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Destination Image Analysis with User-Generated Content: A Computer Vision and Machine Learning Approach

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Abstract

This study proposes an approach to identify the elements that shape the destination image in the minds of potential tourists who peruse social network posts, based on Instagram images of Foça, a touristic district of İzmir, Turkey, in summer 2019. The elements in shared images that contributed to the development of Foça's destination image were identified with computer vision, while word embedding and machine learning were used for element categorization and clustering, respectively. The study demonstrates the proportion of the elements in the photographs shared by Instagram users in 27 categories and subsequently, without any human intervention, constructs a representation of the elements the destination image was most dependent upon. Categorization showed that the categories that were the most representative of the destination image of Foça were sea and landforms, celestial, arts, events, urban, boating and water sports and constructional, respectively. The majority of destination image research with social network data sets relies on observation, interpretation or survey results. These studies are time-consuming and labour-intensive due to the large size of social network data. However, in this study, social network data can be analysed faster and efficiently with artificial intelligence and machine learning compared to conventional methods. Furthermore, the innovative methodology developed in the study contributes to the current tourism literature by proposing a decision support system for making computer-assisted tourism marketing decisions.

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INTRODUCTION

Destination image (DI) is a concept that plays an important role in tourists' decision-making and travel behaviours (Baloglu & McCleary, 1999). Nowadays, conventional DI sources such as brochures, advertisements or official destination websites are not enough for tourism consumers, and User-Generated Content (UGC) shared on social networks (SNs) for tourist experiences influence destination image (Bayram et al., 2016; Ghazali & Cai, 2013). In addition to being perceivers, Internet (or SN) users have also become DI constructors (Dwivedi, 2009). In other words, sharing favourite objects, locations and activities from holiday destinations and thereby creating information sources and DIs have become commonplace with the contemporary prevalence of the Internet, SNs and mobile communication. Thus, this concept, referred to as perceived image in the literature, is shaped by the content tourists share (Govers et al., 2007).

Although SNs have been in our lives for over 20 years, they have become more diversified and have expanded their user bases over the years due to increased mobile device usage, Internet prevalence and popularity. Alongside the widely known microblogs Facebook and Twitter, different SN platforms like Instagram, Flickr, Pinterest, YouTube, Vimeo, Last.FM and SoundCloud that specialize particularly in media sharing (i.e., image, video and music) have emerged. Quite strikingly, the number of monthly active Instagram users have reached 1 billion in June 2018 notwithstanding its sole focus on photo and video sharing (Statista, 2018). This rise in the number of Instagram users indicates a consistent and robust growth since its launch in 2010 (Ting et al., 2015).

In addition to the general tendency of SN users to share things they like, some users share photographs of interesting places or historical buildings that is relevant to tourists (Mukhina et al., 2017). At the same time, SN user posts are also important for other users. SN users can predict potential information needs for themselves or others and share relevant content to facilitate future search, which provides access to information and helps to satisfy future information needs (Goh et al., 2009; C. S. Lee et al., 2015). Furthermore, tourism consumers prefer SNs to obtain more accurate information about destinations experienced by others (Binbaşıoğlu, 2017; Eröz & Doğdubay, 2012). Thus, tourists' need to learn about destinations they wish to visit from SNs and their review of UGC lead to the construction of a positive or negative DI in their minds.

Many researchers have emphasized the function of the Internet and SNs as an important source for learning about a touristic destination (Garay, 2019; Özdemir & Çelebi, 2015; Song & Kim, 2016). With the popularity of the Internet and SNs, posts of both users and Destination Marketing Organizations (DMOs) influence the creation of DIs. It is possible to encounter such studies in the literature. Some studies have investigated the effects of SN utilization of DMOs on DI formation (Molinillo et al., 2017, 2018), while other authors, stressing the significance of UGC, have examined the combined impact of user posts together with DMO websites or SN accounts (Mak, 2017; Paül i Agustí, 2018; Stepchenkova & Zhan, 2013). Yet other studies have focused solely on the influence of UGC on DI (Deng and Lee, 2018; Deng et al., 2019; Galí & Donaire, 2015; Gurung & Goswami, 2017; Kim et al., 2017; Nikjoo & Bakhshi, 2019; Shuqair & Cragg, 2017; Zhao et al., 2018).

These studies either rely on observation and interpretation or employ surveys. Although these studies offer dependable results and approaches, they are time-consuming and labour-intensive due to the sheer size of SN data. Notwithstanding the frequent use of sampling for large number of SN posts (i.e., data), the sample may not always be representative of the entirety of the data.

Knowledge of the factors that act on destination choice of tourists is important to developing effective policies and strategies for tourism. Familiarization with the elements shared the most at destinations tourists like by detailing the UGC on SNs with high popularity, such as Instagram, is significant for the efficiency of appropriate advertisement and investment. Moreover, immediate action by decision-makers to changing tourist tastes for touristic destinations would be possible with instant monitorization of user posts on SNs. Therefore, utilizing artificial intelligence (AI) and machine learning (ML), which partly require human intervention but provide fast and mostly reliable information retrieval from a large number of user-generated text and image data, would facilitate good understanding and interpretation of UGC by researchers or decision-makers in tourism, particularly DI research. Thus, this study addresses the following questions: Can the elements that constitute any destination's image be determined with AI and ML to facilitate fast and accurate decision-making for touristic destinations in the field of tourism? Can this methodological framework be developed and improved upon?

In order to answer these questions, this study proposes a method to identify the elements that shape the image of a destination of choice (Foça, Turkey) from the contents of photographs shared on Instagram (places, buildings, activities, food, objects, etc.) using Computer Vision (CV), Natural Language Processing (NLP) and ML, supported with various computer algorithms. The techniques utilized in the study also contribute to the feasibility of data analysis in tourism. Furthermore, this model can be adopted as a decision support system in tourism marketing, producing a numerical representation of what tourists tend to like in touristic destinations.

Literature Review

Destination Image

The successful promotion of a destination in the targeted markets is possible if it is favourably differentiated from its competitors or positioned positively in the minds of consumers (Echtner & Ritchie, 2003). This differentiation and positioning, which will enable the destination to reach the target market, emerges as a result of creating an effective image or perception about the destination in the minds of the potential customers (Stepchenkova & Mills, 2010). Revealing the current image of the destination and developing it in line with the demands of the targeted market is a critical aspect in successful tourism development and destination marketing due to its impact on both supply- and demand- side aspects of marketing (Tasci & Gartner, 2007). An image that is not correctly determined and positioned can prevent the destination from reaching potential customers, cause promotional activities to move in the wrong direction and negatively affect destinations in economic terms.

Although there is not generally accepted and clear definition in the literature regarding the definition of DI, there is a consensus that DI is the sum of people's ideas, beliefs, impressions and expectations about the destination (Baloglu & McCleary, 1999; Beerli & Martin, 2004; Crompton, 1979; Echtner & Ritchie, 2003; Gallarza et al., 2002; Hunt, 1975; Lin et al., 2021). Crompton (1979) defined DI as "the sum of beliefs, ideas and impressions that a person has of a destination". With a similar approach, Gartner (1993) defined the DI as "the set of perceptions, knowledge, feelings and thoughts about any region". According to another definition, DI is "the sum of expectations and perceptions of potential visitors towards the destination" (Murphy et al., 2000). As the definitions reveal, DI is a subjective concept, which makes it difficult and necessary to manage effectively.

DI is an important concept in understanding the destination selection processes of tourists. Before traveling, tourists develop an image and various expectations regarding that destination (Choi & Chu, 2001). Social media plays an important role in many areas of tourism, especially in information seeking and decision-making behaviour, tourism promotion and focusing on best practices for interacting with consumers (Zeng & Gerritsen, 2014).

Social Networks: Instagram

A social network is a web-based system that allows users to share feelings, opinions, status updates, writings, photos, videos and links with other users via various communication tools. With its considerable user base among SN platforms, the popularity of Instagram is increasing day by day. Instagram users can share photos or videos stored on their mobile devices, as well as photos taken, or videos recorded with device cameras at that instant by optionally adding various filters, hashtags or location information. In addition, other users can engage with posts by liking, commenting and sharing the post in their stories or with third users, which makes it possible for any UGC on Instagram to reach millions of people.

Instead of using photo albums, people currently document their daily lives mostly by posting on photo-sharing social network services like Instagram with their families and friends, and thus store images and mementos to recall past events (Lee et al., 2015; Sheldon & Bryant 2016). Users utilize Instagram with social and psychological motives such as social interaction, escapism or peeking and self-express through posting photographs they like (Biçiçi, 2018; Lee et al., 2015). Users can post in numerous categories on Instagram (Dorsch, 2018; Hu et al., 2014; Jang et al., 2015; Mittal et al., 2017).

Computer Vision

Snyder and Qi (2017) characterized CV as "the process whereby a machine, usually a digital computer, automatically processes an image and reports what is in the image. That is, it recognizes the content of the image". CV is the science that develops the theoretical and algorithmic foundation for automatic extraction and analysis of useful information about an object or scene from an observed image, image set or image sequence, and it is a branch of AI technique dealing with simulating human vision (Gunasekaran, 2010). There are open-source CV libraries such as OpenCV, PyTorchCV or SimpleCV and commercial cloud-based CV systems like Google Cloud's Vision Application Programming Interface (GCV API) or Microsoft Azure Computer Vision. The greatest advantage of cloud-based CV systems is the ability to save computational time with the pre-trained cloud-based APIs (Chen and Chen, 2017) as the training stage required for the extraction of features for image recognition in CV using ML is a prolonged and labour-intensive process.

GCV API, launched in 2016 with various features offers pre-trained machine learning models through REST (Representational State Transfer) and RPC (Remote Procedure Call) APIs (Google, n.d.; Ramanathan, 2016). It implements deep learning algorithms and convolution neural network (LeCun et al., 2015). GCV API services include image classification, OCR and celebrity recognition, as well as face, object, landmark, logo and explicit (i.e. adult and violent) content detection (Google, n.d.).

One of GCV API's most popular features, label detection can detect entities in images and identify general objects, locations, activities, animal species, products, etc. (Google, 2021). An API response includes four objects: a machine-generated identifier (MID) corresponding to the entity's Google Knowledge Graph entry, the label description, the confidence score (CS) ranging between 0 and 1, and topicality, which measures the importance of a label to the overall context of a page (Google, 2020).

CV usage is recent and limited in tourism literature. Koruyan and Karagöz (2018) employed CV to investigate the DI of Sığacık, a tourist destination in Seferihisar, İzmir, using Instagram images as data source. Ma et al. (2018) studied the effect of user-posted photos from TripAdvisor and Yelp on review helpfulness. In the study by Rossi et al. (2018), UGC posted on Instagram regarding events in Venice, such as carnivals or biennials was adopted as data source, CV was used to categorize images, and the change in the frequency and spatial distribution of these categories over time was examined. Zeng et al. (2019) conducted a statistical comparison of the behaviours and perceptions of tourists from different countries, using CV to analyse the contents of Beijing-related images shared on Flickr. Janša et al. (2019) explored how UGC shared on Pinterest represented Thailand and the differences in the posts of private (tourists) and commercial users with GCV API. Another study that utilized GCV API analysed the city image of 222 cities via photos posted on Flickr and proposed a method for city branding and development (Taecharungroj and Mathayomchan, 2020).

Methodology

In the study, the DI of Foça, a touristic district of İzmir, the third largest Turkish city, was investigated using 3549 geotagged Instagram photos of Foça as data source. Data were gathered between June 29 and September 6, coinciding with the beginning and the end of the school year, as Foça is a domestic tourist destination that hosts a greater number of tourists in the summer. Figure 1 shows the study flowchart.

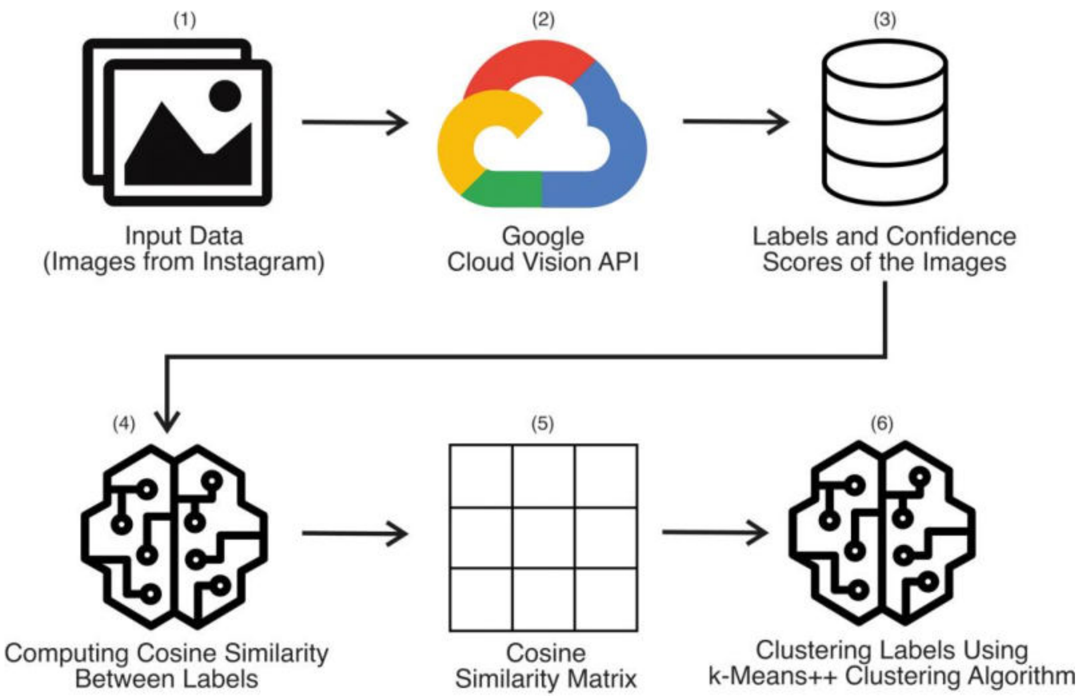

Figure 1. Study flowchart

Using GCV API and Python programming language, each photo's labels and CSs for these labels were obtained. The API generated 66482 total labels and 2422 individual labels as labels can be iterated for different photos. Some examples of images, as well as their labels and CSs are given in Figure 2.

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

Figure 2. Instagram posts from Foça

As seen in Figure 2, CV-generated labels with the highest CSs could be used to identify a small marina with fishing boats in Figure 2a (e.g., Water transportation: 0.98, Boat: 0.96, Harbour: 0.91), an old stone building with turquoise windows in Figure 2b (e.g., Building: 0.91, Turquoise: 0.84, Window: 0.83), an old windmill in Figure 2c (e.g., Windmill: 0.99, Wind turbine: 0.91, Mill: 0.73) and a beach in Figure 2d (e.g., Body of water: 0.99, Sea: 0.96, Beach, 0.90). In addition to the main themes, GCV API also identified minor objects (Figure 2a: Water: 0.81, Sky: 0.73; Figure 2b: Azure: 0.82, Tree: 0.78; Figure 2c: Rock: 0.54, Cumulus: 0.52; Figure 2d: Mountain: 0.74, Palm tree: 0.52, etc.). Moreover, there were instances of incorrect or low-probability labels Figure 2a: Channel: 0.54, Figure 2b: Road: 0.53, Figure 2d: Tropics: 0.56, etc.). Table 1 contains the 40 most frequently recurring CV-generated labels, as well as their frequencies and cumulative frequencies.

Table 1. 40 most frequently recurring labels from Foça-related Instagram posts

ID	Label	f [1]	f% [2]	∑f [3]	ID	Label	f [1]	f% [2]	∑f [3]

1	vacation	2114	3.18	3.18	24	cool	481	0.72	31.48
2	tourism	1490	2.24	5.42	25	selfie	451	0.68	32.16
3	photography	1477	2.22	7.64	26	coastal and oceanic landforms	445	0.67	32.83
4	summer	1337	2.01	9.65	27	bay	435	0.65	33.49
5	sea	1217	1.83	11.48	28	long hair	420	0.63	34.12
6	sky	1171	1.76	13.25	29	recreation	418	0.63	34.75
7	leisure	1088	1.64	14.88	30	house	410	0.62	35.36
8	ocean	919	1.38	16.26	31	sunlight	380	0.57	35.93
9	fun	876	1.32	17.58	32	sunglasses	372	0.56	36.49
10	coast	763	1.15	18.73	33	glasses	366	0.55	37.04
11	beach	725	1.09	19.82	34	fashion	364	0.55	37.59
12	happy	690	1.04	20.86	35	photo shoot	364	0.55	38.14
13	tree	682	1.03	21.88	36	eyewear	350	0.53	38.67
14	water	681	1.02	22.91	37	dress	349	0.52	39.19
15	cloud	664	1.00	23.91	38	landscape	342	0.51	39.71
16	smile	653	0.98	24.89	39	architecture	339	0.51	40.22
17	plant	607	0.91	25.80	40	building	339	0.51	40.73
18	beauty	604	0.91	26.71	⋮	⋮	⋮	⋮	⋮
19	vehicle	597	0.90	27.61	2420	snowshoe	1	0.00	100.00
20	horizon	542	0.82	28.42	2421	mosque	1	0.00	100.00
21	travel	539	0.81	29.23	2422	free-climbing	1	0.00	100.00
22	mountain	525	0.79	30.02		∑	66482	100.00	
23	leg	489	0.74	30.76					

[1] frequency, [2] percentage frequency, [3] cumulative percentage frequency

According to Table 1, the 40 most frequently recurring labels constitute 41% and 2% of the total labels (66482) and the individual labels (2422), respectively. Furthermore, the ratio of labels with a frequency of 1 to individual labels is approximately 39%.

Table 1 helps to easily conclude that Foça is a vacation (1st label, 3.18%) and tourism (2nd label, 2.24%) destination with access to the sea (5th label, 1.83%), a beach (11th label, 1.09%) and scenery (e.g. 20th label: horizon, 0.82%).

In contrast, sea is the 5th most frequent label, whereas ocean and water are the 8th and 11th most frequent, respectively. These labels with different frequencies all represent a body of water. Similarly, sky, cloud, horizon, sunlight are labels associated with celestial, and labels such as coast, beach, coastal and oceanic landforms and bay relate to the seaside. Under these circumstances, individual examination of all the labels will not yield an adequate and accurate result due to the existence of labels with similar meanings and different frequencies. Therefore, label clustering on the basis of semantically similar words, features, structures or functions would facilitate analysing the large set of labels.

As seen in step 4 of Figure 1, constructing a mathematical representation of the labels that a computer can understand and designating semantic similarities are necessary prior to label clustering.

Pre-Trained Word Embeddings and Cosine Similarity

Word Embedding (WE) is a technique commonly used in NLP. In essence, it is a vector space where word meanings are numerically represented as word vectors (Ucan and Akcapinar Sezen, 2019). Mathematical representation of words allows the determination of semantic similarities between words by calculating the Cosine Similarity (CosS) of the vector values (Jatnika et al., 2019). CosS ranges between -1 and 1; the closer the cosine value to 1, the greater the similarity between word vectors, and values closer to -1 indicate semantically non-related vectors.

Several models such as Word2Vec (Mikolov et al., 2013), GloVe (Pennington et al., 2014) and Conceptnet-Numberbatch (CN) (Speer et al., 2017) have been developed for WE. Speer et al. (2017) argued that CN, the model adopted in the present study, performed better than Word2Vec and GloVe. CN combines data from both pre-trained WE and knowledge graphs to produce high-quality WE.

The study adopted the Gensim library developed by Řehůřek and Sojka (2010) in the calculation of vectors and CosS for each label. Gensim computes the CosS between two entities with the similarity function and can find the similarity of noun phrases or meaningful sets of two or more words with one or more sets of words via the n_similarity function.

In the study, stop words and punctuation marks were removed when computing the CosS of label pairs. CosS value for all 2422 labels could not be calculated and the number of labels was reduced to 2359. After calculating CosS for every label, the similarity matrix (SM) illustrated in step 5 of Figure 1 was generated. Figure 3 gives the heatmap for the similarity matrix.

Labels	a la carte food	a line	abacus	abalone	abaya	abdomen	acar	accipitriformes	acorn squash	. . .	zucchini
a la carte food	1.000	0.413	-0.016	0.097	0.016	-0.056	0.035	-0.046	0.000		0.058
a line	0.413	1.000	-0.045	-0.072	-0.048	-0.024	-0.093	-0.115	-0.102		-0.105
abacus	-0.016	-0.045	1.000	0.080	0.065	-0.053	0.100	0.021	0.197		0.020
abalone	0.097	-0.072	0.080	1.000	0.037	0.066	0.043	0.154	0.104		0.167
abaya	0.016	-0.048	0.065	0.037	1.000	0.029	0.236	-0.014	-0.007		-0.015
abdomen	-0.056	-0.024	-0.053	0.066	0.029	1.000	0.090	-0.083	0.028		0.053
acar	0.035	-0.093	0.100	0.043	0.236	0.090	1.000	0.089	0.059		0.168
accipitriformes	-0.046	-0.115	0.021	0.154	-0.014	-0.083	0.089	1.000	0.018		-0.046
acorn squash	0.000	-0.102	0.197	0.104	-0.007	0.028	0.059	0.018	1.000		0.469
⋮											⋮
zucchini	0.058	-0.105	0.020	0.167	-0.015	0.053	0.168	-0.046	0.469	. . .	1.000

Figure 3. Similarity matrix heatmap

k-Means Clustering Algorithm

k-means clustering is conducted by randomly choosing k observations from a set of n data to partition n data into k clusters (Demirkale & Özarı, 2020). It is the most common unsupervised learning method (i.e., without any reference or prior knowledge) that automatically forms clusters of similar things. Based on the principle that a centroid can represent a cluster, it generates k unique clusters, where the centre is the mean of that cluster (Harrington, 2012; Steinbach et al., 2000).

In k-means clustering algorithm, the number of k clusters cannot be automatically determined. Therefore, this study adopted Silhouette analysis frequently used in many studies for determining the number of k clusters (Rousseeuw, 1987). It is recommended to select the number of clusters with the highest Silhouette value after the Silhouette values of the data in the clusters are computed for every k clusters.

Due to the disadvantage of k-means clustering to occasionally fail to choose good cluster starting points, Arthur and Vassilvitskii (2007) developed k-means++ which provided a better algorithm for choosing initial cluster centres.

Although the study tried other clustering methods such as Density-Based Spatial Clustering of Applications with Noise (DBSCAN) and Agglomerative Hierarchical Clustering, k-means++ algorithm yielded the most accurate outcome. With the implementation of k-means++ algorithm to the SM, the highest Silhouette score (0.109) was achieved with 27 clusters (Figure 1, step 6). The number of clusters might seem rather high; however, the results were found to be less accurate with fewer clusters.

At the beginning, the researchers considered frequency values for every label in different clusters to be sufficient for sorting. However, as the same labels extracted from various Instagram photos had different CSs, which was an important criterion that had to be considered, the researchers decided on internal sorting of every element (i.e., label) for every cluster (in Figure 2a and 2d, the sky label has CSs of 0.73 and 0.97, respectively). Moreover, a low CS indicates lower accuracy for that label. Therefore, arithmetic mean of CSs for the same label was calculated to account for the CS of each label, after which the sorting score (SS) was computed by multiplying frequency and average CS as indicated below. The significance ranking of labels for each cluster was thus ascertained.

$SS = f_{lebel}.\overline{CS}$ (f_{label}: frequency of a label, $\overline{CS}$: simple average of CSs of a label)

Results

The places, objects and actions in the Instagram posts used in the study are the same, similar or related. For instance, photos taken at the beach contain the sea, sand, the sun, clouds or people in the same shot and are thereby related. Considering Foça is a sea tourism destination, labels such as sea, sky, photography, summer, leisure, fun and coast are frequently encountered.

Labels for objects or places in the posts, even though semantically related, can be characterized by different words. For example, the object sea in a particular image can be labelled as water, ocean, lake or waterway by GCV API, which complicates carrying out a semantic analysis. Furthermore, notwithstanding the existence of high-frequency labels conducive to designating the DI, there are also labels that have come up only once in the entirety of the posts and yet comprise 39% of all the labels, leading to the creation of a large data set that is not relevant for the purposes of this study. Therefore, semantically close words were clustered to facilitate data analysis, generating 27 clusters (Table 2). The contents of the second column of the same table, Cluster Name, were designated by the authors and denominated according to relevance, while the third column lists important labels in the relevant cluster.

Table 2. Cluster names and major labels

ID	Cluster Name	3 Major Labels	SS[1]	SS%[2]
1	Sea and Landforms (Coastal and Oceanic)	sea, ocean, coast, …	6258.15	12.97
2	Celestial and Temporal	sky, summer, cloud, …	5768.73	11.95
3	Human Related	tourism, happy, smile, …	5526.92	11.45
4	Art	photography, beauty, architecture, …	4013.69	8.32
5	Clothing	eyewear, fashion, sunglasses, …	3942.49	8.17
6	Body Parts	leg, long hair, shoulder, …	3803.70	7.88
7	Events	vacation, fun, event, ...	2778.29	5.76
8	Urban	city, street, town, …	1909.44	3.96
9	Boating and Water Sports	water, boat, boating, …	1890.44	3.92
10	Constructional	house, building, wall, …	1841.06	3.81
11	Colours	blue, black hair, pink, …	1808.20	3.75
12	Uncategorized	travel, model, body of water, …	1478.11	3.06
13	Activities (Physical)	leisure, recreation, team, …	1340.19	2.78
14	Plants (Small)	plant, flower, botany, …	1196.54	2.48
15	Plants (Large)	tree, grass, wood, …	1064.94	2.21
16	Vehicles	vehicle, trunk, car, …	908.74	1.88
17	Furniture	sitting, furniture, room, …	634.11	1.31
18	Pets	fawn, cat, felidae, …	565.16	1.17
19	Food and Cooking	food, meal, lunch, …	428.92	0.89
20	Musical	sound, play, performance, …	286.43	0.59
21	Drinks	drink, glass, liqueur, …	197.10	0.41
22	Animals (General)	carnivore, mammal, vertebrate, …	155.49	0.32
23	Cycling	bicycle, motorcycle, bicycle wheel, …	137.77	0.29
24	Fruits, Vegetables and their Products	crop top, fruit, peach, …	132.83	0.28
25	Birds and Insects	bird, wildlife, feather, …	77.59	0.16
26	Hot Beverages	cup, coffee cup, coffee, …	68.99	0.14
27	Confectionary	dessert, cake, ice, …	49.41	0.10
		$\sum$	48263.42	100.00

[1] sorting score, [2] percentage sorting score

As seen in Table 2, k-means++ algorithm has yielded fairly accurate results; however, some clusters contain semantic errors. For instance, sound, meaning "slightly broad water channel between two bodies of water," was inaccurately classified in the Musical cluster due to possible errors inherent in unsupervised clustering. Likewise, black hair in the Colours cluster which signifies "hair" that is black although it evokes the colour black. These are regarded as algorithm-based errors due to synonymous words or phrases. However, this does not pose a serious problem as their percentage is relatively small.

Images of the sea, the seaside and marine landforms were the most popular Instagram posts about Foça. In other words, these posts most commonly contained places and objects associated with sea tourism, such as sea, beach and bay.

The second most popular cluster was Celestial which comprised labels like sky, cloud, horizon. Labels in this cluster feature particularly in seaside or landscape photographs.

The cluster with the third most frequent posts was Human-Related, such as happy, smile, cool. This stems from people's desire to share photos of themselves in Instagram posts and was not considered as an important criterion for DI. Likewise, the clusters Clothing, Body Parts, Vehicles, Furniture, Pets, Animals, Cycling, Birds and Insects are irrelevant to Foça's DI.

Art cluster especially comprised photography-related labels involving landscape or nature photos taken in Foça. In addition, the high SS for architecture in the same cluster supports the depiction of old stone houses with aesthetically pleasing architecture, as well as the existence of Urban and Constructional cluster.

Events contains some high frequency labels like vacation, fun, event and holiday as the AI has demonstrates Foça's role as a tourist destination from posted photos.

Urban and Constructional clusters were generated because old stone houses and streets that endow Foça with an Aegean town aesthetic were prevalently photographed. Furthermore, as Foça is a coastal town, there is plenty of fishing, marine transportation and water sports taking place, which has led to the generation of Boating and Water Sports cluster. Colours such as blue, white, turquoise, yellow and azure that feature in the top results originate from the sky, the sea and the natural environment.

Physical activity consists of labels related to touristic and sports activities in Foça, i.e. leisure, recreation, physical fitness, etc.

Small and Large Plants classified in two clusters represent Foça's green nature.

Musical cluster indicate the presence, albeit small, of music-related activities in Foça.

Notwithstanding the well-known popularity of Foça's seafood restaurants and seaside cafes and bars, the low percentages of the clusters associated with food and drinking are an interesting finding. Moreover, although agricultural production is widespread in and around Foça, the percentage of Fruits, Vegetables and their Products was low.

Labels the algorithm failed to associate with any cluster were categorized under Cluster 27, which is a subject that needs to be studied in the future. In the clustering tests (DBSCAN and Agglomerative Hierarchical Clustering), attempts with the same number of clusters similarly yielded an Uncategorized cluster containing labels that did not match any of the other clusters.

Discussions

This study proposes a methodology for determining the elements that shape an area's DI by adopting Instagram as data source and using CV, NLP and ML in conjunction. In addition, the study provides a numerical representation of what the contents of Instagram photographs are and what these contents are associated with when tourists want to research and get to know a destination, especially considering tourists consult SNs when they want to learn about a destination. Thus, decision-makers can identify the elements that attract the greatest touristic interest by characterizing human likes as the primary factor, thereby allowing investments, advertisements, websites and SN accounts to be constructed according to what is liked the most.

Unfortunately, the idea presented in the article cannot be tested because there is no DI study in the literature of Foça. However, especially considering the CV results, which are the main source of the processed data, the high frequency labels given in Table 1 give a clear idea about Foça's DI.

Past DI research with SNs involved large data sets with prolonged processing time and generally extensive human intervention. Moreover, these studies are mostly based on observation, interpretation and surveys. In today's information age, the constantly surging SN data is big data, which can be analysed faster and more efficiently with AI and ML compared to conventional methods. The methodology suggested in the present study will influence and contribute to DI research for the processing of such a large amount of data.

This study involved determining the DI and the elements that acted on the DI of Foça, İzmir within a specific time period. The study results yielded 17 classes associated with the designated touristic DI without any human intervention. The study methodology can be implemented irrespective of data size and dynamicity. The methodology also allows tourists' Instagram posts to be examined in major (clusters) and minor (labels) modalities; for instance, demonstrating the frequency of any label in any cluster. Using image posts as data source in DI research using CV also reveals finer details, which provides more accurate results despite increasing the amount of data to be processed.

Since UGC is an important element that determines the destination image, the public, private sector, local administration, destination tourism management office or the DMO, which will be created by the combination of all these, should plan for the determination of the content in specific areas and forms. Within the scope of this planning, these areas should be categorized as natural, historical, culture, and art and should be made attractive for tourists to take pictures. Areas that are frequently used in UGC should be visible along daily tourist travel routes or shopping areas in the destination. If a connection can be established on social media and websites related to these areas and SN contents, attention should be drawn by associating them with city history and city stories. A design created in this way will support DI and ensure that the previous plans are sustainable. In addition, it will ensure that the places, themes and photo formats that are desired to be included in DI are widely included in SN by the users. After the planning and editing activities are completed, the contents will be re-analysed at certain periods and it will be possible to check that planning activities supporting DI has been carried out. In addition, it will ensure that the places, themes and photo formats that are desired to be included in the destination image are widely included in the social media by the users.

In future studies, the inclusion of the social identity of SN users (age, income, education, etc.) into the analysis would enable a different interpretative approach to the study results. In addition, even though the study was conducted in the summer when the destination hosts a greater number of tourists, it is uncertain whether the users who posted Foça photos were actually tourists, which is a criterion that must be considered in future research.

Despite the existence of errors and failing to achieve the best possible results with word similarity and clustering methods, these errors were deemed acceptable, and the study produced the desired results. However, the researchers believes that the utilization of different methods could generate more accurate results in the future.

Declaration

The contribution of all the authors of the article to the article process is equal. The authors have no conflict of interest to declare.

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