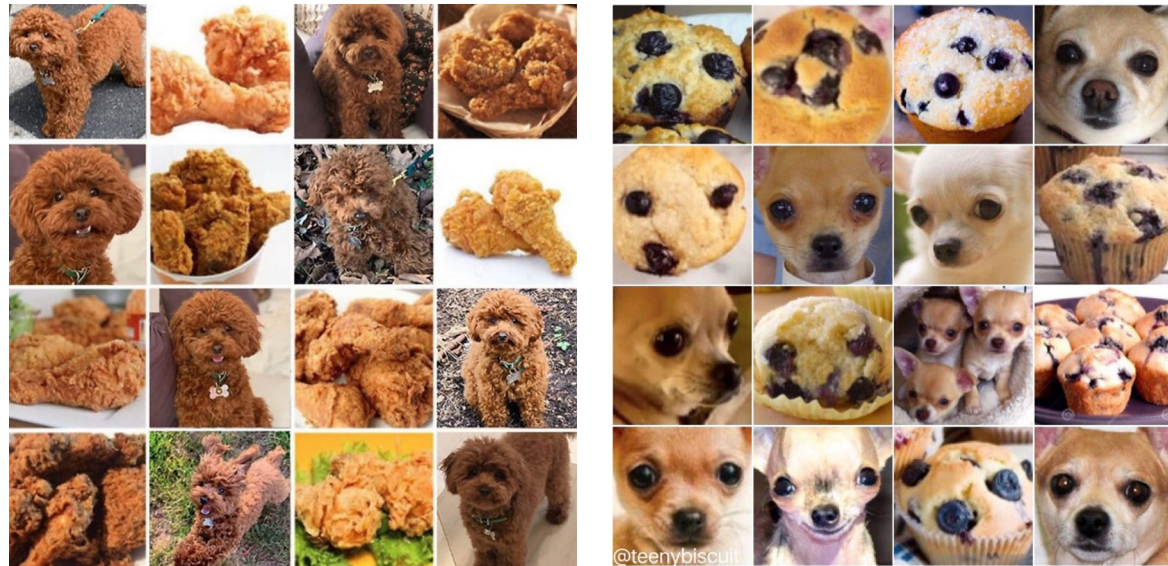


Figure 8. Dog or Food Meme

Unlike human perception, the machine is not able to distinguish objects that have visually similar characteristics. If the data values of two objects are visually identical, the system considers them to be the same objects. One of the most famous examples of this case is the Dogs or Food meme that can confuse the ML system (Figure 8). As far as we know our visual perception and abstract thought has been trained by 540 million years of data and 100 thousand years of data respectively. And we have transferred them into our new inheritance. Answers for newborn baby mathematic skill, and color, visual objects recognition are explained using those facts. Conversely, so far our machine learning capabilities are still not sure about such tasks (Togootogtokh & Amartuvshin, 2018).

K-means Clustering

K-means Clustering is a popular data-clustering algorithm. The K-means is a simple and well-known algorithm used for solving the clustering problem. The goal of the algorithm is to find the best partitioning of n objects into k clusters, such that the total distance between the cluster's members and its corresponding centroid, representative of the cluster, is minimized (Bouhmala, 2016). (Figure 9).

It is attractive in practice, because it is simple, and it is generally very fast. It partitions the input dataset into k clusters. Each cluster is represented by an adaptively-changing centroid (also called cluster center), starting from some initial values named seed-points. (Žalik, 2008)

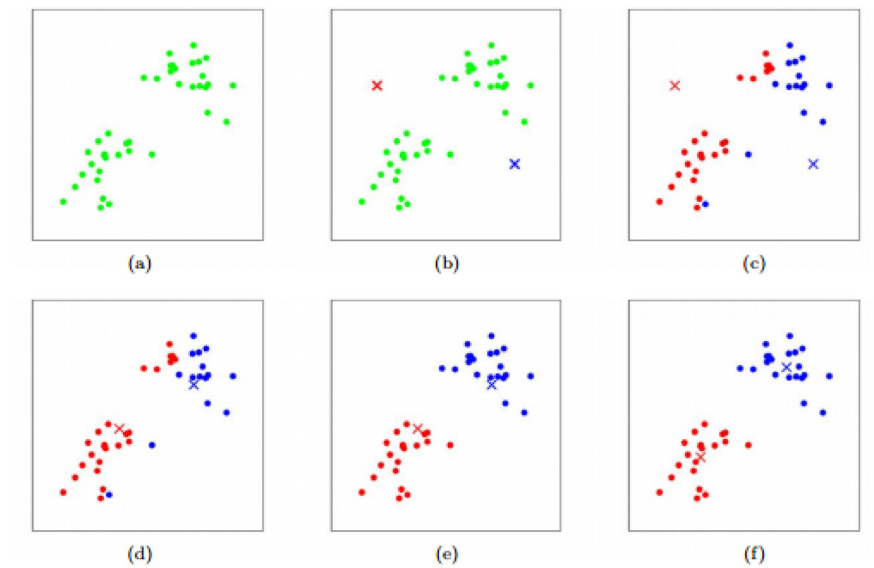


Figure 9. K-Means Clustering(CS221, n.d.)

Color Combination Image Scale

Colorist: A Practical Handbook for Personal and Professional Use is written by Shigenobu Kobayashi. In this book, Kobayashi suggests a useful color combination guide for many works. He presents the color image scale to help people decide on the proper and compatible color in various situations. Kobayashi used these 130 colors systematically, and psychologically representative colors as research samples in various studies using methods such as the semantic differential technique, and developed a Color Image Scale that clearly demonstrated the semantic space of colors (Horiguchi & Iwamatsu, 2018). I designed my project system based on his color combination classification and style names.

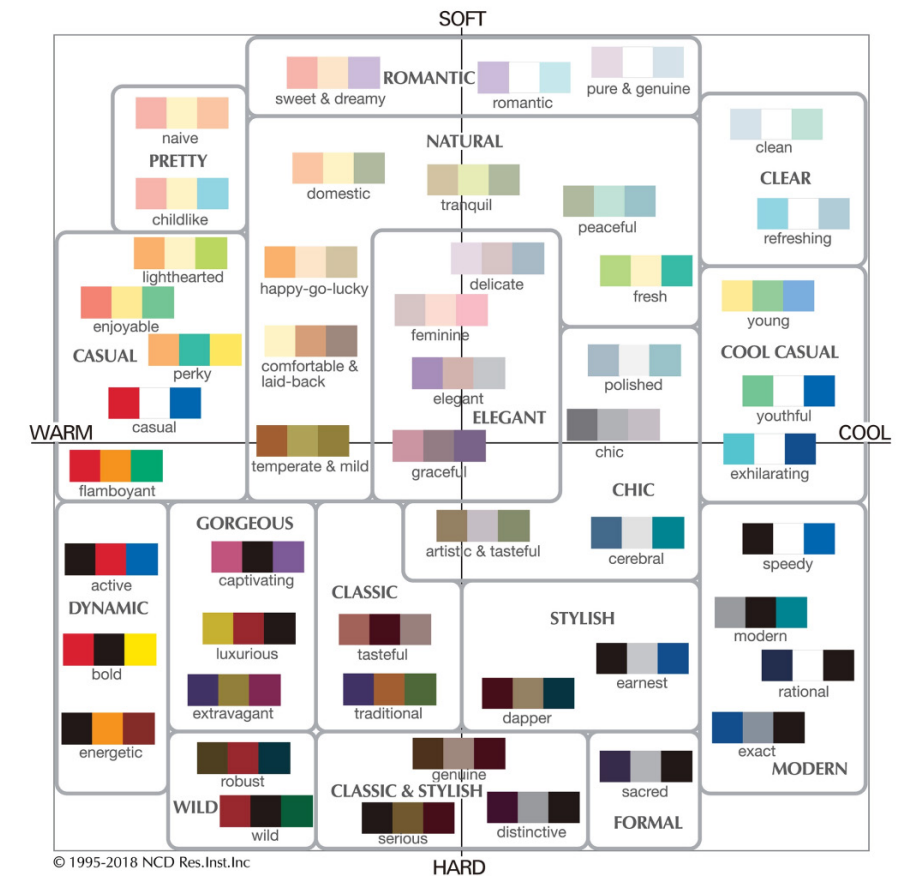


Figure 10. Color Combination Image

Research

Related works

There are many studies on how to classify data using clustering technology. I investigated several related papers with image and style clustering focuses. Usually, this aspect is addressed in the engineering field more than the design field, where they are focused on introducing new mathematic formula that can apply to ML. Therefore, I aimed to confirm the possibility of style clustering.

A. Oil painting style classification

In the paper “Image Style Classification Based on Learnt Deep Learning Correlation features (Chu & Wu, 2018)”, Chu and Wu explored methods of organizing oil painting art based on their visual and material appearance with one of the Deep Learning techniques, Convolutional Neural Network (CNN) (Figure 11, 12). They transformed such correlations of artwork into style vectors and utilized them to achieve image style classification(Chu & Wu, 2018). With these datasets of art styles, Chu and Wu proposed classifying the data by art trend, artist, and style of work.

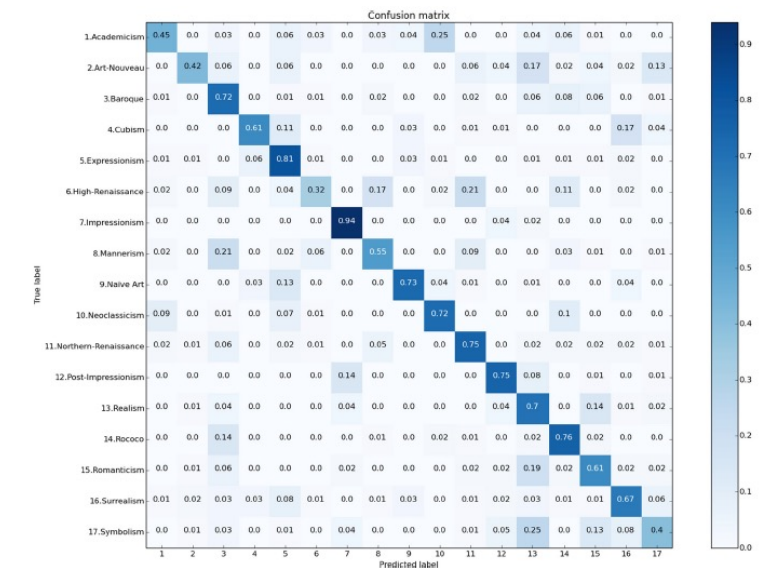


Figure 11. Confusion matrix of classification results for oil painting

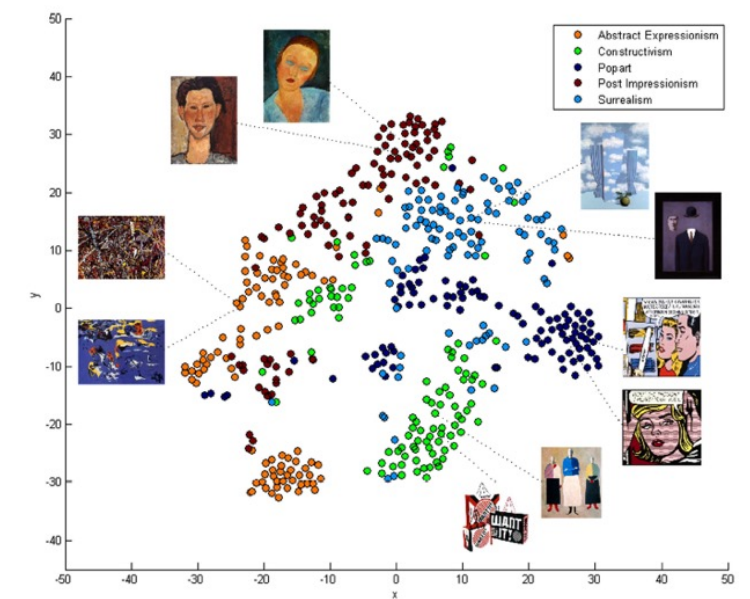


Figure 12. Illustration showing the two-dimensional distribution of selected painting images in the Painting-91 dataset.(Chu & Wu, 2018)

B. Handbag Recognition

In the paper “Image Style Classification Based on Learnt Deep Learning Correlation features (Chu & Wu, 2018)”, Chu and Wu explored methods of organizing oil painting art based on their visual and material appearance with one of the Deep Learning techniques, Convolutional Neural Network (CNN) (Figure 11, 12). They transformed such correlations of artwork into style vectors and utilized them to achieve image style classification (Chu & Wu, 2018). With these datasets of art styles, Chu and Wu proposed classifying the data by art trend, artist, and style of work.

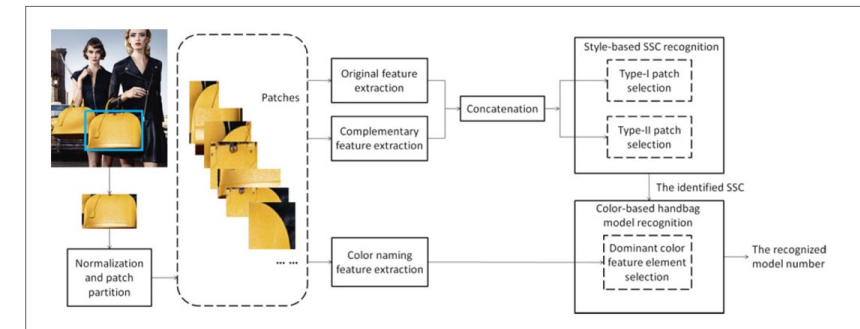


Figure 13. Overview of the designed handbag recognition framework. (Wang et al., 2016)



Figure 14. Examples of feature extraction process and result (Wang et al., 2016)

C. Interior Design Styles classification

Kim and Lee suggested an approach for identifying and appending interior design style information stochastically with reference images and a deep-learning model in their article (Kim & Lee, 2020). Using Deep learning model training, they classified the interior design dataset based on the general definitions of design style. Kim and Lee also applied CNN-based approaches for the recognition of design-related information in images.

The above paper’s projects are about image data classification based on their intangible style criteria with AI technology. In general, those kinds of projects are conducted by engineering disciplines. Therefore, the focuses are on demonstrating that their theory works and on suggesting new formulas that can apply to the algorithm. I wanted to apply their classification task methodology to design new types of user experiences for retail decision-making. Therefore, I developed a speculative app that can analyze users’ color style preferences based on these proven possibilities. It also provides some color recommendations to apply to their daily lives - especially in home interior design.

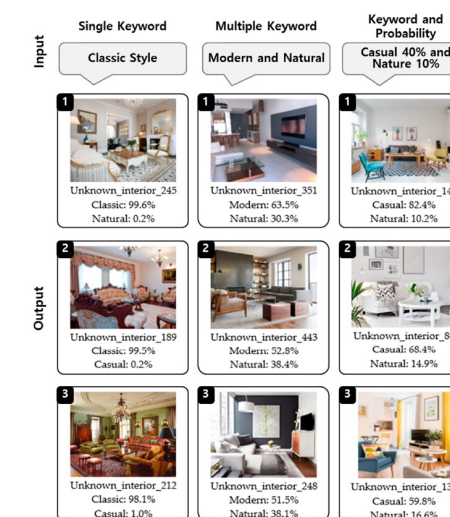


Figure 14. Examples of retrieval of a reference image with detected style information from the database (Kim & Lee, 2020)

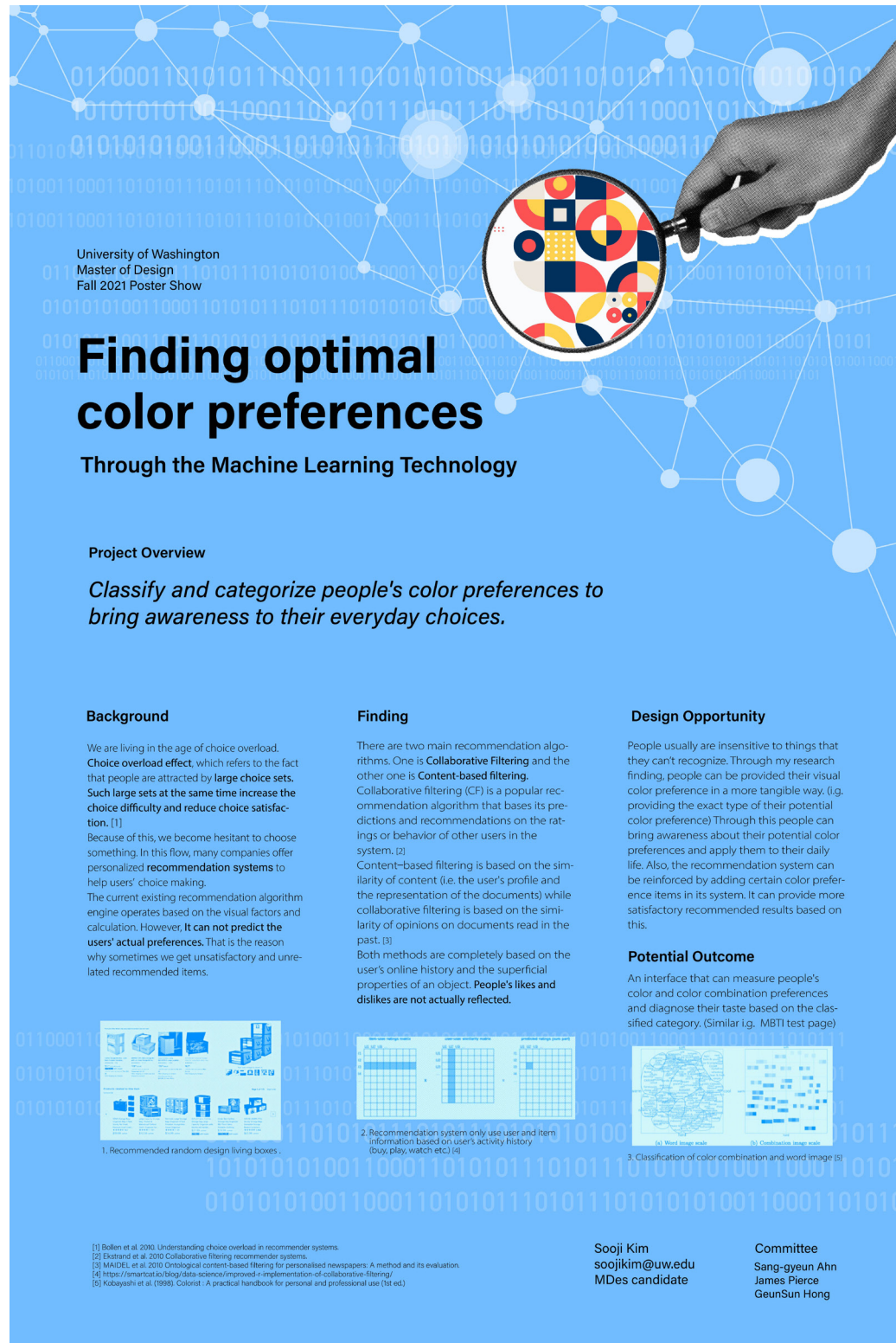


Figure 16. Thesis Poster

Process

Thesis Poster Show

In December 2021, we had the UW MDes Poster Show. We invited our alumni and acquaintances to discuss and get advice on the thesis projects we have done so far. During the session, the main feedback I got was, "What is your final deliverable going to be?" Also, people were curious about my focus because at that time, my subject was an unfamiliar concept to everyone.

Throughout the poster show, I realized that my thesis concept was challenging to explain and uncertain for others. Therefore, I tried to decide on the final output first. Through ideation sessions with my committee members and an AI expert, I determined that my final deliverable should be a chatbot that can diagnose users' color preferences in interior design.

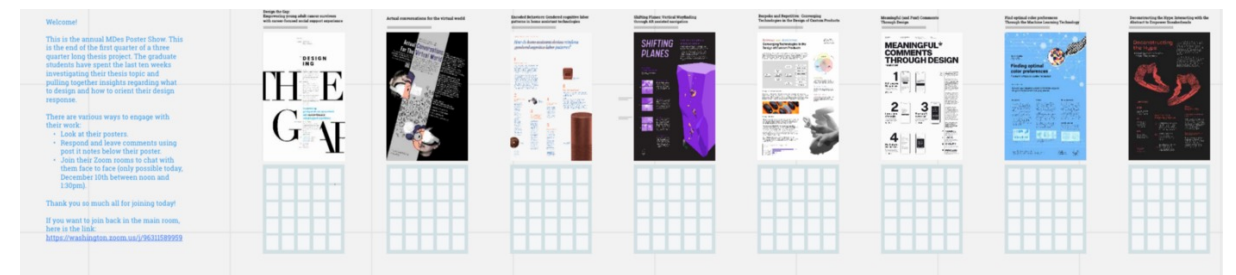


Figure 17. UW MDes Poster Show

User Research

Before I designed the app, I conducted user research. According to Jacob Nielsen, the best results come from testing no more than five users and running as many small tests as we can afford (Nielsen, 2000). At first, I interviewed five participants in their 20s, which is the ideal number for user research. I asked about their first home interior decoration experience and its difficulty. Based on the resulting insights, I created two primary personas to explore the necessity of my potential output.

Sarah is a thirty-two-year-old marketing intern, who recently moved into the area, but due to limited time and budget, she cannot pay much effort into her interior design (Figure 17). Jonathan is a thirty-five-year-old engineer who recently got a better job offer. Therefore, he and his partner moved into a new house, but they struggled to choose a wall paint color (Figure 18).

In addition, I made more specific user storyboards to focus on the app-using situation. Both situations are about moving with different problems. In Sarah's case, she needs the app to make a prompt and efficient decision on her home interior. On the other hand, Jonathan and his partner need to identify their style preferences to negotiate their opinions on the wall color. I also tracked their user journeys and emotions on each step to find opportunity spaces for my potential service.

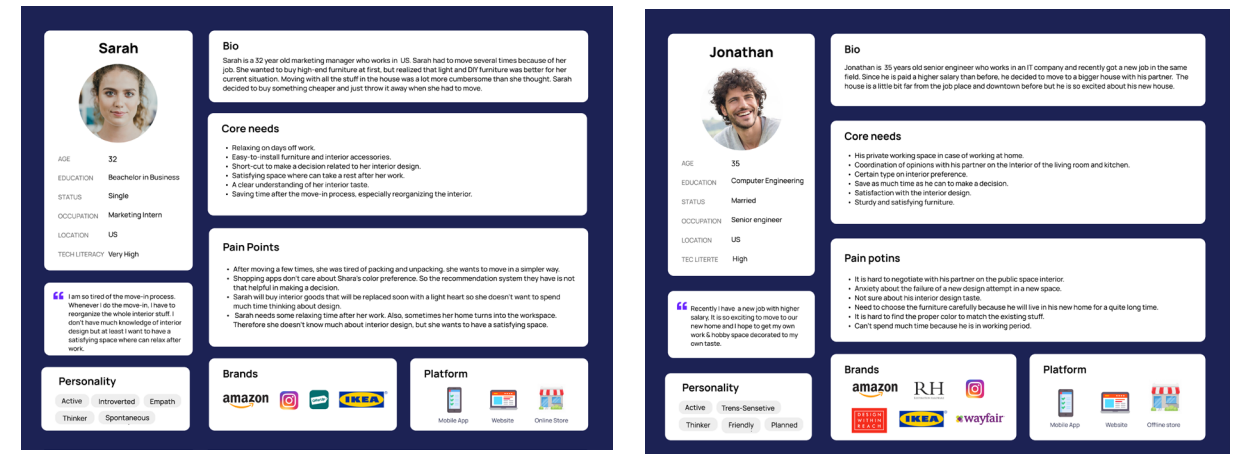


Figure 18, 19. User Persona

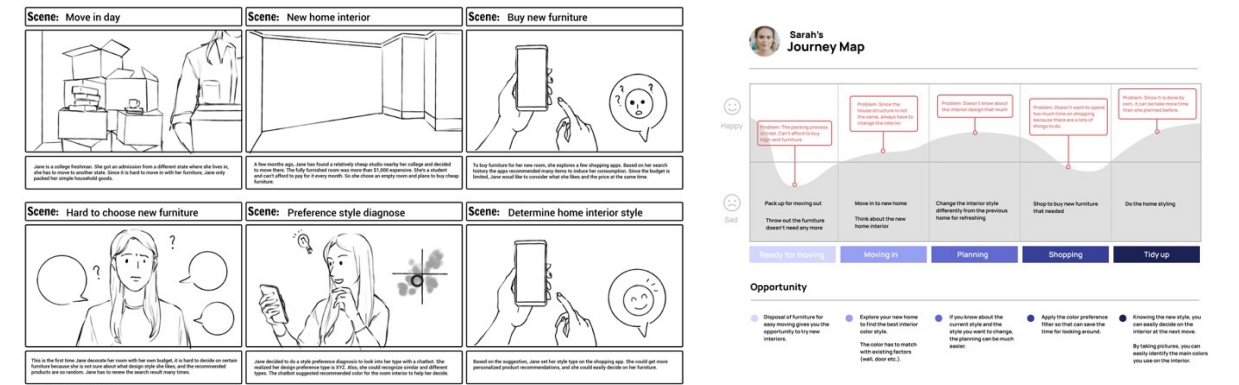


Figure 20. Sarah's storyboard and user journey map

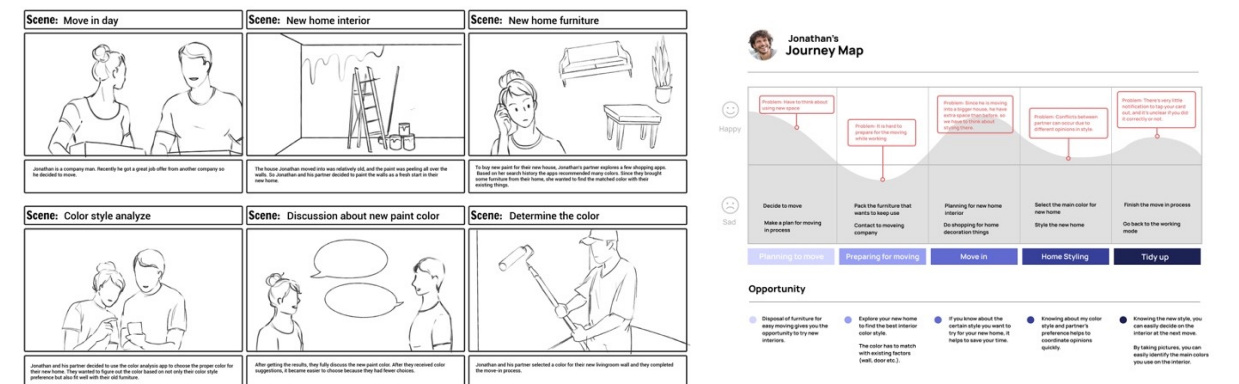


Figure 21. Jonathan's storyboard and user journey map

Ideation

My initial idea was to build a chatbot to analyze users' interior style preferences by reflecting Kim and Lee's aforementioned "Interior Design Style Classification" study. The concept of this idea is through a simple Q & A process with the chatbot. Users can quickly get interior style suggestions based on their preferences.

I discussed the chatbot idea with an AI expert and developed the idea based on his feedback. Through this process, I mainly learned about how the chatbot works in general and the pros and cons of many variables that will occur in the chatbot. In summary, I realized that I need a massive dataset to conduct image style clustering using ML, and it is hard to make the chatbot work. Therefore, I put forward my chatbot as a speculative design project and decided to focus more on interface design rather than how I could make it a real product.

After more discussions with the expert, I made a draft chatbot processing wireframe (Figure 22). It follows the general machine learning task performing process:

1. Gather training data
2. Label (Classify) training data
3. Deploy model
4. Run the model (provide the result value) (Big Endian Data, 2017).

I expected to collect an interior style data set as the first step and identify each style through clustering technology. Users can deploy the chatbot function using a Q & A session, with the chatbot drawing on this accumulated data. Throughout this process, users can get results about interior style preferences.

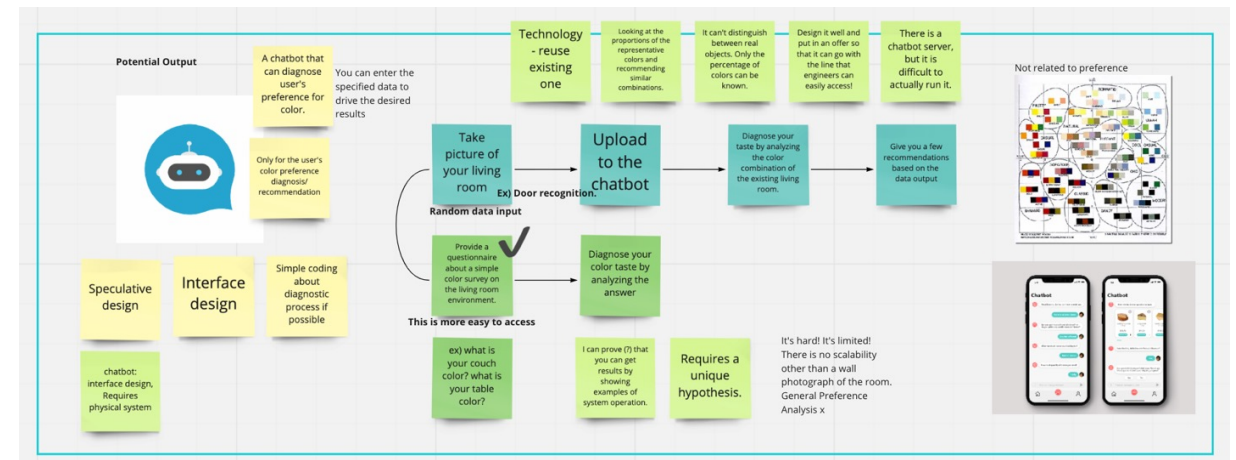


Figure 22. Discussion about the chatbot system and feedback from AI expert

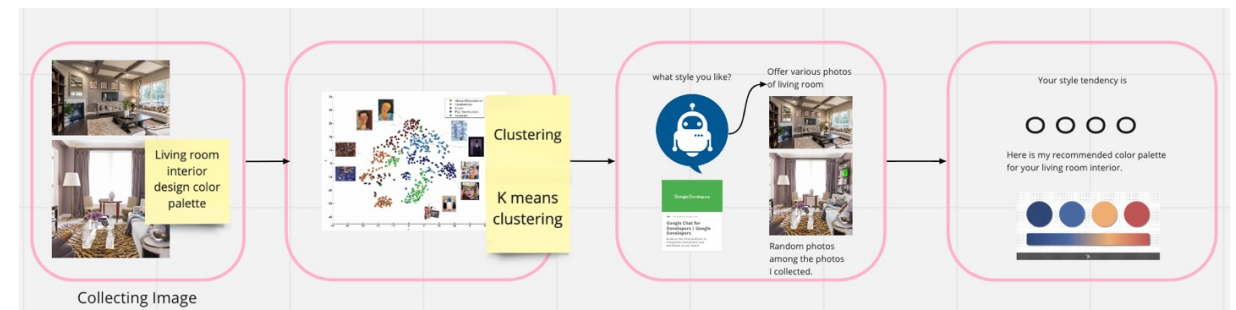


Figure 23. Early ideation of the chatbot process

Database

The first step to building a chatbot is to create a database that the machine will learn. I tried to create an interior design-style database for this process consisting of many (around 7k-10k) interior photos. Since it could not download more than 7k photos manually, I found a program named Extreme Picture Finder. Extreme Picture Finder (Figure 23) is a powerful tool that can automatically download and save related images online (from various websites). It allows users to save many pictures at once.

I downloaded more than 10k home interior photos online using this program (Figure 24). I thought 10k was enough to make the database. I stopped collecting them and then studied how I could put the data into the machine to conduct the ML process.

I asked another AI expert for his advice, and from him I learned that only collecting a large number of images is not enough. To use these images in a database, I realized that all images in the data set should be modified into the same perspective, composition, size, and name.

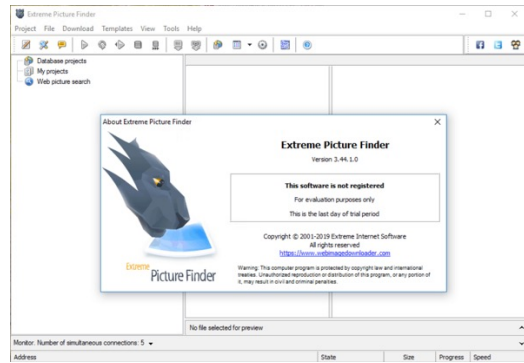


Figure 24. Extreme Picture Finder

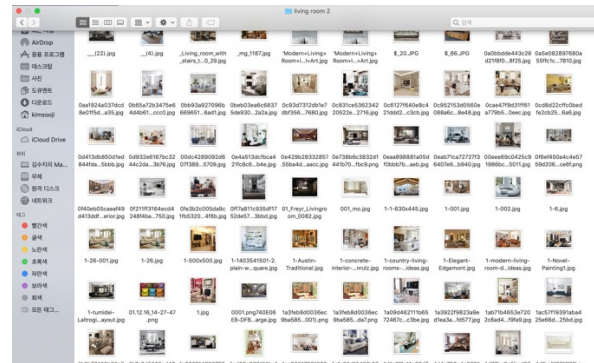


Figure 25. Collected Interior Design Style Images

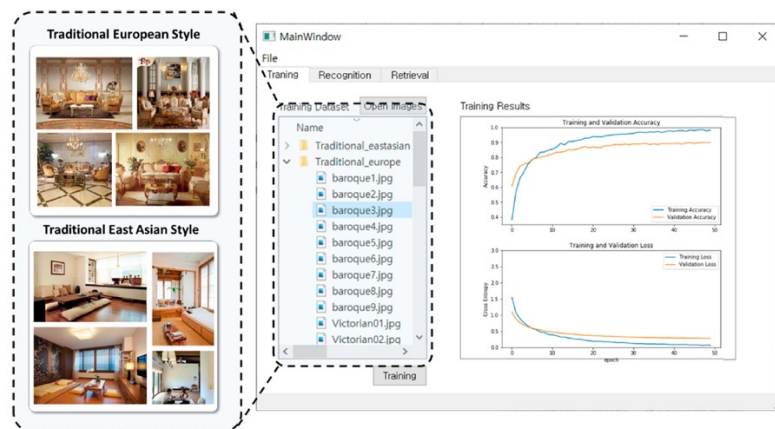


Figure 26. Ideal interior design classification database (Kim & Lee, 2020)

Color Combination and Proportion

After noticing it could not classify these styles by the deadline, I decided to slightly change the thesis focus. I began concentrating on color and color combination, which is easier to recognize for non-experts. Color is a powerful communication tool and can be used to signal action, influence mood, and even influence physiological reactions [4]. People perceive the same color differently depending on the color combination. Cotopaxi is an outdoor brand that creates unique design products. What makes Cotopaxi unique is their color combination. Even bags of the same design can look completely new depending on the color combination. (Figure 26). Color combinations can create different vibes such as dazzle, soothe, or charm. We can all use and enjoy a broad spectrum of colors in our lives, regardless of our income level or profession. (Sutton, 2020).

Color proportion is also one of the most important factors that can impact color perception. The proportions of color affect the visual aesthetic quality of the landscape. Ma et al.'s study demonstrated the Visual Aesthetic Quality (VAQ) of landscape through combination with other colors rather than only one-color feature (Ma et al., 2020).

Based on these characteristics of colors, I changed direction from home interior style analysis to home interior "color" style analysis. A new color analysis app was conceived because color combinations and proportions can be used to create various styles.



Figure 27. Cotopaxi bags from official website

K-means Clustering Coding

To experiment with the possibility of this potential app's operation system, I conducted the ML coding in Google Colaboratory environment. Colaboratory, or "Colab" for short, is a product from Google Research. Colab allows anybody to write and execute arbitrary python code through the browser and is especially well suited to machine learning, data analysis, and education [5].

I used the existing K-means Clustering method [6],[7] to extract the dominant color palette from home interior images. The clustering technique of K-means is one of the simplest and most popular clustering algorithms that can get representative colors of the images (Pavan Kumar et al., 2020). Therefore I could easily access the example code sources. The first process to consider is the proper determination of the k number of clusters. In this experiment, the number of colors that appear as the color palette depends on the number of k's. In general, color can be classified into RGB color and Black and White. Therefore, I set k to 5 so that there are five colors of the dominant color palette that appears.

I also connected my Google Drive with Colab so that I could input images that I wanted to analyze. After I uploaded an interior design image, I resized it to reduce the memory occupation for agile processing. With this code, I could confirm the palette of five dominant colors used in home interior design and the approximate proportion of the colors (Figure 27). At first, these were satisfactory results for me. However, from the user's point of view, I decided that providing the accurate color proportion would be more helpful to them in adjusting their home color ratio.

I applied another code that had a similar input method and processing method, but only the result value can be displayed differently [7]. At this time, the practice code itself contained operators that could not be processed in my environment, so I modified and compiled them. After I ran the code, I could get ideal results regarding the color palette and proportion

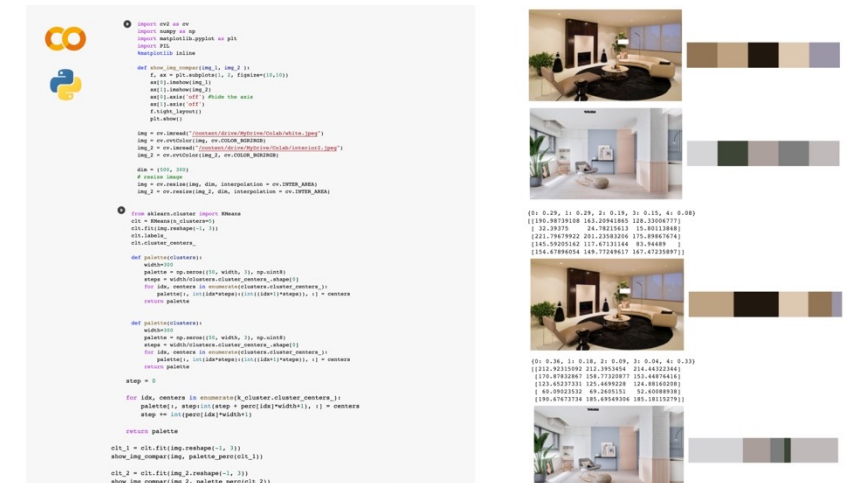


Figure 28. Color Palette Extraction with K-means Clustering



Figure 29. Color Palette Extraction with K-Means Clustering with Exact Proportion

Clustering and Data Similarity Measure

As I mentioned above, Clustering is the technique of organizing data with similar characteristics into groups. As a result of this, each group has its own characteristics because clustering is an algorithm that amasses similar data. Also, when clustering results are represented in two-dimensional graphs, clusters of similar characteristics will be located close to each other and away from clusters of different features. (Figure 29).

Based on these aspects, when the researcher finds the similarity measurement of each cluster data, they find the distance between two clusters and classify clusters with lower distance values between them as similar data, and higher distance values between them as different data. There are four popular methods of similarity measurement: Euclidean distance, Mahalanobis distance, Minkowski distance, and Cosine similarity

Therefore, if we suppose Figure 10 (Color Combination Image Scale) is a clustering result, I propose the recommendation algorithm of the app to be based on similarity measurement (Figure 30). Assume the Elegant style as a reference point (pink area). A similar style would be the styles in the purple area. In contrast, the green area would have the opposite styles. When the user gets their home interior color style result, the system calculates the distance of each style and then recommends color based on the closest distance. More specifically, if someone gets an “Elegant” result in color analysis, that person will get color and style recommendations in the purple area. As a result, users can get similar style recommendations that reflect their preferred color style.

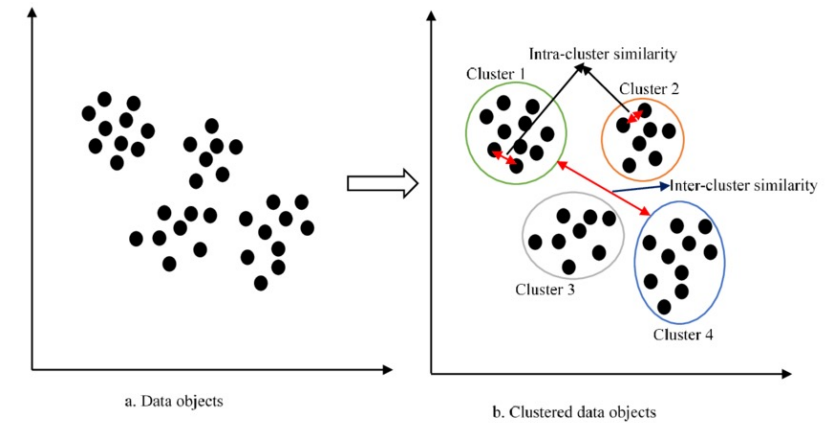


Figure 30. Clustering Results and Similarity (Ezugwu et al., 2021)

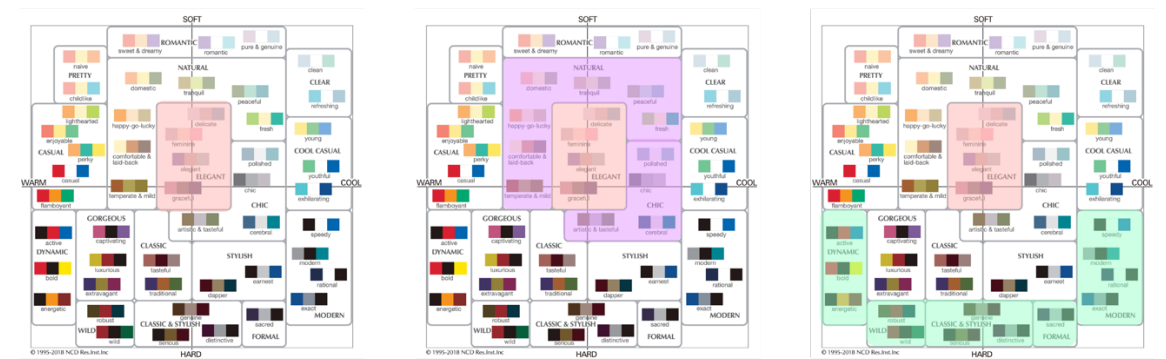


Figure 31. Similarity Measurement on Color Style

Wireframing

Following the project concept change, I redesigned the app's wireframes based on the process I designed during early ideation (Figure 31). I focused on the collaboration between ML technology and the color analysis function on the app. The app service offers a better experience to shoppers by making shopping offers centered on user-preferred color styles. In addition, the color recommendation and shopping offers are based on intentionally provided user data. To use the app service, users must select the interior design image that they want to get analyzed. This process can make more refined results because the given data is based on the user's real-life preferences, not arbitrary online data. Therefore, this app can exclude potentially unrelated offers in advance. Rather than making many functions on My Color, I focused on making style analysis the core service.

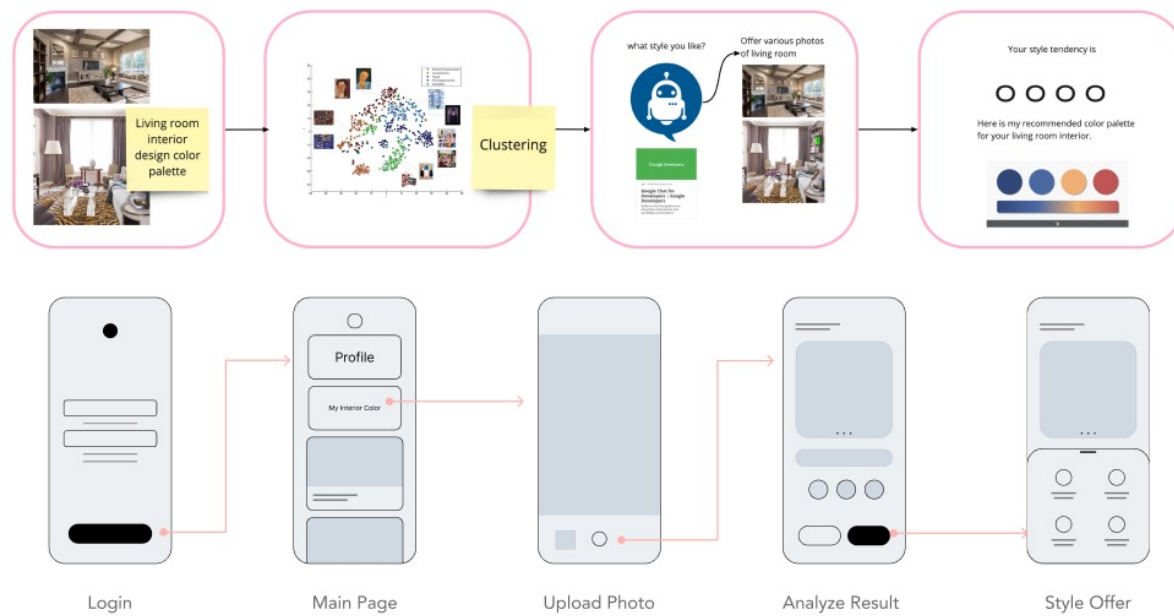


Figure 32. My Color Wireframing

Result

Applying what I studied about ML, I propose the speculative app prototype named My Color. It has four main processes:

1. Upload an online image or photo (input data)
2. Analyze dominant colors and proportions (featured extraction)
3. Match a color style (classification)
4. Show the result (output).

I designed the My Color app prototype and created a promotion video as part of the final deliverables. The video is not only for my thesis work, but also for the Master of Design's graduation exhibition at the Henry Art Gallery. Therefore, I couldn't include the entire thesis research process. The My Color video instead focused more on the user journey storyboard and app features as opposed to the technology research. It consisted of two main parts. The first part is Will's story, who needed the My Color service for his moving situation. I organized user research as one case and made-up Will's case to evoke more empathy.

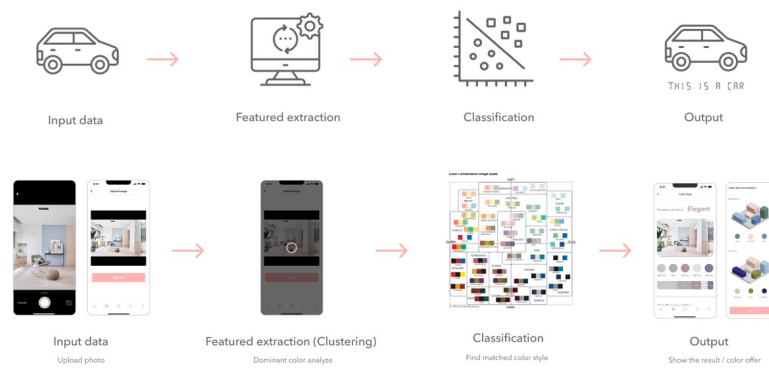


Figure 33. How Does My Color Work?



Figure 34. My Color Mockup

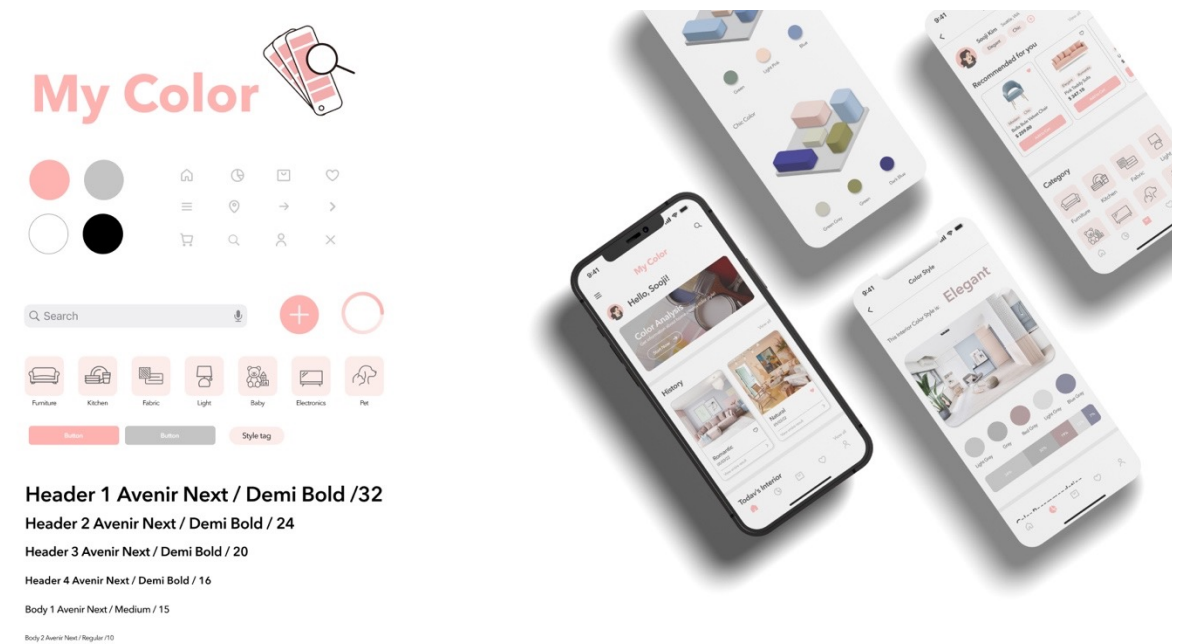
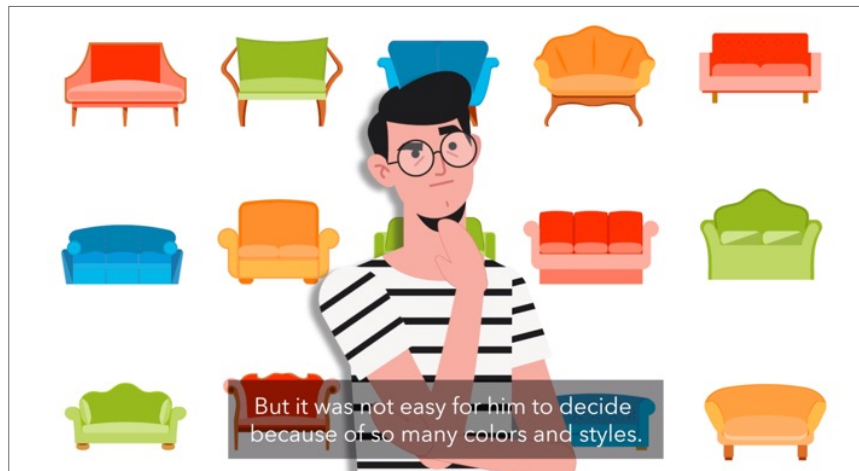


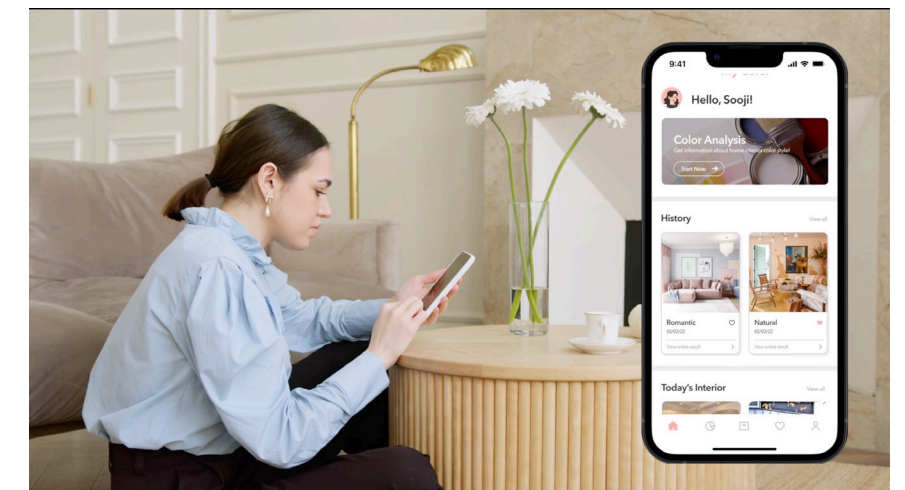
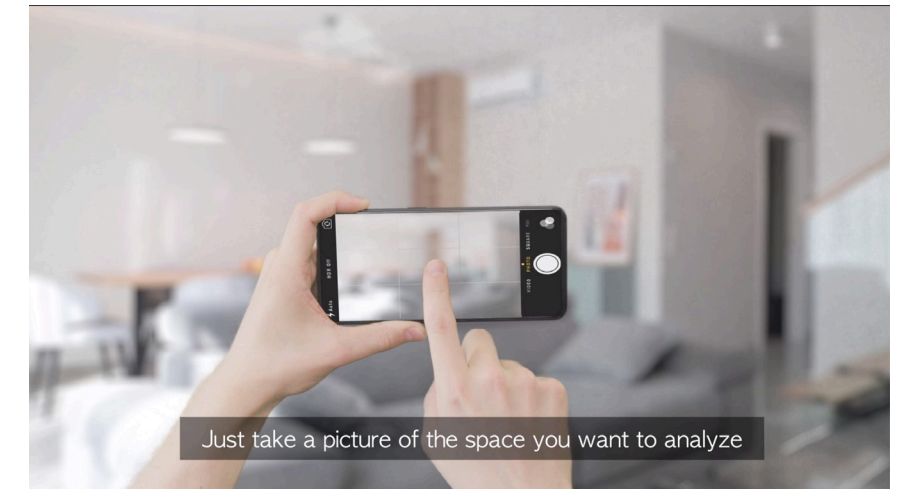
Figure 35. My Color Design System



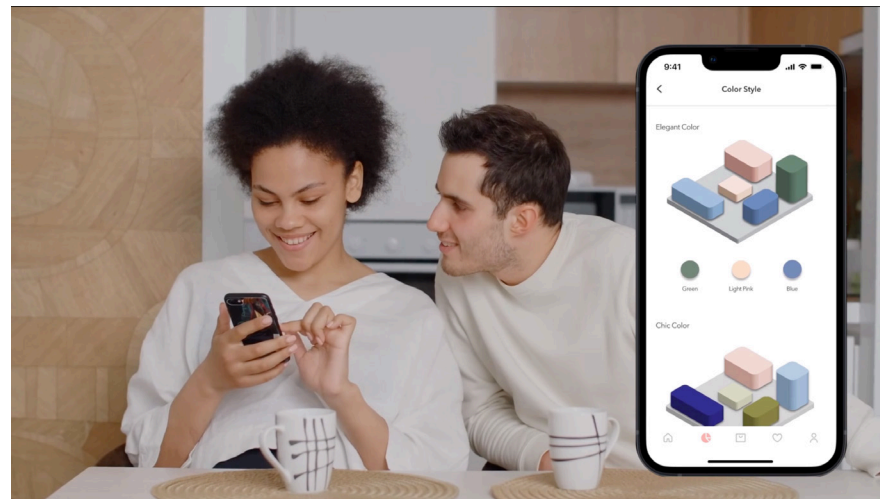
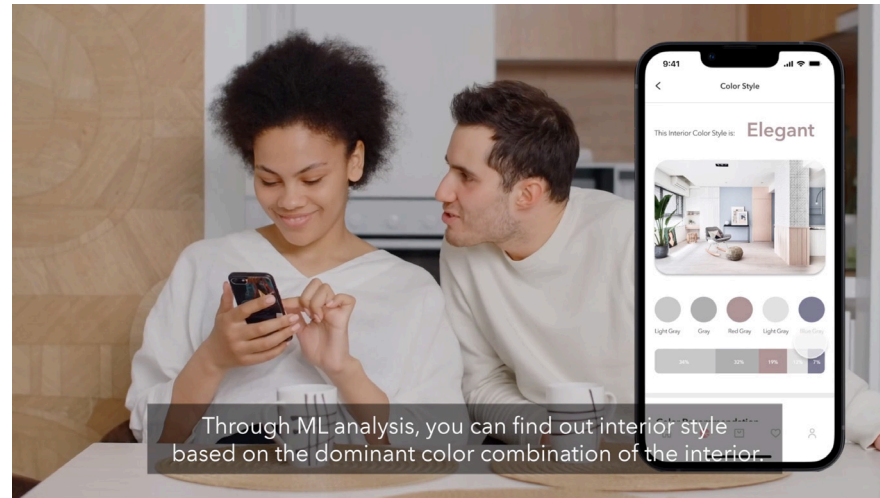
Will's Moving Story

In the story, Will is a 31-year-old software engineer who got a new job offer with a higher salary in New York. He decided to move for the job and prepared for a long journey. Since Seattle to New York is long-distance, to save on moving costs, Will only brought useable furniture and threw away old and broken stuff. After arriving in New York, Will faced a new problem. He needed to buy the furniture he lacked and he also wanted their colors to be based on his existing furniture. However, Will was not familiar with interior design. In addition, this was his first time picking a style for his new home. Furthermore, there are so many furniture options to go through. Even though he cannot make up his mind quickly, the day he starts working was coming up soon.

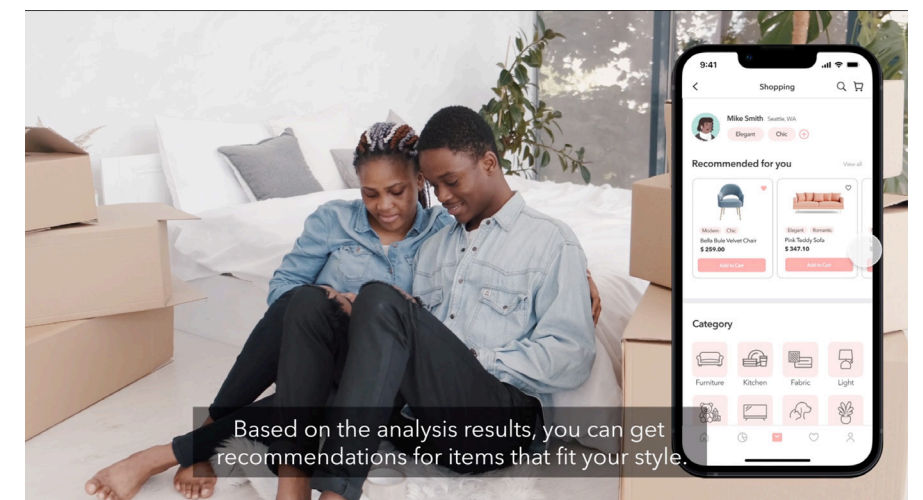
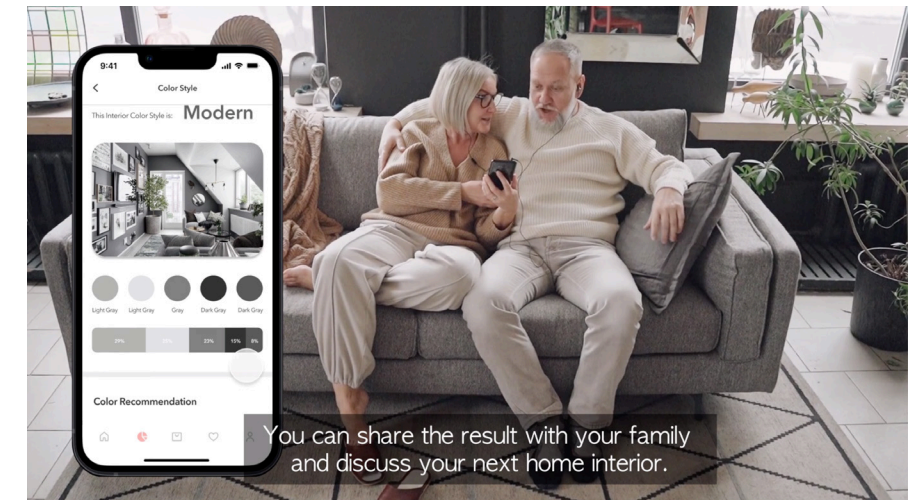
How to Use My Color



First, input a home interior design image on the analyzing page. Users can take a picture of their home interior or any other interior design they want to refer. Also, if users already have an interior design image from another source that they want to try, it is possible to upload from their photo album to the app.



Second, receive the color style result of the interior design and try a new color. In this process, ML technology is applied and provides the result promptly. K-means clustering extracts the dominant color palette and color proportion. Based on the color image scale, the result is mapped on the two-dimensional environment, and a matched style can be founded.



Third, share their style results with their family members and get personalized offers based on their color style. Using the My Color app, they can perceive their color style and adjust their opinions on their possible new home interior with their family members efficiently. In addition, with a personalized shopping offer that considers their color preference, users can make quick and satisfying decisions on their shopping.

Reflections

One of the main purposes of my work was to explore UX design work that could apply ML. I have done this by making a speculative color analyzing app prototype that proves this realistic possibility through understanding and practicing ML coding. Through my thesis project, I understood the basic concepts and capabilities of ML. When I brainstormed about the design concept, I started to think about the technical aspects as well, and I was able to look for possibilities in a wider range.

ML plays an increasingly important role in how new products and services deliver an improved user experience. Today, UX designers face challenges in understanding ML capabilities, envisioning new products and services, and collaborating effectively with data scientists. (Yang et al., 2018) Interdisciplinary work has been emphasized as the boundaries between academic fields became increasingly ambiguous, and the importance of communication and interests between each field is gradually emerging. With this trend, it is inevitable that future designers will have work with various technologies. I think it is essential for designers to have a basic knowledge of these emerging technologies and learn how to incorporate them into their future work. If designers start doing this, there will be no limitations constraining their design expression.

Conclusion

In this paper, I explored ML-related methods that improve user experiences through shopping recommendations. Applying my research into ML technology, I proposed My Color, a speculative application design project for getting personalized color style analysis and color recommendations. I also conducted end-to-end UX research to make the project more specific and realistic. Based on this study, I confirmed the possibility of ML and UX collaboration work.

I proposed the My Color app, a new method to provide more personalized shopping offers that consider the user's interior design preferences. The app's operation follows ML data processing procedures; Clustering and K-means Clustering were applied to the app's color style analysis.

Throughout the project, I figured out what kind of design work could be done through using ML as a part of the project. In addition, I wanted to discuss how designers can regard ML as one of their design tools, like Adobe Creative Suite or Figma, and how they can actively use it in their design work. I think one of the main reasons designers are unfamiliar with technology is their frequency of exposure to them. Getting used to technology is probably the best way to use it correctly without being overwhelmed. However, one question remains for the future: How might designers frequently encounter new technologies in their daily lives? I also hope to do more research into how interdisciplinary projects between design and other fields can be conducted.

Bibliography

1. Bouhmala, N. (2016). How Good is the Euclidean Distance Metric for the Clustering Problem. 2016 5th IIAI International Congress on Advanced Applied Informatics (IIAI-AAI), 312-315. <https://doi.org/10.1109/IIAI-AAI.2016.26>
2. Choonho Kim & Juntae Kim. (2003). A recommendation algorithm using multi-level association rules. Proceedings IEEE/WIC International Conference on Web Intelligence (WI 2003), 524-527. <https://doi.org/10.1109/WI.2003.1241257>
3. Chu, W.-T., & Wu, Y.-L. (2018). Image Style Classification Based on Learnt Deep Correlation Features. IEEE Transactions on Multimedia, 20(9), 2491-2502. <https://doi.org/10.1109/TMM.2018.2801718>
4. CS221. (n.d.). Retrieved June 10, 2022, from <https://stanford.edu/~cpiech/cs221/handouts/kmeans.html>
5. Dove, G., Halskov, K., Forlizzi, J., & Zimmerman, J. (2017). UX Design Innovation: Challenges for Working with Machine Learning as a Design Material. Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems, 278-288. <https://doi.org/10.1145/3025453.3025739>
6. Ezugwu, A., Shukla, A., Agbaje, M., José-García, A., Olaide, O., & Agushaka, O. (2021). Automatic clustering algorithms: A systematic review and bibliometric analysis of relevant literature. Neural Computing and Applications, 33. <https://doi.org/10.1007/s00521-020-05395-4>
7. Gan, G. (2021). Data clustering: Theory, algorithms, and applications (Second edition.). Society for Industrial and Applied Mathematics.
8. Horiguchi, S., & Iwamatsu, K. (2018). From Munsell color system to a new color psychology system. Color Research & Application, 43(6), 827-839. <https://doi.org/10.1002/col.22286>
9. Hu, L., Song, G., Xie, Z., & Zhao, K. (2014). Personalized recommendation algorithm based on preference features. Tsinghua Science and Technology, 19(3), 293-299. <https://doi.org/10.1109/TST.2014.6838200>
10. Kim, J., & Lee, J.-K. (2020). Stochastic Detection of Interior Design Styles Using a Deep-Learning Model for Reference Images. Applied Sciences, 10(20). <https://doi.org/10.3390/app10207299>
11. Kobayashi, S. (1981). The aim and method of the color image scale. Color Research & Application, 6(2), 93-107. <https://doi.org/10.1002/col.5080060210>
12. Leban, J. (2020, May 21). Essentials of recommendation engines: Content-based and collaborative filtering. Medium. <https://towardsdatascience.com/essentials-of-recommendation-engines-content-based-and-collaborative-filtering-31521c964922>
13. Ma, B., Hauer, R. J., & Xu, C. (2020). Effects of Design Proportion and Distribution of Color in Urban and Suburban Green Space Planning to Visual Aesthetics Quality. Forests, 11(3), 278. <https://doi.org/10.3390/f11030278>
14. Ongsulee, P. (2017). Artificial intelligence, machine learning and deep learning. 2017 15th International Conference on ICT and Knowledge Engineering (ICT&KE), 1-6. <https://doi.org/10.1109/ICTKE.2017.8259629>
15. Pavan Kumar, I., Hara Gopal, V. P., Ramasubbareddy, S., Nalluri, S., & Govinda, K. (2020). Dominant Color Palette Extraction by K-Means Clustering Algorithm and Reconstruction of Image. In Data Engineering and Communication Technology (pp. 921-929). Springer Singapore. https://doi.org/10.1007/978-981-15-1097-7_78
16. Pignatiello, G. A., Martin, R. J., & Hickman, R. L. (2020). Decision Fatigue: A Conceptual Analysis. Journal of Health Psychology, 25(1), 123-135. <https://doi.org/10.1177/1359105318763510>
17. Schwartz, B. (2016). The paradox of choice: Why more is less (Revised edition.). Ecco, an imprint of HarperCollins Publishers. <https://doi.org/10.1109/TMM.2016.2581580>

18. Togootogtokh, E., & Amartuvshin, A. (2018). Deep Learning Approach for Very Similar Objects Recognition Application on Chihuahua and Muffin Problem (arXiv:1801.09573). arXiv. <http://arxiv.org/abs/1801.09573>

19. Wang, Y., Li, S., & Kot, A. C. (2016). On Branded Handbag Recognition. *IEEE Transactions on Multimedia*, 18(9), 1869-1881. <https://doi.org/10.1109/TMM.2016.2581580>

20. Yang, Q., Scuito, A., Zimmerman, J., Forlizzi, J., & Steinfeld, A. (2018). Investigating How Experienced UX Designers Effectively Work with Machine Learning. *Proceedings of the 2018 Designing Interactive Systems Conference*, 585-596. <https://doi.org/10.1145/3196709.3196730>

21. Žalik, K. R. (2008). An efficient k-means clustering algorithm. *Pattern Recognition Letters*, 29(9), 1385-1391. <https://doi.org/10.1016/j.patrec.2008.02.014>

[1] <https://www.weforum.org/reports/the-future-of-jobs-report-2020/>

[2] <https://kaifulee.medium.com/10-jobs-that-are-safe-in-an-ai-world-ec4c45523f4f>

[3] <https://thedecisionlab.com/reference-guide/economics/the-paradox-of-choice>

[4] <https://www.verywellmind.com/color-psychology-2795824#:~:text=Color%20is%20a%20powerful%20communication,%2C%20increased%20metabolism%2C%20and%20eyestrain.>

[5] <https://research.google.com/colaboratory/faq.html>

[6] https://gist.github.com/mrakelinggar/4a619268765500da2969467b443a8af1#file-common_color_loadandshow-py

[7] <https://machinelearningprojects.net/most-dominant-colors-in-an-image/>