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**Assessment Cover Page**

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Chapter 1: Introduction

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  2. Research problem
  3. Research questions
  4. Research hypothesis (Ho, Ha)
  5. Research objectives

paragraph

Chapter 2: Literature review/ related works

2.1 Technologies you are using (machine learning)

Paragraph (summarise your related work)

Chapter 3: Methodology

Write one or two sentences that describe the aim of your project.

Add architectural diagram of your project.

3.1 Dataset information

3.2 Data analysis and preprocessing

3.3 Model training (3 models)

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4.1 Results from ED

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Paragraph (discuss your result and compare with research hypothesis)

Chapter 5: Conclusion (brief about research problem, aim, solution, research, contribution to the body of knowledge, and future work).

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# Introduction

## Motivation

“Over the last decade, Iceland has experienced an unprecedented tourism boom, establishing itself as a highly attractive destination due to its unique natural beauty, culture, and safety”, as noted by Johannesson et al. (2010, p.278), “tourism in Iceland has evolved from a marginal activity to a central component of the national economy”. This growth in tourism has brought significant economic opportunities, but also important challenges related to strategic planning. Understanding the profiles of visitors travelling to Iceland non only allows for the improvement of tourism services but also supports the implementation of more effective public policies. In this context, data analysis has become an important tool for transforming information into applicable knowledge. Techniques such as clustering enable the segmentation without the need for pre-labelled data, helping to uncover hidden patterns. Applying these methods to the study of tourists visiting Iceland can offer new insights into their behaviours, thus contributing to more informed decision-making by industry stakeholders.

## Research Problem

Currently, there is limited profiling of tourist visiting Iceland. Available information often focuses on general statistics by country of origin, without deeper segmentation based on variables such as age, length of stay, and income. This lack of segmentation limits the ability of tourism institutions to develop targeted marketing campaigns and promote a more personalised experience.

## Research Question

Given the above problem, the research question which will guide this research is: How can clustering techniques be applied to identify relevant tourist segments visiting Iceland, based on age, length of stay and average income?

## Research Hypothesis

Null Hypothesis (H0): There are no clear segmentation patterns among tourists based on the analysed variables.

Alternative Hypothesis: (Ha): There are significant segmentation patterns among tourist, and these can be identified using unsupervised clustering algorithms.

## Research Objectives

The main objective of this project is to explore the effectiveness of unsupervised algorithms in segmenting tourists visiting Iceland according to 3 variables: age, length of stay, and income. To achieve this general aim, there are some other objectives such as, analyse and prepare a tourism dataset, apply and compare 3 clustering models, evaluate their performance, visualise and interpret the segments generated by each method to identify relevant tourist profiles, and discuss the implications of the findings.

# Literature Review

The use of machine learning techniques in tourism research has grown significantly over the past years, offering new ways to analyse tourist behaviour, segment markets, and support strategic decision-making. Unsupervised learning techniques have gained attention due to their ability to uncover patterns without the need for labelled data. Tourism is a complex industry influenced by diverse demographic, behavioural and economic factors. Traditional statistical methods have often fallen short in capturing this complexity. According to the UNWTO (2023), “big data and advanced analytics offer the opportunity to shift from reactive to proactive destination management”. This has encouraged researchers to adopt machine learning models to improve decision-making in areas such as tourist flow prediction, experience personalisation, and visitor segmentation.

## Clustering Techniques

Clustering is a type of unsupervised machine learning that groups data points into clusters based on similarity. It is particularly well-suited to tourism studies, where traveller behaviour can be segmented based on attributes such as demographics, spending habits, and travel motivations. Several studies have demonstrated the value of clustering for segmenting tourist markets. For instance, Dolnicar (2022) reviewed numerous data-driven segmentation studies and concluded that clustering techniques offer more meaningful tourist profiles than traditional demographic approaches. Her work highlights the importance of including behavioural and psychographic data, such as travel motivations and preferences, in addition to basic variables like age or income.

The present study compares three clustering methods (K-Means, Hierarchical, and DBSCAN) to a tourism dataset from Iceland in the year 2023. While prior work has largely focused on larger-scaled datasets, this research seeks to explore how even small, structured dataset can yield valuable insights into tourist behaviour based on age, length of stay, and income. By testing different clustering methods and looking at the groups they create, this study adds to the discussion on how data can help improve tourism planning. The results can help with making better decisions and creating more suitable services for visitors in Iceland.

To sum up, many studies have shown that clustering methods can help understand and organise tourist data better than traditional ways. Researchers now use more detailed data, like behaviour and preferences, instead of just age or income. This project uses three clustering methods to study a real dataset. Even though the dataset is small, it can still give useful information about tourist groups. The literature shows that machine learning, especially unsupervised methods, can support better planning and decision-making in the tourism industry.

# Methodology

## Project Aim

The aim of this project is to explore tourist behaviour in Iceland during 2023 by applying different clustering algorithms to a structured dataset. By identifying distinct groups based on age, length of stay, and income, the project seeks to provide insights that can support more targeted tourism strategies and service designs.

## Methodological Framework

This project was developed following the CRISP-DM (Cross-Industry Standard Process for Data Mining) methodology, which provides a robust and systematic framework for carrying out data mining tasks. The process involved six stages: Business Understanding, Data Understanding, Data Preparation, Modelling, Evaluation, and Deployment. Each stage contributed crucially to the project’s overall aim of exploring tourist behaviour in Iceland during 2023, by identifying meaningful segments based on demographic and behavioural patterns.

### Business Understanding

The initial step focused on defining the project’s objectives and understanding the underlying business problem. Tourism authorities and stakeholders in Iceland increasingly need to customise their services and marketing efforts to diverse tourist profiles. Understanding how tourist differ in age, stay duration, and income can guide better-targeted strategies, enhance visitor satisfaction, and promote sustainable tourism development. The project’s primary goal was thus to uncover distinct tourist segments through unsupervised learning techniques.

### Data Understanding

After clarifying the business goals, the next step involved familiarising with the available data. The dataset was obtained from the official Icelandic Tourism Board (Ferdamalastofa) via the 2023 Visitor Survey, available at <https://www.ferdamalastofa.is/en/recearch-and-statistics/visitor-surveys> . It consisted of aggregated survey data in an Excel format, reflecting the behaviour of visitors from different nationalities.

### Data Preparation

### Modelling

Three clustering algorithms were applied to uncover patterns in the data:

* K-Means Clustering: a popular and robust method for partitioning data into k non-overlapping clusters. K-Means assumes spherical clusters and minimizes intra-cluster variance.
* Hierarchical Clustering: this method built a hierarchy of clusters using a bottom-up approach (agglomerative clustering). A dendrogram was created to visually identify possible numbers of clusters.
* DBSCAN (Density-Based Spatial Clustering of Applications with Noise): unlike K-Means and Hierarchical clustering, DBSCAN does not require pre-specifying the number of clusters and is able to detect noise points.

For K-Means, it was essential to determine an optimal number of clusters. The number of clusters (k) was explored between 2 and 5. The rationales behind this range was based on the relatively small size of the dataset (21 observations), a high number of clusters would overfit the data and result in meaningless or extremely small groups; practical considerations, tourism segmentation strategies typically prefer a limited number of targetable groups for operational practicability; and the exploratory dendrogram from hierarchical clustering suggested 3-4 natural divisions. To evaluate the optimal k value. Two interval validation indices were used: silhouette score, which measures how similar an object is to its own cluster compared to other clusters. Values close to 1 indicate well-clustered data, and Davies-Bouldin index, which measures the average similarity between clusters, where lower values represent better partitioning. By systematically applying both metrics, it was found that four clusters offered a strong balance between high internal consistency and interpretability. The Davies-Bouldin index minimized at k=4, and the silhouette score was second-highest for four clusters, supporting the selection.

### Evaluation

The clustering outcomes were assessed not just validation metrics, but also through heatmaps, where cluster centres were visualised to observe how different nationalities grouped across age, stay duration, and income variables; and ANOVA testing, to statistically verify if the formed clusters significantly differed across the variables, this involved examining the F-statistic and p-values for each variable between clusters. It was found that significant differences existed primarily in age-related variables and length of stay, while income showed little to no significant variance among clusters. Hierarchical clustering, explored primarily via dendrogram analysis, reinforced the selection of 3-4 cluster divisions. However, when conducting ANOVA on clusters derived from hierarchical clustering, the results showed fewer significant differences compared to K-Means clustering. Thus, K-Means was chosen for the final analysis. DBSCAN was tuned using manual adjustments of eps (radius) and min\_samples (minimum points to form a cluster). However, a portion of the dataset was consistently labelled as noise (indicated by cluster label -1). Given the compact nature of the dataset (small number of nationalities), DBSCAN’s performance was suboptimal compared to K-Means. It was concluded that DBSCAN was the least suitable for this context

### Deployment

Once the final clusters were established, an in-depth interpretation was conducted, clusters were profiles according to their demographic and behavioural features and strategic recommendations were derived, suggesting how Icelandic tourism authorities might customise services and marketing efforts based on these profiles.

In conclusion, this methodological framework enabled a comprehensive and systematic exploration of tourist segmentation in Iceland. The project demonstrated how structured data analysis, coupled with robust machine learning techniques, can reveal actionable insights to support destination management and planning. Future work could extend the methodology by incorporating larger datasets, unstructured data sources (like social media posts), and by applying alternative clustering validation techniques to further strengthen the findings.

## Architectural Diagram

Chapter 3: Methodology

Write one or two sentences that describe the aim of your project.

Add architectural diagram of your project.

3.1 Dataset information

3.2 Data analysis and preprocessing

3.3 Model training (3 models)

3.3.1 Neural networks

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3.4 Model evaluation

# Results and Discussion

This section presents the outcomes of the clustering analysis and subsequent ANOVA tests conducted to validate the hypothesis. Following the comparison of various clustering methods, K-Means clustering with four clusters was identified as the most suitable solution for segmenting tourists visiting Iceland in 2023. The selection was grounded in the evaluation of internal validation indices: Davies-Bouldin index highlighted four clusters as the optimal choice, while silhouette score corroborated this by ranking it as the second-best option. Heatmaps were generated to visually examine the distribution of demographic, behavioural, and economic variables across the clusters. The visual inspection indicated clear distinctions between clusters, particularly with respect to age groups and length of stay. Besides K-Means, hierarchical clustering and DBSCAN were also explored to determine the most suitable segmentation method. Hierarchical clustering was primarily employed to visualise the potential number of clusters through a dendrogram, which suggested a division into three groups. However, this method was not pursued further for final clustering due to less distinct separation between groups when interpreted the heatmap. DBSCAN was also tested as a density-based alternative, but it did not yield satisfactory results, the algorithm classified a large portion of the data as noise and only formed a few small clusters, indicating that the dataset’s characteristics were not ideal for density-based clustering. Based on these findings, K-Means was selected as the final method for segmentation, offering better interval validation metrics, clearer and more interpretable clusters structures, and a more practical basis for informing targeted marketing and destination management strategies.

To statistically verify the significance of differences across clusters in K-Means, an ANOVA (Analysis of Variance) test was conducted. The results were interpreted at a 95% confidence level (α= 0.05).A comparison of the ANOVA results between K-Means and Hierarchical clustering further supported the selection of K-Means for this study. Although both methods revealed significant differences in key variables such as the 25-34 years and >55 years groups, as well as lengths of stay from 2 to 12 nights, K-Means provided stronger and more consistent statistical evidence. K-Means captured significant differences among the youngest visitors (< 24 years) and those staying for longer durations (> 13 nights), which hierarchical clustering did not. Furthermore, while hierarchical clustering detected some variation in income categories, the differences were weaker and less aligned with the study’s initial focus on age and behavioural patterns. In addition, the p-values obtained with K-Means were generally lower, indicating clearer separation between clusters.

The outcomes in K-Means are summarised as follows:

* Age group
  + < 24 years: significant difference among clusters (p= 0.0102).
  + 25-34 years: highly significant difference (p= 0.0002).
  + 35-44 years and 45-54 years: no significant differences observed (p> 0.05).
  + > 55 years: significant difference (p= 0.0190).
* Length of stay
  + 2-3 nights: significant difference (p= 0.0011).
  + 4-5 nights: very strong significance (p< 0.0001)
  + 6-8 nights and 9-12 nights: significant differences (p= 0.0016 and p= 0.0002).
  + >13 nights: significant difference (p= 0.0368)
* Income
  + Low, low average, average, high average and high: no significant differences were observed (p> 0.05).

The findings of this study offer valuable insights into the segmentation of tourists visiting Iceland. By applying K-Means clustering, four distinct tourist profiles were identified, differing notably in demographic characteristics and patterns of stay. The significant differences observed among the younger age group (<24 years) and the 25-34 age category underline age as key differentiator among tourist segments. This aligns with prior studies (Dolnicar, 2022) that underscore the critical role of demographic variables in market segmentation. Younger tourists typically display different travel motivations, preferences, and expenditure behaviours compared to the older people. The significant variation observed in the > 55 years age category further emphasis the need for age-specific tourism strategies. Older visitors may prioritise comfort, accessibility, and cultural experiences, while younger tourists might favour adventure, affordability, and social opportunities. In terms of the length of stay, clear distinctions among clusters were apparent. Significant differences in stay 2-3 nights, 4-5 nights, 6-8 nights, and 9-12 nights suggest the presence of short-term visitors and those opting for medium to extend stays. Destination managers can leverage this knowledge to customise services, accommodation options, and marketing strategies to the needs od different segments. The lack of significant differences for ‘Did not stay overnight’ and 1-night stays implies a more homogeneous distribution for very short-term visitors, possibly due to stopover travellers. Unexpectedly, the analysis revealed no significant differences in income across clusters. Given Iceland’s high living costs and the limited range of budget options, it is plausible that tourists, regardless of demographics background, tend to exhibit similar spending behaviours. Future studies could integrate more granular economic variables, such as types of expenditures (e.g. accommodation, dining, activities), to assess whether differences emerge at a more detailed level.

Each of the four clusters identifies through K-Means clustering represents a distinct tourist profile based on age and length of stay, as suggested by the heatmap of cluster centres and confirmed by the ANOVA test results.

Cluster 0: Young Short-stay travellers. This cluster is mainly composed of younger tourists, particularly those aged under 24-

The selection of K-Means clustering over hierarchical clustering was well-supported by internal validation indices and the interpretability of the results. Although hierarchical clustering yielded reasonably distinct grouping, the segments derived from K-Means were clearer and more actionable for practical tourism management purposes.

Chapter 4: Results and Discussion

4.1 Results from ED

4.2 Classification result from machine learning algorithms

4.3 Regression result from machine learning algorithms

Paragraph (discuss your result and compare with research hypothesis)

Chapter 5: Conclusion (brief about research problem, aim, solution, research, contribution to the body of knowledge, and future work).

# References