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Enhancing Information Architecture with Machine Learning for Digital Media Platforms

Taylor N. Mietzner

Georgia Southern University

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By

Taylor Mietzner

Under the mentorship of *Dr. Christopher Kadlec*

ABSTRACT

Modern advancements in machine learning are transforming the technological landscape, including information architecture within user experience design. With the unparalleled amount of user data generated on online media platforms and applications, an adjustment in the design process to incorporate machine learning for categorizing the influx of semantic data while maintaining a user-centric structure is essential. Machine learning tools, such as the classification and recommendation system, need to be incorporated into the design for user experience and marketing success. There is a current gap between incorporating the backend modeling algorithms and the frontend information architecture system design together. The aim of this research is to discover how machine learning technology can enhance the information architecture for user experience across multimedia platforms. For practical demonstration, there will be a novel, proposed information architecture model with machine learning input to recommend a topic selection system presented on the user-facing design.

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1. Introduction

Information architecture (IA) is significant in fostering the backbone of communicating big data in a presentable format by transforming raw data into accessible knowledge on a graphical interface (Rhem, 2023). IA guides content to be consumed, generated, organized, accessed, and displayed on an interface that can be easily understood by users. Information architecture is a subset of user experience design, lying at the intersection of design and data science. User experience (UX) design is the process of helping consumers attain their goal when interacting with a digital product by designing the system to be functional and usable. Data science is a broad term that describes how scientific methods, algorithms, and systems extract insights and knowledge from structured and unstructured data, often employing machine learning (ML) techniques to analyze patterns and make predictions.

An expanding amount of data on the digital realm makes designing effective IA for digital landscapes crucial. Curating the IA of a static website can be a simple process, but the challenge rises to new heights as millions of multimodal forms of media are being uploaded to a platform daily. User-generated content (UCG) platforms, such as social media and customer-to-customer (C2C) commerce networks, are the leading internet applications for users to create and exchange content in the form of text, images, and videos. UCG platforms encompass all the websites and apps that allow people, creators, and C2C sellers to communicate and exchange digital media with one another. With 4.76 billion social media users around the world, equating to 60 percent of the global population, the amount and variety of data on these platforms is continuously increasing (Kemp, 2023). Because of this, static information architecture is no longer sustainable.

With this much data being processed, ML knowledge and techniques need to be incorporated into the UX design process. ML transforms the need for the traditional UX method of reactive design, where changes in the system architecture are made based on a conducted analysis of user feedback, to proactive design, where the system architecture is continuously refined in realtime. (Yang et al., 2018). Additionally, designing digital products is no longer suitable for the mean, but is able to be customized for each person. Traditionally, usability tests would be conducted for how the average person would respond to a product, but now the focus is not on the average across the population but adjustments for each individual user. Originally, software was built for the response of an average user, but now the software can be used by those who are even a few standard deviations away from the mean. UX designers need to be aware of the capabilities and features of artificial intelligence (AI) and machine learning to integrate them into both the design and the design process.

This paper is organized as follows. It will first explore the need for using ML for information architecture and user experience design in a literature review. The literature review will explore the best measures of an effective user experience within an information architecture design. It will state the need for knowledge of ML in the UX design process. Then, a case study will be presented on how ML can be integrated into common platform wireframes that involve a mass amount of user-generated content, such as social media sites. A novel information architecture prototype will be presented with a visual example and explanations of how ML helped form the demonstrative model. The study will explore how the proposed design better aligns with UX principles than the traditional design and how it compares to current information architecture features of the three top multimedia sites. There will be a section to address future work and a section for the evaluation conclusions.

2. Literature Review

From past research, there are key elements that are needed for the most effective information architecture design. These range from user experience design practices to ML techniques. Good UX design offers a multitude of benefits. Applications with excellent UX design typically increase conversion rates by 400 percent (Permatasari et al., 2021). It increases conversion through prolonged user engagement, reaching the target audience, and prompting users to take action.

Personalization within social media has been shown to be the foremost defining factor of user experience (Al Qudah et al., 2020). Personalization for content is defined as "customization of the presented data content to the needs of users, restricting the available functionality to the goals and preferences of users, and tailoring the web presentation according to used devices and style options" (Dillon, 2001). A highly personalized algorithm system is crucial for retaining the user's interest in the presented content, which elevates user experience and engagement, by determining the topic categories that a user finds interesting and uninteresting (Permatasari et al., 2021). The more personalized a digital interaction is, the more engaging a user finds it to be. The more accurately the machine is able to identify user interests, the more relevant suggested content and personalized advertisements become for users.

With both social media and E-commerce platforms rising in popularity, they have become intertwined due to their revolutionary approach with personalized and targeted advertisements. Marketers utilize this personalized experience to enhance ad relevance for targeted advertisements. Improvements in the personalization of advertising messages help to improve retention of customers, maximize marketing efficiencies, and improve the return on investments

(Choi & Lim, 2020). ML creates the recommendation system for content consumption and personalized advertisements.

Machine learning (ML) holds significant promise for refining the personalization of a product, search result accuracy, fostering engagement, and streamlining tasks. ML's capacity for personalization is among its most sought-after applications (Wu et al., 2019). By analyzing user behavior and preferences, recommender systems can deliver more relevant and personalized results for e-commerce, social media, and online advertising, thereby enriching user engagement and experience. E-commerce platforms leverage ML for personalized product recommendations and dynamic pricing optimization, enhancing user personalization (Szabo & Genge, 2020). Similarly, social media networks harness ML for content recommendation by extracting key topics and sentiments for a more personalized and engaging experience. Authors Zahavy et al. state, “classifying products precisely and efficiently is a major challenge in modern e-commerce. The high traffic of new products uploaded daily and the dynamic nature of the categories raise the need for machine learning models that can reduce the cost and time of human editors.” (Zahavy et al., 2018).

A primary concern of information architecture with a recommender system is to present users with avenues for navigation that are most relevant to their information needs through a series of recommendations (Shepitsen et al., 2008). Recommender systems decrease effort expenditure and act as personalized decision guides for users (Lamche et al., 2015). It is crucial to ensure that a machine gives enough aid where humans must exert a minimal amount of cognitive effort to make a decision in order to maintain a positive user experience. This is where the machine learning algorithms are needed in topic modeling curation (Pu et al., 2012). In the interaction between human users and AI-based algorithms, users actively engage with algorithms to refine personalized labels, while AI streamlines label creation efforts, ultimately reducing the exertion required for a user (Kang & Lou, 2022).

It is important to not only consider the underlying data, but how the data will be present in the interface design. When constructing a user journey, it is essential to consider the capabilities of ML applications within a digital product architecture as it can lead to untapped potential (Dove et al., 2017). Since ML can help create categories of user interest and a better navigational experience, UX designers must craft how the consumer interacts with ML features within an information architecture design. Designers will not be able to fully exploit ML's strong potential if they do not understand the technical capability of ML. Secondly, a lack of awareness of ML's full potential can lead to setbacks in employing it as a design material (Abbas et al., 2022).

The need for employing ML goes beyond the features within an information architecture but also extends into the design process. The integration of ML into the UX design process unfolds across various phases, from research to evaluation. Usability tests are essential to the design process and the nature of these tests are changing as AI furthers its ability to track copious and unbiased data. It continuously learns from user interactions to constantly improve and adapt the user interface. It's able to conduct tests, such as A/B testing, in an automated fashion. There is now a shift in defining the user personas, as there is now a wider range of more focused groups and relating them to the surrounding context (Abbas et al., 2022).

AI has brought transformation to information architecture in crafting both ML experiences for the user and using ML to enhance the design process. The days of thinking about IA design from only a visual standpoint are behind us, and instead, designers must consider how the user will interact with the ML employed on the content and how that will take form on the graphical interface.

3. Case Study

This study will present a proposed design model with a ML component to demonstrate the comparison between a traditional information architecture design and a design that incorporates ML. It will demonstrate the need to include ML into the IA system. This will propose an information architecture model for UGC platforms because they need ML components the most given their constant stream of uploaded data. It will identify current and common issues and themes within the traditional information architecture of these platforms and propose a solution.

3.1. Problem Statement

UCG platforms, such as social media sites, have voluminous amounts of data that express a wide range of user interests, ranging across a virtually unbounded number of categories distinct for each user. The categorization of this information is essential for the personalization of each user's recommendation system experience.

There are two general ways UCG platforms classify and categorize the topics for each media upload. One is the user-facing side, where the user provides metadata for the content through the host architecture's category selection and inputting hashtags (alphanumeric strings preceded with a hash symbol). The other is the machine learning (ML) algorithm, which classifies media through computer vision, which involves deep neural networks, support vector machines, and natural language processing (NLP). Currently, user-generated classifications and machine-generated classifications are almost completely distinct from one another, operating entirely apart from one another. User-generated categories consist mainly of hashtags or high-level keyword selection. This is only accessed when a user manually inputs a unique hashtag or selects a category from a list of choices. The classifications under which machines organize their datasets cannot be accessed on the user-facing side, and without labels that are recognizable by human language.

Traditionally, hashtags have formed the basis of segmenting posts based on the user's target classification and retrieving posts related to a specific topic (Chakrabarti et al., 2023). However, due to the absence of restrictions or boundaries for word selection when tagging items, users create tags without constraints, leading to free-formed tags that carry semantic ambiguities and synonyms. Semantic ambiguities arise when a single tag name holds different meanings for different users, while tag synonyms occur when different tags convey identical meanings. These drawbacks pose challenges in utilizing tags to accurately describe item topics or profile users' preferences (Al Qudah et al., 2020). Furthermore, the classification from hashtags is unable to capture the links between tags and organize them into levels of abstraction (Song et al., 2011). An unlimited amount of tag options and classification through user input on both social media and C2C applications not only increases the time it takes to classify a post, but has been shown to create cognitive load. This creates mental fatigue when uploading a post or trying to retrieve specific posts (Kusuma et al., 2023).

Machine learning advances provide a means to remedy these problems by reducing noise and guiding the user in automated topic selection (Shepitsen et al., 2008). This can be done through hierarchical topic clusters generated by ML, which provides the basis for effective personalized IA on the user-facing side. With clustering, redundant labels can be compiled and the ambiguity can also be diminished. Because only machine learning algorithms accomplish this, personalized recommendation strategies are needed to aid the user as they interact with the system for automated topic selection. To assist in sorting this copious influx of data, multimedia applications utilize ML techniques to develop categories for content. Machine learning accomplishes this by analyzing the content of the images or videos to identify and classify objects and recognize patterns, shapes, and colors. From this, it categorizes the multimedia content by clustering similar data points together based on certain features or characteristics into distinct categories that align with user interest. This helps the machine curate an algorithm used to suggest personalized content to each user.

This research will propose an enhanced information architecture (IA) model for uploading user-generated content and how it is displayed within the platform. It will propose a model that utilizes machine learning and displays the data to the interface using a dendrogram, or otherwise known as a hierarchical agglomerative clustering model, for topic classification. This system can be implemented into the information architecture of UCG platforms, and assist in a more effortless search and upload of content aided by machine learning. It enhances the user experience of the application by decreasing the information overload and cognitive effort required to search for and upload media as it employs machine learning to suggest topics that a user can quickly and easily select from a drop-down hierarchy, instead of manually inputting text. This model demonstrated the need for knowledge of how ML works to be able to integrate its algorithm capabilities into the user journey.

3.2. Research

When conducting a new information architecture, first designers must consider each function the digital product needs to accomplish and then research and collaborate with data scientists to discover how machine learning can accomplish this function. Since this proposed model focuses on user interest classification, research was enacted on how machine learning algorithms classify and label data.

Digital media platforms use ML to analyze messages, images, videos, and audio and then identify certain features and classify them into clusters. These clusters represent user interest categories and are not labeled with any human terminology but only identified by the machine because of its features and characteristics. However, since the rise in text-to-image, text-to-video, and image-to-text AI, researchers have risen to the challenge of machines identifying the human terminology for its clusters (Liu et al, 2024). Traditional methods, such as hashtags and high-level topic selection, are still mostly applied to the information architecture of digital media sites.

Several attempts have been put forward to fix the need for an enhanced labeling system with the use of AI. Many have sought to create hashtag systems that connect with the machine cluster labels, which users are able to select from (Chakrabarti et al., 2023). Some proposed systems focus more on e-commerce category selection. The HiLAP model is one created that focuses more on how a dendrogram can assist with machine-aided topic selection on the user-side for E-commerce applications (Mao et al., 2019).

For these content labels to be displayed, ML must analyze the semantic meaning of the content. There are several different approaches to this type of classification that can be grouped into several types to create a multi-modal architecture. In Image classification, CNNs are widely considered the best models, and achieve state-of-the-art results on the ImageNet Large-Scale Visual Recognition Challenge (Davies, 2022). The image encoder functions as a convolutional neural network (CNN), analyzing the image to extract pertinent features which are transmitted to the language decoder, typically implemented as a recurrent neural network (RNN), responsible for producing the textual description. Convolutional neural networks (CNNs) and Recurrent NNs can efficiently capture the sequence of the text. These methods are typically applied directly to the distributed embedding of words, without any knowledge on the syntactic or semantic structures of a language (Zahavy et al. 2018). From a machine learning perspective, studies show that combining multimodal sources for classification yields much higher results. The results indicate that using both texts and images together yields the highest accuracy (96.55%) in classifying user interests, surpassing the accuracy of text-only (41.38%) or image-only (93.1%) approaches and recommendations to the user through options that align with the content generated by ML can increase the accuracy of the classification by 3.5% (Hong et al., 2020). This means, for the most accurate predictions, ML can use hierarchical clustering to group together multimodal content, consisting of images and text.

The proposed model for this case study demonstrates how machine learning can assist the IA system by generating topics based on images, videos, audio, and text while recommending the most effective topics for users to select from. Though some aspects draw similarity to these previously created models, the novel approach presented in this research focuses on machine-generated labels rather than hashtags for recommendation. It also leans heavier on the user experience aspects than the formerly proposed research. It also goes more in-depth on how it affects the surrounding information architecture of the multimedia platform.

3.3. Methodology

The proposed model will capture the design of this demonstrative information architecture. It will show the user journey of using the ML component within the system and how it affects the rest of the information architecture throughout the site. It will also describe the general process behind how the machine learning algorithm is able to be enacted behind the scenes and displayed in a simplistic format for the user interface.

Before presenting the generated data to a user, first, the media categories have to be generated. This IA has three levels of hierarchy for image classification. There are the top-level categories, the second-level subcategories, and the third-level descriptives. For this model, agglomerative hierarchical cluster analysis generates a distinct arrangement of nested categories or clusters through the successive pairing of variables. The variable within the cluster that exhibits the highest average intercorrelation defined by the correlation matrix is then designated as the new cluster with the most highly-used term on the platform representing the category. These categories will be presented in a hierarchy from more inclusive ones to less inclusive ones (Rodriguez et al., 2019).

OpenAI has a ML model, CLIP, that works with neural networks to extract textual information from images. OpenAI's technology is suitable due to its zero-shot classification. Zero-shot image classification is a computer vision task to classify images into one of several classes, without any prior training or knowledge of the classes (Ji et al., 2020). This is essential for big data platforms because there is too large an influx of data to create supervised models for each domain.

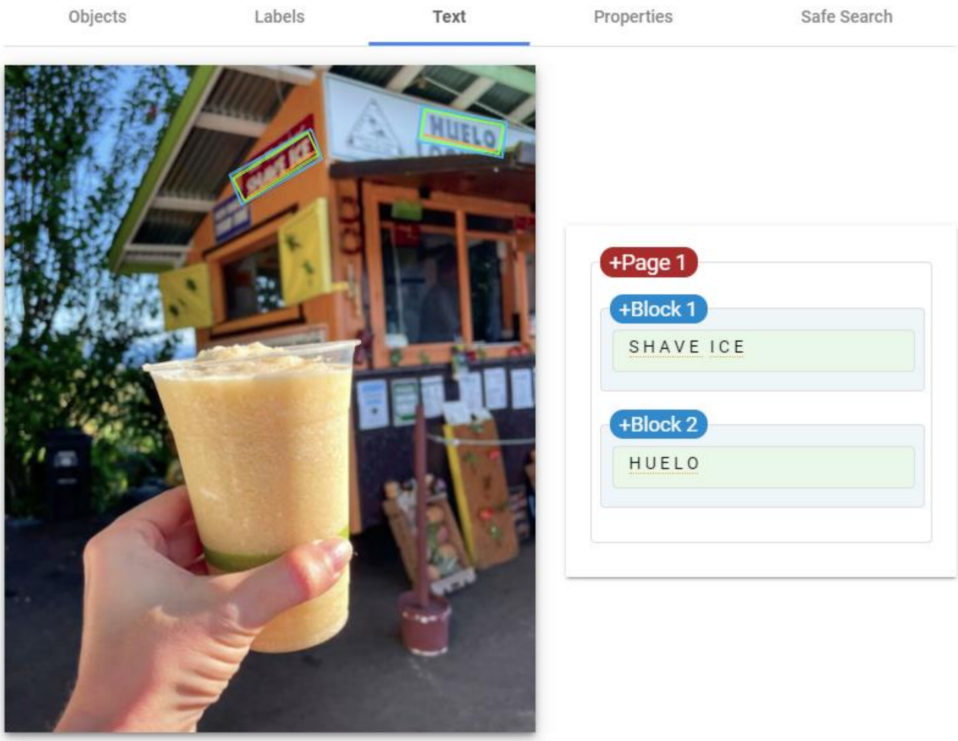
For additional keyword variables for the clusters, Google has also released an image labeling toolkit that can extract keywords from a given image. The benefit of this technology includes prominent object detection that automatically determines the most prominent object in an image and leaves out object labels from the background. NLP draws keywords and ontology from the caption generated by the user to be included with ML-generated keywords. All the cluster data can be combined in a digitized format, such as JSON, to be delivered to an NLP model to represent human ontology in a hierarchical format. This proposed model shows the capability of

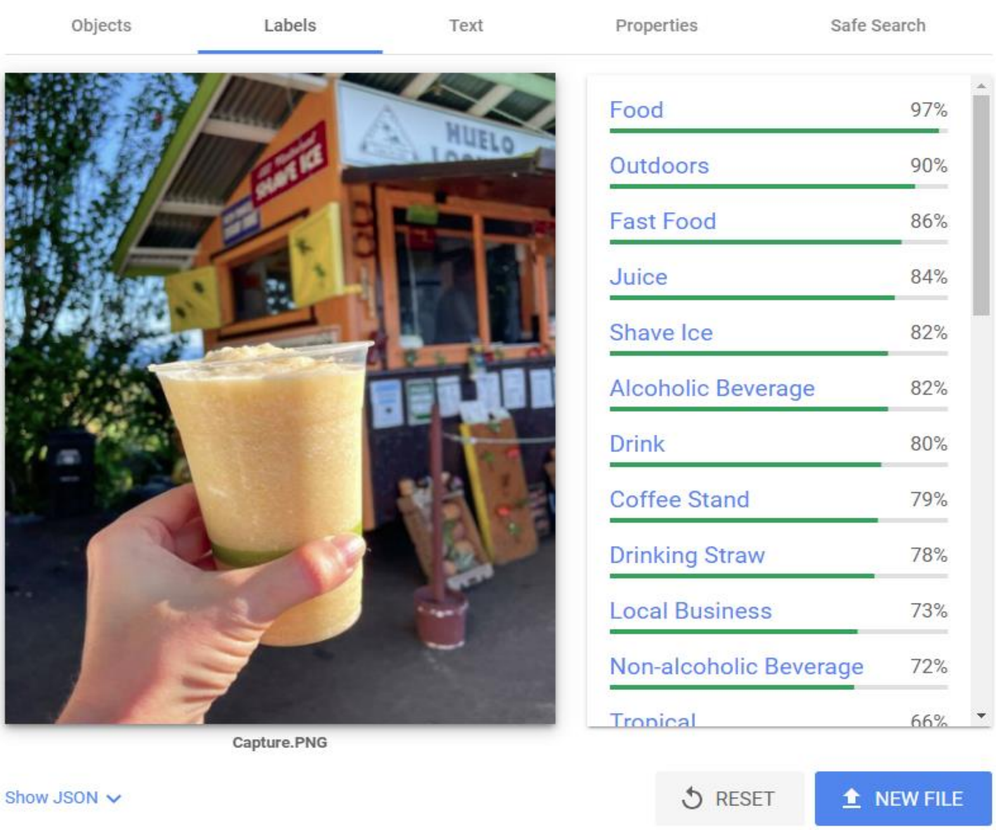
AI through OpenAI models to generate a hierarchical format dendrogram for these keywords that makes sense to human mental modules.

These hierarchical keywords stored in the backend are then displayed on the frontend graphical interface with a dropdown selection. The program is coded to hide a set of keywords unless the user selects the category or subcategory above it. This eliminates the need for users from having to select topics from long lists or manually input them while reducing cognitive load.

This architecture is not only presented when a user is uploading information but when consuming content as well. The dropdown selection is displayed on the top of the application's main feed, allowing users to dive into content that falls under a certain category. This allows for categorized algorithms for users to view, which do not currently appear on any main social media application.

The following is a demonstration of the methodology behind the ML component for this proposed IA system. The following image was used as an example post by a user randomly selected from an open-source social media data set (Geng et al., 2015). From this image, various labels are extracted using ML Google Vision. The image example is displayed below:



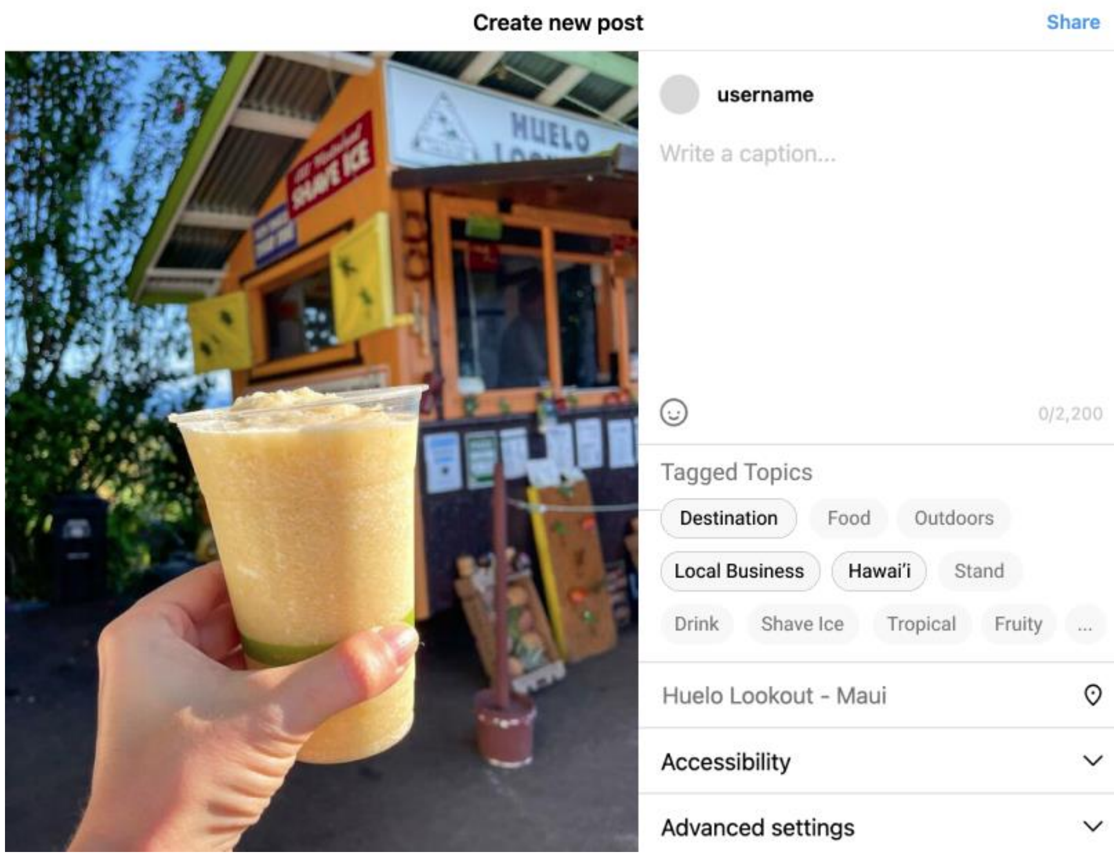


After the labels were extracted from the content, a 3-tier dendrogram was created where

OpenAI software was able to sort these labels into category clusters. The JSON code was able to inform OpenAI about the relational hierarchy and labels within the image.

```sql
Destination
|
├── Local Business
|
├── Hawaii
|   └── Huelo
|
├── Restaurant
|
├── Food
|   ├── Fast Food
|   |   └── Coffee Stand
|   ├── Mocktail Recipe
|   └── Drink
|       ├── Juice
|       ├── Alcoholic Beverage
|       ├── Shave Ice
|       ├── Non-alcoholic Drink
|       └── Drinking Straw
|
└── Outdoors
    ├── Hiking
    |   ├── Trees
    |   ├── View
    |   └── Sunny
    └── Tropical
```

This can then be displayed for the users to select on the front-end. The topic expands only when it is chosen. Though it is ML generated, it can still be worked into the frontend design when a flexible IA structure is added. Here is what the machine-generated structure looks like in the design:

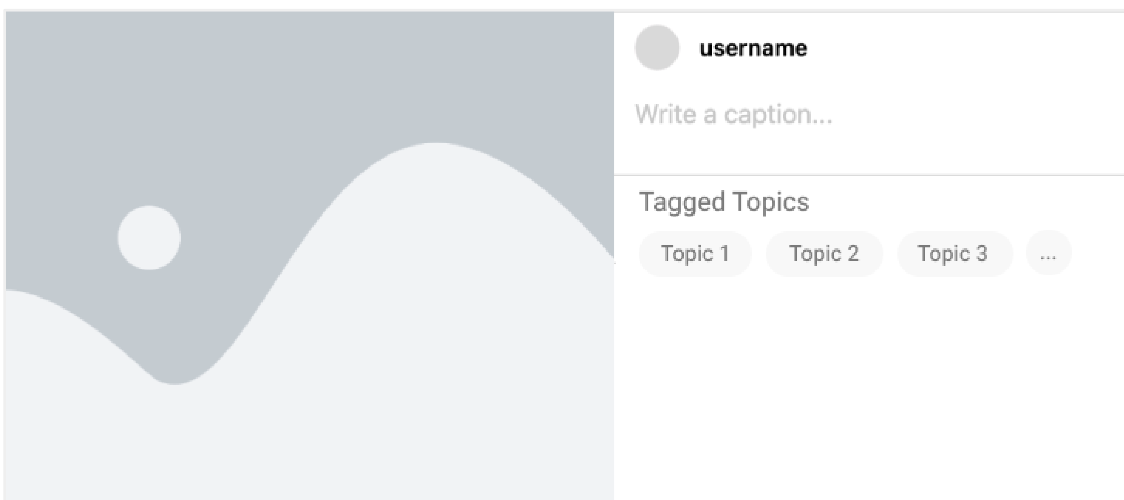


This is the topic selection system displayed to the user. It allows machine learning to connect with the frontend for topic selection. The user is able to choose the tagged topics of which the highest accuracy rating is displayed in descending order. This means the most potentially relevant tags are displayed first. Additionally, the topics are displayed from most general to most specific in a top-down order. For example, "destination" is displayed first while giving options such as Hawai'i on the second tier and the descriptions in the third tier. The bolded topics are the ones this user selected in the demonstration.

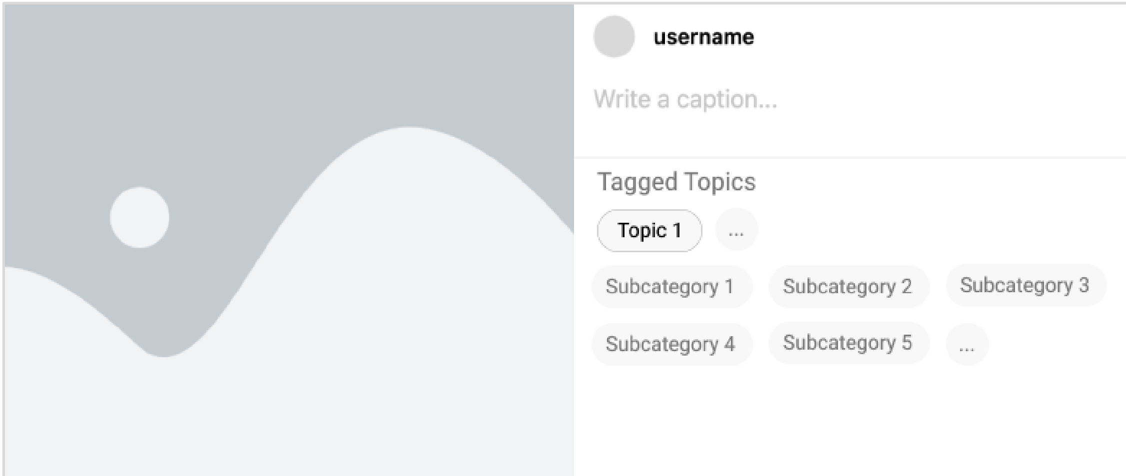
These topics allow for the creation of browsing connecting to the display portion of the site. Users can browse through categories that the ML algorithm positions to be most relevant to them within the IA. Almost all digital media platforms have a place in the IA design where the most relevant feed is displayed on a page. With the updated ML user experience, it gives the user the ability to scroll through and browse the related content they wish to view without having to search. It allows the user to have content suggestions rather than active searching. It works as follows in the example below.

3.4. Proposed Model

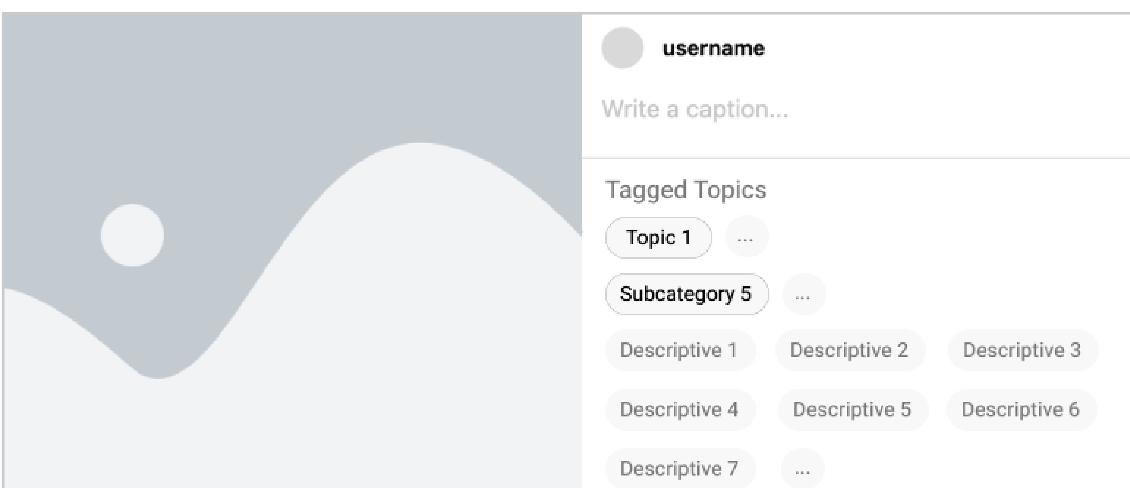
The proposed model will show an information architecture for displaying posts on a multimedia site. This section will walk through the user process and how they interact with the interface. A proposed model was created of the topic selection system detailed above to give a visual view of the written explanation. The image represents the user-generated content that is uploaded and the tagged selections represent the ML-generated labels that are actively being selected.



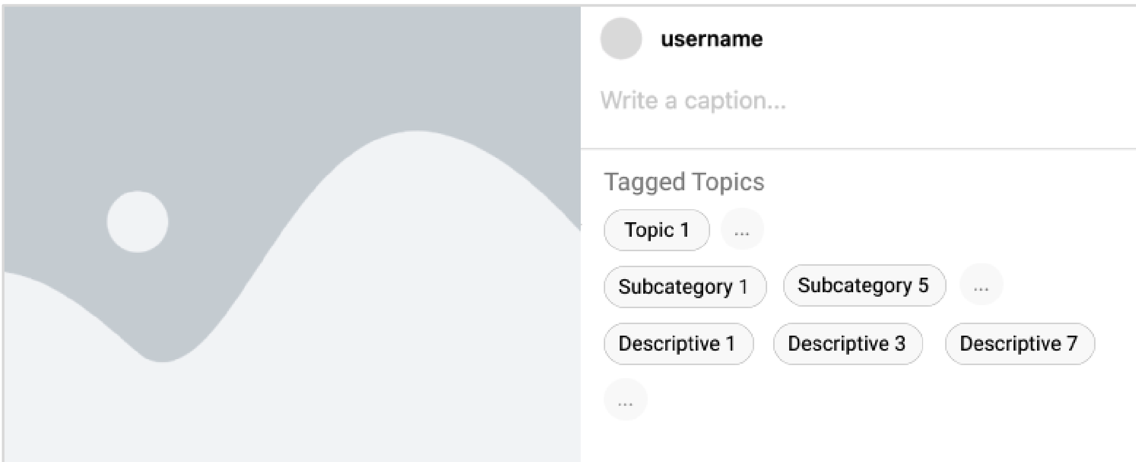
The “topic X” labels are generated according to the machine’s overall perceived purpose of the image. It is the high-level category that captures the essence of why a user is viewing the post. This can include labels such as tutorials, ideas, humor, travel, art, tips, etc. This allows a user to select from a high-level list of topics, displaying the most accurate three at a time.



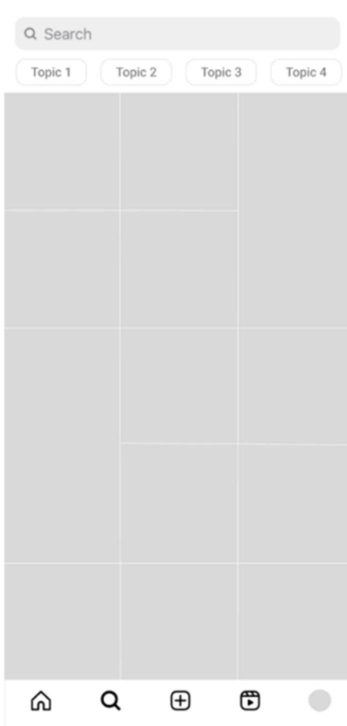
Once the foremost topic is selected, the hierarchical cluster set linked to the chosen topic is displayed. Users are again able to select subcategories from the display list. For example, a subcategory of 'Nutrition' could be keto, low carb, macros, calorie tracking, whole foods, etc. The purpose of the subcategory is to engage people's specific interests within a general topic. With the ellipses on the current tier, they have the option to type their own category. To modify or choose additional topics from the first tier, users can click on the ellipses next to the topic they have already chosen.



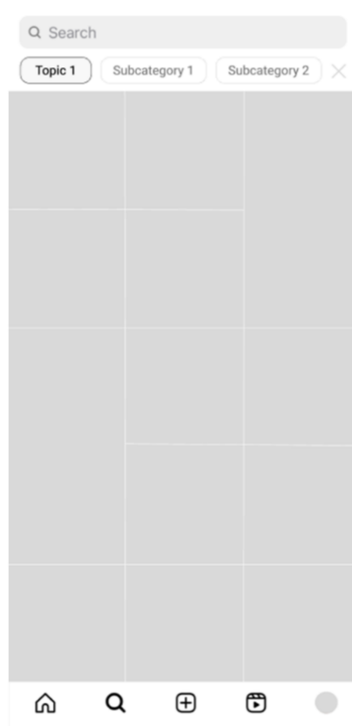
After the subcategory is chosen, the last tier drops down displaying different descriptives. These can be generated from qualities in an image or keywords in a video. The user can then select the one most applicable to the content.



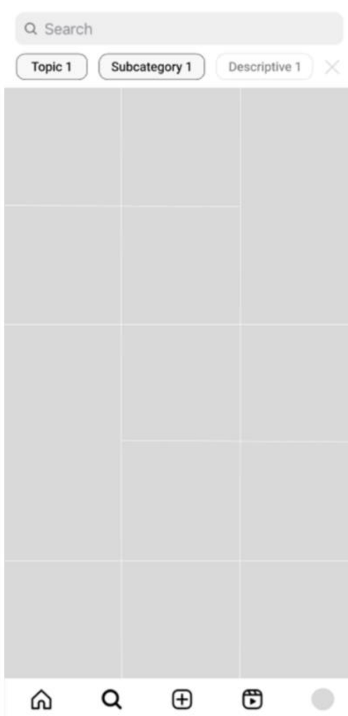
After the descriptives are chosen, the user has successfully described a 3-tier topic category for their post within a matter of clicks with minimal typing. These topics then help the recommender system, displaying content that aligns with a user's interested topic and specifics. The topics can be used to generate more than a single algorithm on a feed. If a person wants a categorized feed, they could select topics with their subcategories. This tree-like selection system can be applied to several UX systems, such as a social network's exploratory page, an interest selection system when first creating an account, e-commerce categorization, as well as the overall information architecture of a platform and how it ties into the recommendation system.



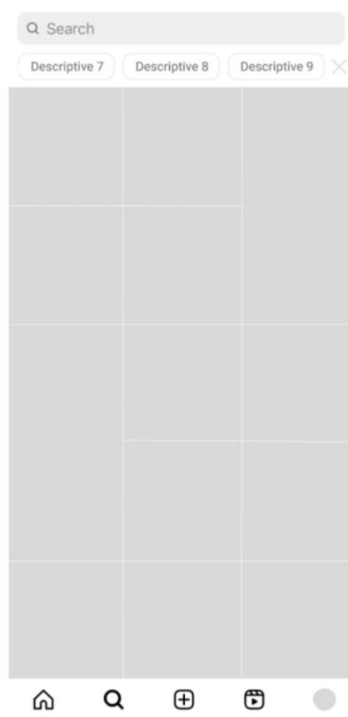
Step 1



Step 2



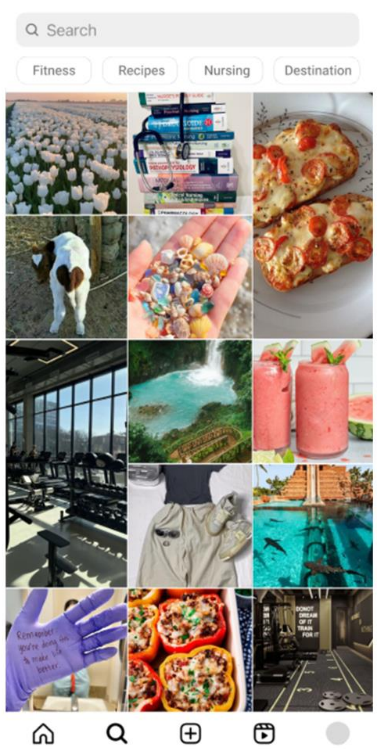
Step 3



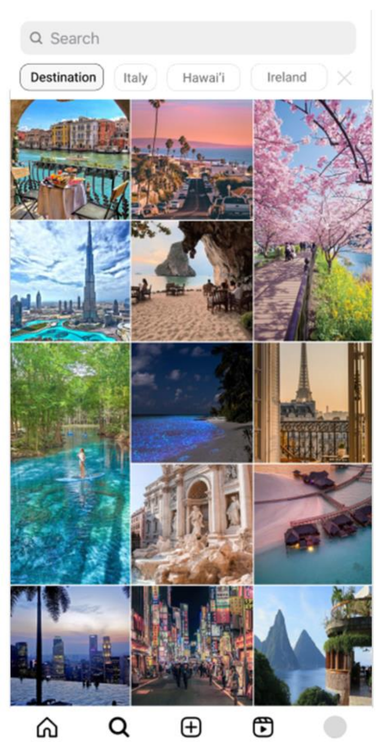
Step 4

In the feed, where all uploaded content is exhibited, the categories that are most interesting to the user, according to the ML algorithm, are displayed, shown in step 1. When a user selects a topic in step 2, the subcategories rated to the selected topics are shown. The user could browse the high-level topic or look for something more specific. The 'X' action button clears out the selection to show the original exploratory feed. If a subcategory is chosen, the different descriptives are displayed to choose from as seen in step 3. A person may scroll through these options to browse them or clear the selection result.

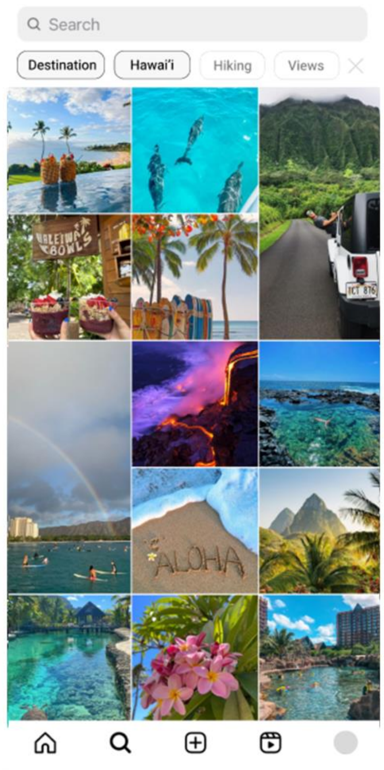
Here is a demonstration using real images on a feed. This displays the feed of a demonstrative user persona. The user persona is a female who the algorithm has determined enjoys viewing fitness, recipes, nursing, and travel/destination content as her top selection. Here is how this user may interact with the content:



Step 1



Step 2



Step 3

Step 4

Step 1 demonstrates her exploratory feed of social media content. Since she wishes to view media destinations to travel to, she selects this option. The algorithm again generates topics related to her topic that she may choose from. She may select another topic within the topic hierarchy. In this user flow, the selects to view local business in Hawai'i and the algorithm displays all the relevant results. As a result, users can explore and engage with relevant content by searching for or browsing through specific tags of interest.

In this way, the machine can help suggest content labels under the same information labels that both the machine and a populous number of users search for, while remaining true to the intended specific niche. This is important because the more machines understand the way human mental modules classify information, the more accurate the classification will be for the audience and the creator. This proposed model will allow the machine to represent human thinking as closely as possible and make affirmed predictions about the content it is labeling.

Having an information architecture design that supports both user and machine labels will enhance the user experience in both uploading content and viewing desired media. This allows users to view an algorithm focused towards a particular category of content when desired and explore machine-generated topic labels, engaging both the backend technicality of uploaded data and the frontend presentation of information. This remedies cognitive overload in media classification and enhances the information architecture of the application, leading to increased personalization with advertisements, engagement, searchability, and user experience. These different applications and how they compare to current architectures will be explored in the next section.

4. Evaluation

In this section, the top three digital media sites will be compared with traditional categorization systems and ones with ML built-in to the IA. It will be compared to the top eight principles of IA and UX design principles. The platforms used for a comparative analysis will be Instagram and Facebook, which engages multimodal forms of content, and YouTube, which primarily displays video content (Walsh, 2023).

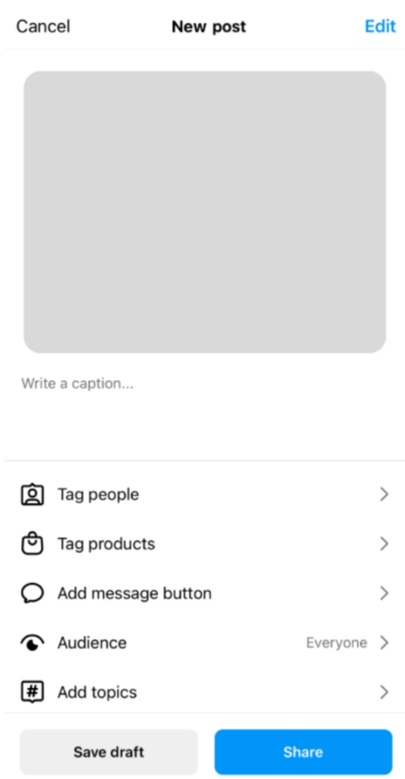
4.1. Principles of User Experience Design and Information Architecture

Lidwell, Holden, and Butler say in the introduction to their book, "the use of well-established design principles increases the probability that a design will be successful" (Lidwell et al., 2010). The main design principles are already laid out for information architecture. According to Brown, the eight principles of information architecture are as follows: the principle of objects, the principle of choices, the principles of disclosure, the principle of exemplars, the principles of front doors, the principle of multiple classification, the principle of focused navigation, and the principle of growth. The principle of objects refers to object-oriented programming, in which the term "object" refers to a structured entity with defined methods, behaviors, and properties, serving as a template for website content with consistent internal structures and discrete sets of behaviors. The principle of choices refers to keeping a number of limited and meaningful choices for the users. The principle of progressive disclosure communicates that users can only retain so much information at once, but there should be a navigation to more layers of information. The principle of exemplars states that users want examples of what would be contained within a content category. The principle of front doors states that users arrive at the platforms from different sections of the site. The principle of multiple classification communicates that users classify content in multiple different ways. The principle of focused navigation states to not reveal different types of classifications in one content category. Lastly, the principle of growth is used for the anticipation of a growing amount of content (Brown, 2010).

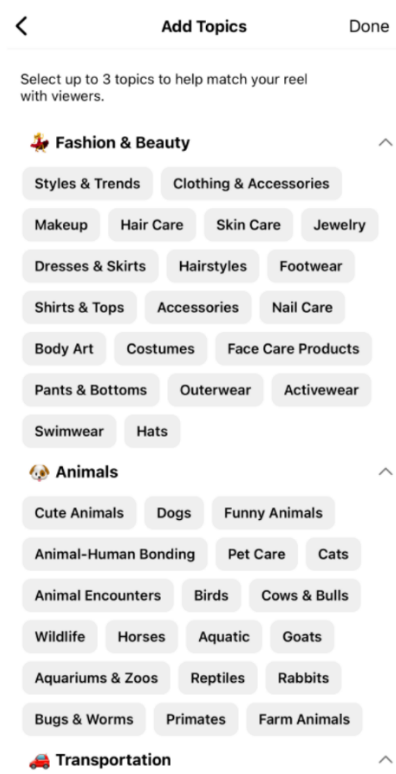
For an evaluation, the current information architecture of the top three social media types will be compared to the novel information architecture using these principles for measure. The ML used for content categorization can help the information have a better structure, especially when dealing with large amounts of data. With these principles, we can thoroughly analyze how ML can contribute to better IA within platforms.

4.2. Instagram Comparative Analysis

For Instagram, a person has an ‘Add Topics’ section when uploading content, which takes them to a list of topics for their selection preferences they can scroll through. This page has many subcategories listed under category labels to select from. This is the current wireframe displaying the user flow for uploading content and the system design for selecting a topic:



Step 1



Step 2

This differs from the proposed IA because it does not work in conjunction with the ML algorithm. It does not detect topics related to the image, but only lists popular high level topic selection. Within each of these categories, there is a copious number of subcategories which typically only a few that aligns the post with an actual descriptive label. This also results in a feed not suitable for personalized viewing. It does not have the browsing search component proposed above.

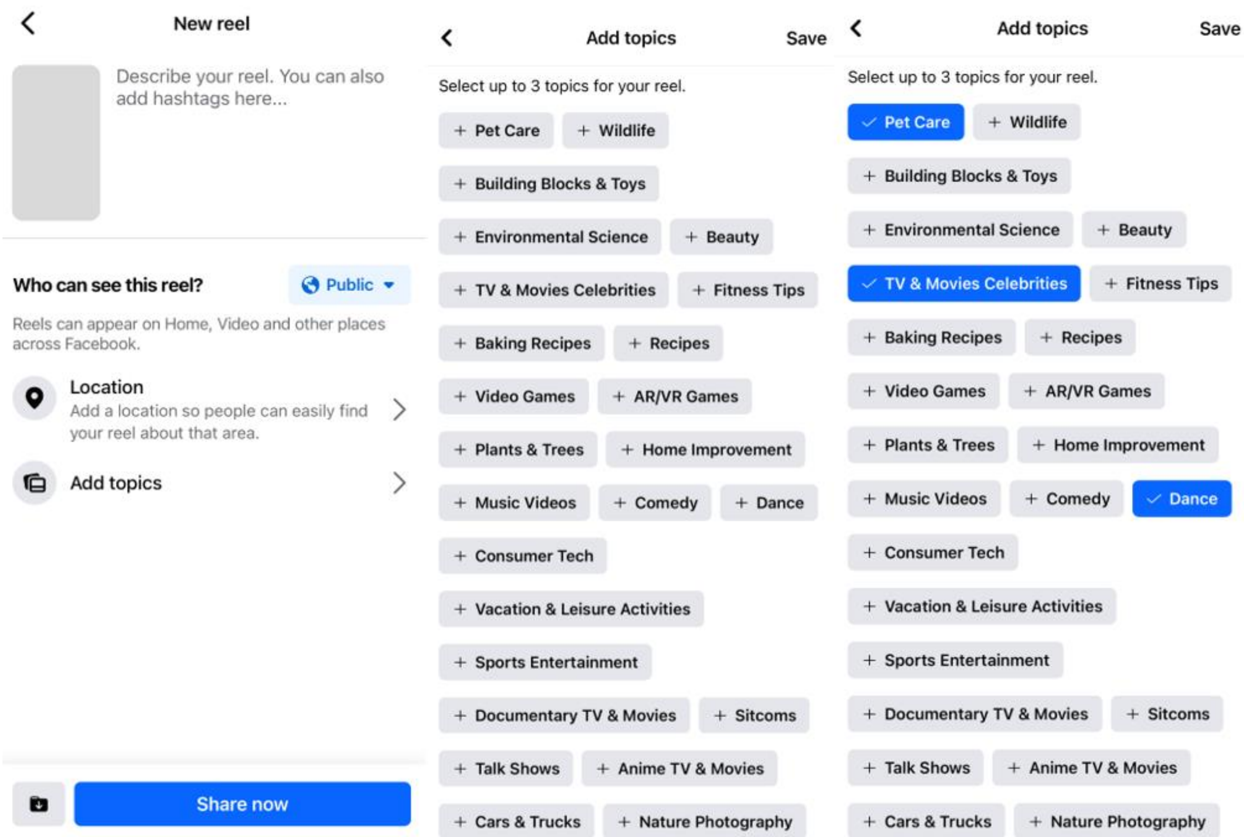
The proposed architecture meets several IA principles that are not attained with this current structure on the Instagram wireframe. The Instagram wireframe does not capture the principle of progressive disclosure because there are no layers to the selection the user must make. Most notably, it does not attain the principle of focused navigation or the principle of attained growth. This is because it mixes many unrelated topics and these topics do not naturally expand with the uploading of new content.

The proposed IA remedies this with its ML component. It presents the information in tiers that expand. Additionally, it only displays the topics that are meaningful to the user's post, which can expand based on different types of content.

Hick's law states that the design should seek to avoid overwhelming users by highlighting recommended options. ML can help to highlight the options that are most relevant to the user. Similarly, Miller's Law states that options for users should be limited from two to seven. Traditional designs have to display all the options, as seen in the wireframe for Instagram, but ML narrows it down for the user. Additionally, Fitt's law states that the most relevant selection should be in proximity to what is most easily acquired. ML helps sort the most relevant in descending order, with the top appearing as the most relevant. Lastly, it also helps accomplish the Law of Proximity and Law of Uniform Connectedness by placing the labels in a hierarchical label set with three tiers, rather than just a list of seemingly random categories (Yablonski, 2024).

4.3. Facebook Comparative Analysis

Facebook's information architecture has a similar interface to Instagram's, but it does not sort the topics into categories and subcategories, which creates more of an information overload on the user. Like Instagram, it uses a scrollable page to select content categories from.

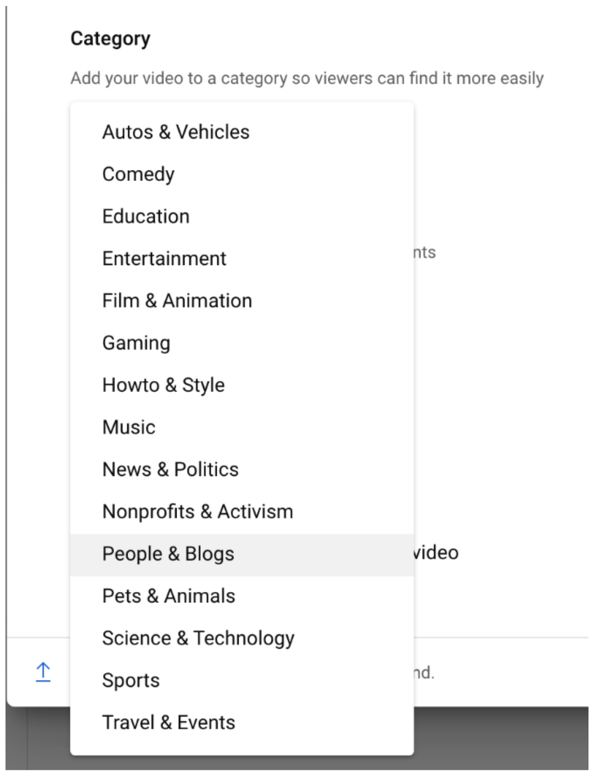


Step 1 Step 2 Step 3

This list does not adhere to the exemplar principle as well as Instagram's, because there is no graphical representation or overarching category label. It only slightly upholds the multiple classification principle, as it helps combine many user-generated labels into a single term to select from. However, the proposed IA outperforms both these principles as it draws labels from the upload with ML and recommends the terms for the user. It encompasses a much larger set of terms but only displays a few at a time to the user to prevent cognitive load.

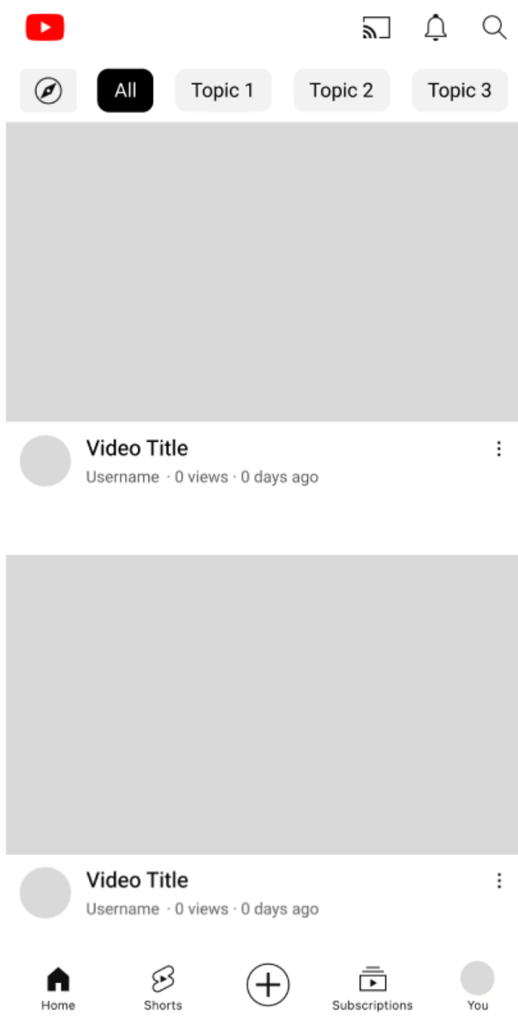
4.4. YouTube Comparative Analysis

YouTube has a dropdown structure for category selection. This does not analyze the uploaded content with ML to make recommendations. This is seen in the image below, which shows the graphical interface of the category selection section when uploading a video.



This drop-down menu does not amount to the same level of efficiency as a hierarchical ML-generated selection. The principle of choices states that the number of choices should be limited to decrease cognitive load. Additionally, it does not adhere to the principle of objects, as these are only descriptions in a list and not workable entities. The proposed IA exhibits all the UX laws exhibited in Instagram’s interface comparative analysis section. With the proposed IA curating content and features to match user needs, it effectively reduces information overload, ensuring users are presented with only relevant information, and optimizes their experience.

YouTube already employs ML on the user interface when suggesting content on the main output feed. Users may select different topics to browse and narrow their feed, which is a function present in the proposed IA. This enhances the personalized browsing experience. YouTube's interface wireframe can be viewed below.



This ML content categorization will only become more accurate with time. This will allow for hyper-personalization of content and different hierarchies of content organization. The future advancements, along with the limitations, of ML within the user experience will be further explored in the next section.

5. Limitations and Future Work

Although ML can do more than society once thought possible, it still contains major limitations. There are holes and gaps that AI simply cannot fill. This calls for even more trained and experienced workers within technology and design to see above the work ML creates and bridge the gap between artificial intelligence and human cognition. Expertise is needed to fix the errors and gaps in what AI produces. Only humans can entirely understand what the goal of the company and how it relates to the work at hand. Artificial intelligence is built on the layer of human intelligence and only humans can connect the dots to employ the technology AI has to offer.

With this said, professionals can still harness the powers of AI to optimize their work. AI offers many tools to expedite the process. They can not only employ AI or ML in the design process but integrate it into the human-computer interaction that is being created. This is needed especially in the field of information architecture with the ever-growing amount of data.

There is still limitations on how ML perceives data compared to humans. ML classifies data based on its recognized features and allocates them into clusters, whereas humans think of data in terms of concepts assigned with language definitions. Progress is still needed to close these two gaps and to allow ML to categorize content by connecting the dots between multimodal forms of data. When machine classification can identify its clusters in terms of human semantics, it can bring a revolutionary transformation to IA systems.

ML capabilities continue to grow, creating a plethora of opportunities for future human-computer interaction designs. This leads to a massive amount of creative potential as ML and UX professionals can collaborate to create novel user systems. Companies are now trying to incorporate AI into new digital functions, such as SnapCalorie, which allows to estimate one's calorie count by taking a picture of their food, or Amazon’s upcoming creation of Amazon Go, which uses AI to simply check out a user from a store without any manual process (Ives et al., 2019). With this, there will be new apps that give virtual experiences beyond a 2D interface. In the future, this can help users in making purchasing decisions and optimize the efficiency of systems. There is a call for more research in how the two fields of ML and UX can connect because within that connection lies untapped potential.

6. Conclusion

Machine learning aids user experience from the design process to the functions and features within the design. It revolutionizes the function of information architecture, allowing for more personalized systems in how data is displayed. The demonstrative case study within this research exemplifies novel ways to incorporate ML into the information architecture of a digital platform. The novel information architecture demonstrates how UX helps accomplish the different principles of design to make a more efficient system. Though AI still has its limits, and needs expertise to see through those limitations, user experience can coincide with ML to create more advanced and effective applications.

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