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Posted Date: 4 January 2024

doi: 10.20944/preprints202401.0318.v1

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Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 4 January 2024 doi:10.20944/preprints202401.0318.v1

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AliAmbra - Enhancing Customer Experience through the Application of Machine Learning Techniques for Survey Data Assessment and Analysis

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Abstract: AliAmbra [1] is a project developed to explore and promote high-quality catches of the Amvrakikos Gulf GP to Artas' wider regions. In addition, this project aimed to implement an integrated plan of action, to form a business identity with high-added value and achieve integrated business services adapted to the special characteristics of the area. The action plan for this project was to actively search for new markets, create a collective identity for the products, promote their quality and added value, engage in gastronomes and tasting exhibitions, dissemination and publicity actions, as well as enhance the quality of the products and markets based on the customer needs. The primary focus of this publication is to observe and analyze the data retrieved from various tasting exhibitions of the AliAmbra project, with a target goal of improving customer experience and product quality. This publication delved into a thorough analysis, by retrieving data from surveys that took place in the gastronomes of this project, with the assistance of Google Forms. The data retrieved, utilized demographic data, alongside graded products. In addition, we developed a robust recommendation system, with the retrieved data. Finally, this publication includes a review of various data-driven and model-driven algorithms that were of use for the implementation of the recommendation system. The algorithms in question are MLP BFGs, RBF, GenClass, NNC, and FC.

Keywords: grammatical evolution; computational intelligence; neural networks; feature construction; data analysis; recommendation system

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1. Introduction

In recent years, there has been a growing emphasis on sustainable and high-quality catches from regional areas, aiming to not only preserve local ecosystems but also to create business opportunities with a distinctive identity and added value.

The AliAmbra project stands as a noteworthy initiative, specifically focusing on the exploration and promotion of premium catches from the Amvrakikos Gulf, extending its reach to the broader regions of Artas. The core objective of the project is to establish an integrated plan of action, fostering a business identity characterized by high-added value and tailored services that align with the unique features of the area.

Figure 1. AliAmbra Project Logo

This paper centers its attention on scrutinizing and interpreting data obtained from various tasting exhibitions associated with the AliAmbra project. The overarching goal is to enhance

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product quality, contribute to the ongoing action plan of AliAmbra on improving the quality of the products [2], and ultimately elevate the customer experience [3,4]. The methodology employed involves a comprehensive analysis of survey data collected during gastronomic events facilitated by the project, utilizing Google Forms to gather insights into both demographic information and product evaluations.

Furthermore, the publication extends its inquiry into the development of a robust recommendation system based on the acquired data. A pivotal aspect of this research is the incorporation of data-driven and model-driven algorithms to optimize the recommendation system's efficacy. The model-driven analysis focused on the application of several ML/DL algorithms. The algorithms explored are MLP BFGs [5], RBF [6], GenClass [7], NNC [8], and FC [9]. Through this multifaceted approach, the paper seeks not only to contribute valuable insights to the AliAmbra project but also to advance the broader understanding of the application of diverse algorithms in optimizing recommendation systems for projects of similar nature and scope.

Similar studies on the improvement or assessment of the quality of food products using machine learning or deep learning techniques have shown promising results. Computer Vision is also one of many ways to determine or help improve the quality of food products. One study applied convolutional neural networks [10] in food reviews to classify the quality of products using images as inputs, this task was achieved by segmenting the contents of the plate into multiple sections. Another similar study [11] used Computer Vision to analyze the color of coffee beans and classify their quality. In addition, machine learning is capable of assessing the quality of products through large-scale reviews with the assistance of demographic data or food product data. Two studies mention the use of ML algorithms, one focused on the association of demographic data and food choice motives [12] and the other focused on food quality assessment [13].
Moreover, machine learning techniques have also applied to food safety models [14,15], food sales prediction [16,17], evaluation of food quality [18,19], food security [20,21] etc.

The latter sections thoroughly convey the process of each analysis. Materials and Methods, Section 2, discusses the methodologies, tools, and techniques used in each analysis. Section 3 clarifies the development of our dataset, including the structure. Finally, Section 4 expands the analysis by inspecting and visualizing the results of the models with the developed dataset.

2. Materials and Methods

This section will begin with the basic principles of Grammatical Evolution and a full example of producing valid expressions and continue with a full description of the methods used to effectively evaluate the data collected during the execution of the project.

Furthermore, this section covers information about the tools applied in the analysis of this project including the methodologies applied to the model and data-driven analysis.

2.1. Grammatical Evolution

Grammatical evolution [22] is a genetic algorithm with integer chromosomes. Genetic algorithms was proposed by John Holland [23] and they are considered as biologically inspired algorithms. The algorithm produces potential solutions of an optimization problem randomly and these solutions are gradually altered in a series of iterations through the application of the genetic operators of selection, crossover and mutation [24,25]. Genetic algorithms have been used in a series of real - world problems, such as electromagnetic problems [26], combinatorial problems [27], water distribution problems [28], neural network training [29,30] etc. The main advantage of genetic algorithms is that thet can be easily parallelized [31,32] using programming techniques such as MPI [33] or OpenMP [34]. The chromosomes in the Grammatical Evolution represent production rules of the provided BNF (Backus–Naur form) grammar [35]. Any BNF grammar G can be defined as the set $G = (N, T, S, P)$, where

1. N denotes the set of non terminal symbols of the underlying grammar.

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2. T stands for the set of terminal symbols, where $N \cap T = \emptyset$.
3. The terminal symbol S is named start symbol of the grammar.
4. P is a finite set of production rules in the form $A \rightarrow a$ or $A \rightarrow aB,\ A, B \in N,\ a \in T$.

The Grammatical Evolution starts from the symbol S and produces valid programs, expressed only with terminal symbols, selecting production rules from the grammar. The production rules are selected using the following procedure:

- Read the next element V from the chromosome that is being processed.
- Get the rule: Rule = V mod R, where R is the total number of production rules for the current non – terminal symbol.

As an example, consider the grammar of Figure 2 used to produce valid expressions in C - like programming language.

```
S::=<expr>                                    (0)

<expr> ::=   ( <expr> <op> <expr> )           (0)
             | <func> ( <expr> )              (1)
             |<terminal>                      (2)
<op> ::=       +                              (0)
             | -                              (1)
             | *                              (2)
             | /                              (3)

<func> ::=    sin                             (0)
             |cos                             (1)
             |exp                             (2)
             |log                             (3)
<terminal>::=<xlist>                          (0)
             |<digitlist>.<digitlist>         (1)

<xlist>::=x1                                  (0)
             | x2                             (1)
              ___                             ___
             | xN                             (N)

<digitlist>::=<digit>                         (0)
             | <digit><digitlist>             (1)
<digit>   ::= 0                               (0)
             | 1                              (1)
             | 2                              (2)
             ____                             ___
             | 9                              (9)
```

Figure 2. An example BNF grammar, used to produce expressions in a C - like programming language. The numbers in parentheses denote the sequence number of the corresponding production rule to be used in the selection procedure described above. The variable N denotes the dimensionality of the problem.

Also, consider the chromosome $c = (9, 8, 6, 4, 16, 10, 17, 23, 8, 14)$ and $N = 3$. The steps to produce the final string (x2+cos(x3)) are outlined in Table 1

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Table 1. Example of production.

String	Chromosome	Operation
<expr>	9,8,6,4,16,10,17,23,8,14	9 mod 3=0
(<expr><op><expr>)	8,6,4,16,10,17,23,8,14	8 mod 3=2
(<terminal><op><expr>)	6,4,16,10,17,23,8,14	6 mod 2=0
(<xlist><op><expr>)	4,16,10,17,23,8,14	4 mod 3=1
(x2<op><expr>)	16,10,17,23,8,14	16 mod 4=0
(x2+<expr>)	10,17,23,8,14	10 mod 3=1
(x2+<func>(<expr>))	17,23,8,14	17 mod 4 =1
(x2+cos(<expr>))	23,8,14	23 mod 3=2
(x2+cos(<terminal>))	8,14	8 mod 2=0
(x2+cos(<xlist>))	14	14 mod 3=2
(x2+cos(x3))		

The Grammatical Evolution has been used in a variety of problems such as as function approximation[36,37], solution of trigonometric equations [38], automatic music composition of music [39], neural network construction [40,41], creating numeric constraints[42], video games [43,44], estimation of energy demand[45], combinatorial optimization [46], cryptography [47] etc. Recent extensions of the Grammatical Evolution procedure include the Structured Grammatical Evolution [48,49], parallel implementations [50,51], the Probabilistic Grammatical Evolution variant [52], the Multi-Objective Grammatical Evolution approach [53] etc.

2.2. *Construction of Classification Rules*

A basic technique that will be used in conducting the experiments is that of constructing classification rules using Grammatical Evolution. This method was initially proposed in [7] and the corresponding software was described in the [54]. This technique constructs classification rules with the assistance of Grammatical Evolution. The main steps of the used method are provided below.

1. **Initialization Step**
   (a) **Set** with N_C the number of chromosomes that will participate.
   (b) **Set** the total number of allowed generations N_G.
   (c) **Produce** randomly N_C chromosomes. Each chromosome is considered as a set of integer values representing production rules of the underlying BNF grammar.
   (d) **Define** as p_S the used selection rate, with $p_s \leq 1$.
   (e) **Define** as p_M the used mutation rate, with $p_m \leq 1$.
   (f) **Read** the train set $\text{TR} = \{x_i, y_i\},\ i = 1..M$ for the corresponding dataset.
   (g) **Set** iter=0.
2. **Fitness calculation Step**
   (a) **For** $i = 1 \ldots N_G$ **do**
      i. **Create** a classification program C_i. As an example of a classification program consider the following expression:
      $$\text{if } x1 >= (x_2 + \cos(x_3))\ \text{CLASS} = 0 \text{ else CLASS} = 0$$
      ii. **Compute** the fitness value f_i as
      $$f_i = \sum_{j=1}^{M} \left(C_i\left(x_j\right) \neq y_j\right) \tag{1}$$
   (b) **EndFor**
3. **Genetic operations step**

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(a) **Selection procedure.** The chromosomes are sorted initially according to their fitness values. The first $(1 - p_s) \times N_C$ chromosomes with the lowest fitness values are copied to the next generation. The rest of the chromosomes are replaced by offsprings produced during the crossover procedure.

(b) **Crossover procedure**: For every pair of produced offsprings two chromosomes (z, w) are selected from the current population using the tournament selection. The process of tournament selection has as follows: Firstly, create a group of $K \geq 2$ randomly selected chromosomes from the current population and the individual with the best fitness in the group is selected. These chromosomes will produce the offsprings $\tilde{z}$ and $\tilde{w}$ using one point crossover. An example of one point crossover is shown in Figure 3.

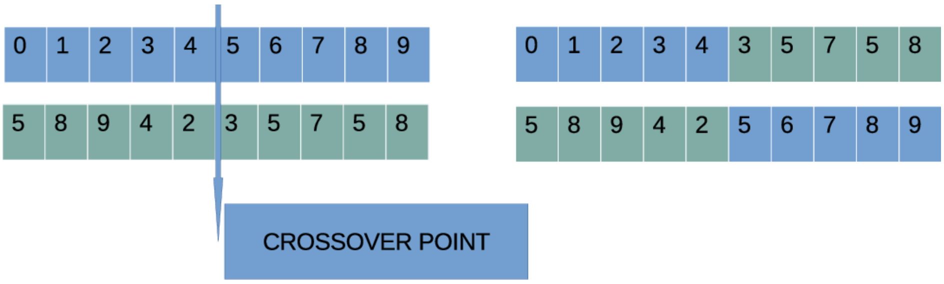

Figure 3. An example of the one point crossover procedure.

(c) **Perform** the mutation procedure. In this process a random number $r \in [0, 1]$ is drawn for every element of each chromosome and it is altered randomly if $r \leq p_m$.

4. **Termination Check Step**

   (a) **Set** $iter = iter + 1$

   (b) **If** $iter \geq N_G$ terminate else goto step 2.

2.3. Neural Network Construction

Another technique that makes the most of Grammatical Evolution is the production of artificial neural networks using it [8]. This technique can simultaneously construct the optimal structure of an artificial neural network and also estimate the values of the network weights minimizing the training error. The steps used in neural network construction are listed below.

1. **Initialization Step**

   (a) **Set** as N_C as the number of chromosomes.

   (b) **Set** as N_G the total number of generations allowed.

   (c) **Produce** randomly N_C chromosomes, as a series of production rules expressed in integer format.

   (d) **Set** the selection rate p_S and the mutation rate p_M.

   (e) **Read** the associated train set $\text{TR} = \{x_i, y_i\},\ i = 1 \ldots M$.

   (f) **Set** iter=0.

2. **Fitness calculation Step**

   (a) **For** $i = 1 \ldots N_G$ **do**

      i. **Construct** an artificial neural network $N_i(x, w)$. The neural networks constructed by this procedure are in the form:

$$N_i\left(\overrightarrow{x}, \overrightarrow{w}\right) = \sum_{j=1}^{H} w_{(d+2)j-(d+1)}\sigma\left(\sum_{k=1}^{d} x_k w_{(d+2)j-(d+1)+k} + w_{(d+2)j}\right) \quad (2)$$

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where d stands for the dimension of the input dataset and H denotes the number of processing nodes in the neural network. The function $\sigma(x)$ stands for the sigmoid function:

$$\sigma(x) = \frac{1}{1+\exp(-x)}$$

ii. **Compute** the corresponding fitness value f_i as

$$f_i = \sum_{j=1}^{M} \left(N_i\left(x_j, w\right) - y_j\right)^2 \tag{3}$$

(b) **EndFor**

3. **Genetic operations step**

   (a) **Selection procedure.** Initially the chromosomes are sorted according to their associated fitness values. The first $(1-p_s) \times N_C$ chromosomes with the lowest fitness values are transferred to the next generation without changes. The rest of the chromosomes are replaced by offsprings produced during the crossover procedure.
   (b) **Crossover procedure**. For each pair of newly added chromosomes two parents are selected using tournament selection. The new chromosomes are created using one point crossover.
   (c) **Perform** the mutation procedure. In this process a random number $r \in [0,1]$ is drawn for every element of each chromosome and it is altered randomly if $r \leq p_m$.

4. **Termination Check Step**

   (a) **Set** $iter = iter + 1$
   (b) **If** $iter \geq N_G$ terminate else goto step 2.

2.4. Feature Construction with Grammatical Evolution

The Grammatical Evolution was also used as the base to construct artificial features from the original one for classification and regression problems [9]. The artificial features that create this procedure will be evaluated using a Radial Basis Function (RBF) network [6]. The RBF network has an extremely fast and efficient training procedure with the incorporation of the K-means [55] method and additionally RBF networks has been used with success in a variety of problems, such as physics problems [56,57], estimation of solutions for differential equations [58,59], robotics [60], chemistry [61] etc. The procedure of creating artificial features is divided in a series of steps listed subsequently.

1. **Initialization Step**

   (a) **Set** the number of chromosomes N_C.
   (b) **Set** the total number of allowed generations N_G.
   (c) **Produce** randomly N_C chromosomes as random sets of integer.
   (d) **Set** the selection rate p_S and the mutation rate p_M.
   (e) **Set** as F the number of artificial features that will be constructed by the procedure.
   (f) **Read** the train set $\mathrm{TR} = \{x_i, y_i\},\ i = 1..M$.
   (g) **Set** iter=0.

2. **Fitness calculation Step**

   (a) **For** $i = 1 \ldots N_G$ **do**

      i. **Produce** F artificial features from the original ones of the dataset.
      ii. The original training set TR is mapped to a new one using the artificial features produced. Denote this new training set as TR_i.
      iii. Train an RBF network $r_i(x, w)$ using the set TR_i.
      iv. **Compute** the fitness value f_i as

$$f_i = \sum_{j=1}^{M} \left(r_i(x_j, w) - y_j\right)^2 \tag{4}$$

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   (b) **EndFor**

3. **Genetic operations step**
   (a) **Selection procedure.** Chromosomes are sorted based on the fitness of each one. The first $(1 - p_s) \times N_C$ will be transferred without changes to the next generation, while the rest will be replaced by chromosomes created in the crossover process.
   (b) **Crossover procedure**: For every pair of produced offsprings two chromosomes (z, w) are selected using tournament selection. These chromosomes will be the parents for two new offsprings $\tilde{z}$ and $\tilde{w}$ created with one-point crossover.
   (c) **Mutation procedure.** For each element of every chromosome a random number $r \in [0, 1]$. if $r \leq p_M$ then this element is altered.
4. **Termination Check Step**
   (a) **Set** $iter = iter + 1$
   (b) **If** $iter \geq N_G$ terminate else goto step 2.

2.5. Statistical Analysis

The statistical analysis was to calculate the frequency of occurrences of all entries. Data visualization was achieved using Python libraries that are capable of generating interactable pie charts as a web application.

The frequency calculation for each entry was achieved by counting each occurrence of an entry for each question. The following formula was used to calculate the frequencies of every answer separately.

$$X_{\text{freq}} = \sum_{i=1}^{n} \delta(a_i = x) \quad (5)$$

Figure 4. Where n is the total number of answers, a_i references the index and value of a given answer to a question. x represents the given answer we want to count. $\delta(a_i = x)$ evaluates as 1 if a_i is equal to x, otherwise as 0.

Once every frequency for each answer and each question is calculated, the data is prepared to be visualized with the help of graphing libraries.

2.6. Plotting Libraries

Streamlit is a highly capable open-source framework [62], that allows users to deploy web applications exceedingly fast and easily in Python. It is compatible with many modern third-party frameworks and was created for data scientists, as well as ML, DL, and computer vision engineers. Furthermore, Streamlit has been a perfect use case for our analysis, not only for the visualization of our data but also for the interaction data charts. Plotly is a high-level low-code graphing library [63], that allows users to create interactive graphs from their data. Plotly is fully supported by Streamlit, allowing users to build professional dashboards under the influence of their data. Seaborn [64] is a high-level Python data visualization library based on Matplotlib. Seaborn was primarily used to plot the prediction data results of the models we reviewed.

3. Datasets & Data Retrieval

The development of our dataset was instigated once we had completed a large portion of the data retrieval. We retrieved data from a total of eight different exhibitions/locations.

It was earlier mentioned, that we received data by interacting with each customer in the tasting exhibitions. The information retrieved was demographic data, alongside graded products and general questions involving the experience they've had and their preferences.

The data retrieval was achieved with the assistance of the members of the AliAmbra project. Google Forms allowed us to build a very simple and fast survey to use. Our members approached each individual once they had tasted each or some of the samples and were provided with several questions about the experience they had with the products.

Prior to the processing of the dataset by the models, we made sure to clean and process any dormant values, to remove possible casualties and improve the model's performance. Any sample that wasn't tasted by the customers was attributed as a NULL value (0). Finally, we made sure to convert the data to numerical values, for the models to detect successfully.

3.1. Survey Structures

There were two types of surveys used in the exhibitions. The first survey included mostly data for a thorough visualization and statistical analysis. We retrieved a total of 366 entries. The second survey included data appropriate for prediction and recommendation systems. Both surveys included timestamps which allowed us to differentiate the locations of each exhibition that every entry was retrieved from. The structure of the first survey included general questions involving the experience they've had with the products, as well as questions referring to each product, how much they liked it, and what they enjoyed the most about it.
The samples included in the first survey are the following

1) Beetroot risotto with smoked eel
2) Fried Sardine
3) Fish croquettes with mullet
4) Sea bream Ceviche with lemon cream and pickled fennel

Table 2. First survey structure. Includes two grading questions repeated for each sample and two general questions. Data retrieval locations: Neoxori Arta 06/11/2023 GP, Kommeno Arta 08/04 GP, Koronisia Arta 08/18 GP, Bigla Artas 08/19 GP, Skoufa Plazza Artas 09/21 GP, Saint Dimitris Plazza Arta 09/22 GP, Zerva Plazza Arta 09/23 GP.

General Questions	**Answers**	**Description**
Which Sample did you enjoy the most?	Sample_Name	The name of the sample
Do you prefer modern or traditional recipes?	Traditional, Modern, Both, None	
Grading Questions	**Answers**	**Description**
Sample Rating	Didn't like it, Neutral, Liked it a bit, Liked it, Liked it a lot	How much did the customer like the sample. Repeated for each sample.
What did you enjoy the most?	Taste, Cooking method, Appearance	Multiple choice question

The structure of the second survey included three demographic questions and five questions involving the grading of the products within the exhibitions. The structure of the survey included three demographic data questions and five questions for each product that took place in the exhibition. The samples included in the second survey are the following

1) Grilled Eel
2) Baked Eel
3) Grilled Sea Bream
4) Grilled Chub
5) Sardine

 doi:10.20944/preprints202401.0318.v1

Table 3. Second survey structure. Includes three demographic questions and five sample grading questions. Data retrieval locations: Psathotopi Artas 10/15 GP.

Demographic Questions	**Sample Rows**	**Description**
Gender	Male or Female	Gender of each customer
Age	15-25, 26-35, 36-45, 46-55, 56-65, 66-75	Age of each customer
Marital Status	Married, Not-married	The marital status of each customer
Product Grading Questions	**Sample Rows**	
Grilled eel	1=not at all, 5=a lot	
Baked eel	1=not at all, 5=a lot	
Grilled Sea Bream	1=not at all, 5=a lot	
Grilled Chub	1=not at all, 5=a lot	
Sardine	1=not at all, 5=a lot	

The second survey is an equivalent of the first, however, the products displayed in the exhibition were different compared to the previous ones. For the general questions of the second survey, it focused on the demographic data, to analyze and determine the preferences of the masses based on the person.

4. Results

4.1. Experimental Results

We conducted a thorough experiment by breaking down the structure of the second survey into two different phases. For the first phase, we used the models mentioned previously to predict the customer preferences using only demographic data. For the second phase, we made the models to predict the customer preferences using the demographic data, including the rest of the products as class features for each entry.

The experiments were executed 30 times for all used methods and in each experiment different seed was seed for the random number. To execute the experiments the freely available QFc software [65] was used and it is available from https://github.com/itsoulos/QFc/(accessed on 7 December 2023). The results are validated using the 10 - fold cross validation method. The execution machine eas an AMD Ryzen 5950X with 128GB of RAM, running Debian Linux and the programs were compiled using the GNU C++ compiler. The values for the parameters of the used methods are shown in Table 4 and the results for the first phase of the experiments are outlined in Table 5 and for the second phase in Table 6 respectively. In the tables with the experimental results the following applies:

1. The column DATASET denotes the tested preference.
2. The column MLP stands for the application of an articificial neural network [66] with H hidden nodes to the dataset. The network is trained using the BFGS variant of Powell [67].
3. The column GENCLASS refers to the application of the GenClass method, used to construct classification rules using a Grammatical Evolution guided procedure.
4. The column NNC stands for the application of the neural network constrcution method analyzed previously.
5. the column FC2 refers to the application of the Feature Construction method of subsection 2.4 to the dataset.
6. In the experimental tables an additional row was added with the title AVERAGE. This row contains the average classification error for all datasets.

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Table 4. The values of the experimental parameters

PARAMETER	MEANING	VALUE
N_C	Number of chromosomes	500
N_G	Maximum number of allowed generations	200
p_S	Selection rate	0.90
p_M	Mutation rate	0.05
H	Number of processing nodes	10
F	Constructed features (Feature Construction method)	2

Table 5. Experiments for the first phase: Demographic data-based dataset preferences

DATASET	MLP	RBF	GENCLASS	NNC	FC2
Grilled eel	25.11%	27.89%	18.00%	21.67%	22.22%
Baked eel	23.78%	33.56%	26.22%	23.11%	25.67%
Grilled Sea Bream	33.22%	40.67%	36.45%	37.34%	32.00%
Grilled Chub	30.22%	35.00%	30.78%	31.45%	28.00%
Sardine	30.22%	35.00%	31.55%	26.33%	28.00%
AVERAGE	**28.51%**	**34.45%**	**28.60%**	**27.98%**	**24.87%**

Table 6. Experiments for the second phase: Dataset with the demographic data counting the rest of the Product Preferences

DATASET	MLP	RBF	GENCLASS	NNC	FC2
Grilled eel	17.11%	13.22%	15.67%	18.22%	15.00%
Baked eel	28.56%	27.89%	22.67%	23.00%	20.00%
Grilled Sea Bream	25.45%	26.78%	24.22%	20.89%	19.56%
Grilled Chub	20.44%	17.22%	16.89%	16.45%	14.33%
Sardine	14.22%	20.44%	19.66%	16.44%	16.22%
AVERAGE	**21.16%**	**21.11%**	**19.82%**	**19.00%**	**17.02%**

4.2. Data Visualization

This section includes visualizations of the analysis applied to the exhibition data, using streamlit [62], plotly [63], and seaborn [64].

4.2.1. Prediction Results

In this section, we present the experimental findings derived from the analysis of the first Table 5 and second Table 6 phases. We utilized the box plot In the current section, the experiment results of the first Table 5 and second Table 6 are plotted using box plots to visualize and better understand the prediction results

 doi:10.20944/preprints202401.0318.v1

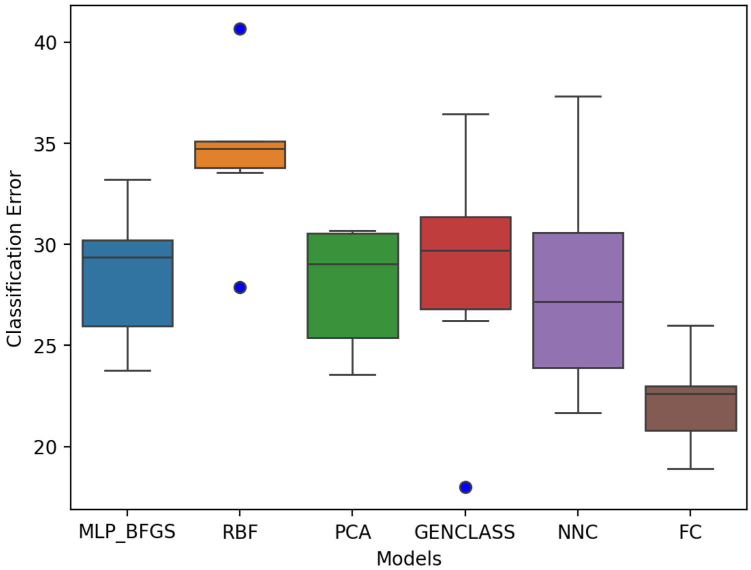

Figure 5. FC2 displays a smaller overall gap and a lower classification error compared to the other model results, meaning that FC2 performed best for the first phase using only the demographic data. On the other hand, the Radial Basis Function (RBF), displays the highest classification error and gap with two visible outliers, compared to the other models. In other words, it displays the least favorable performance in terms of two visible outliers.

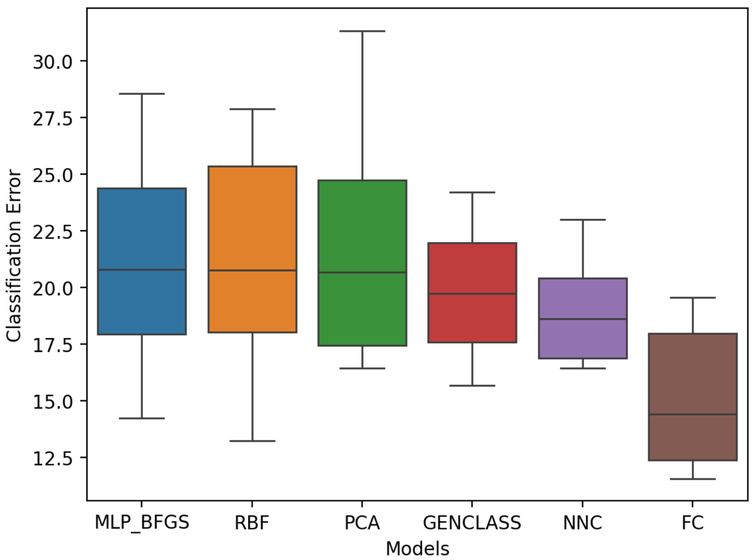

Figure 6. In the second phase, the results display a better distribution among the models compared to the first phase Figure 5. FC2 demonstrates superior performance, displaying a more favorable overall range and median classification error than the other models. MLP BFGS, RBF, and PCA present a rather suboptimal performance, with the overall range and median classification error much higher compared to the other models, however, NNC appears to perform well in terms of the distribution between each product.

4.2.2. Data Analysis

The first survey contained a total of 366 entries for all exhibitions. The second survey contained 39 entries that were retrieved in only one exhibition.

The data analysis results of the first survey are as follows.

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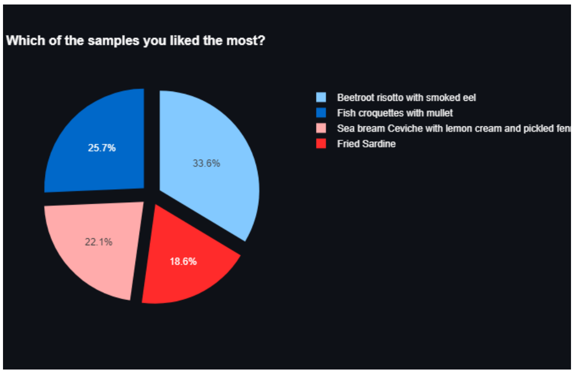
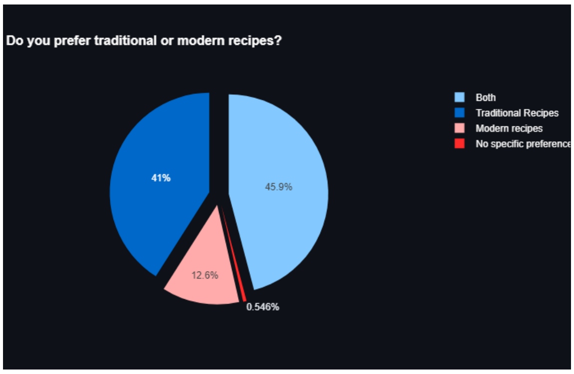
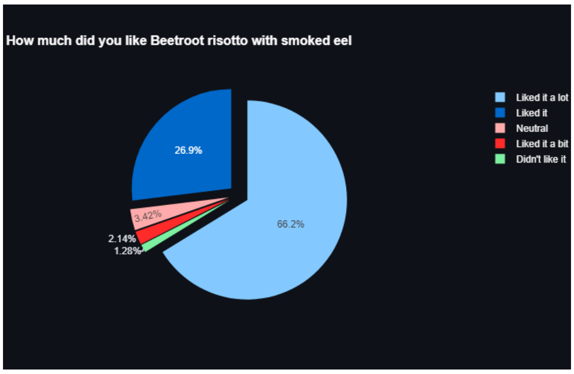


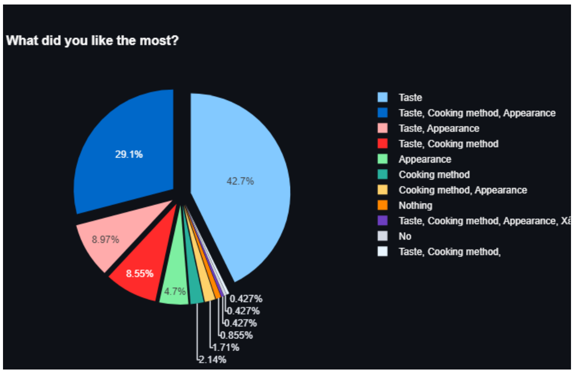


Which sample you liked the most

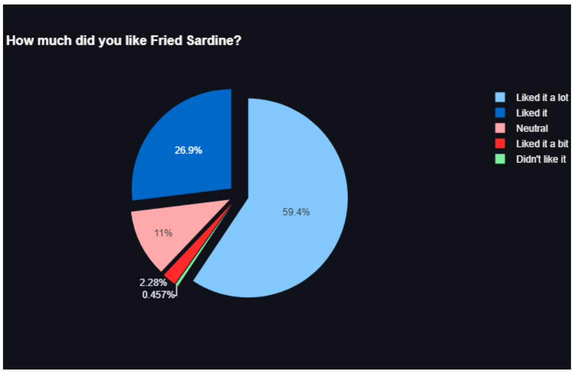
Traditional or Modern Recipes

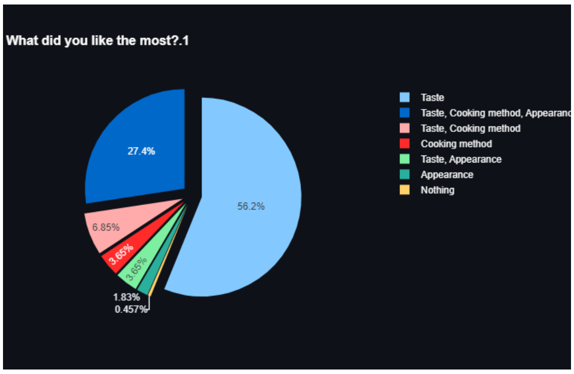
Figure 7. General Question results of the first survey





Beetroot risotto with smoked eel





Fried Sardine

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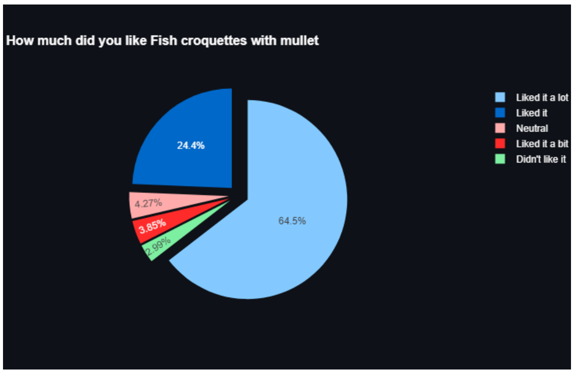
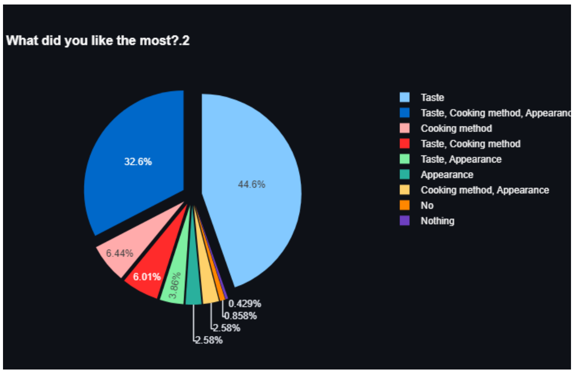
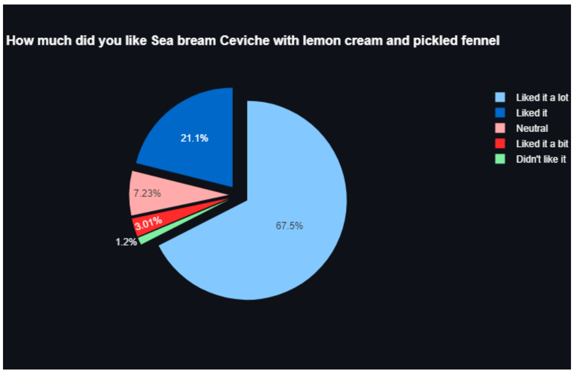
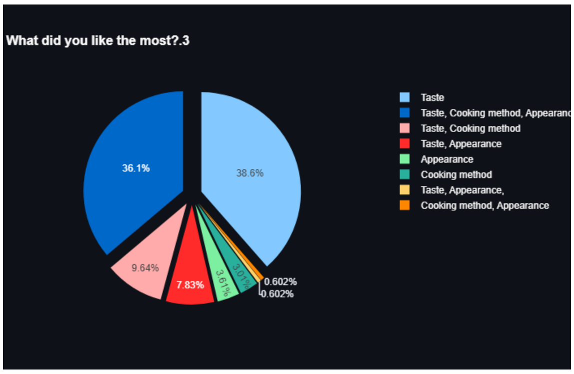




Fish croquettes with mullet



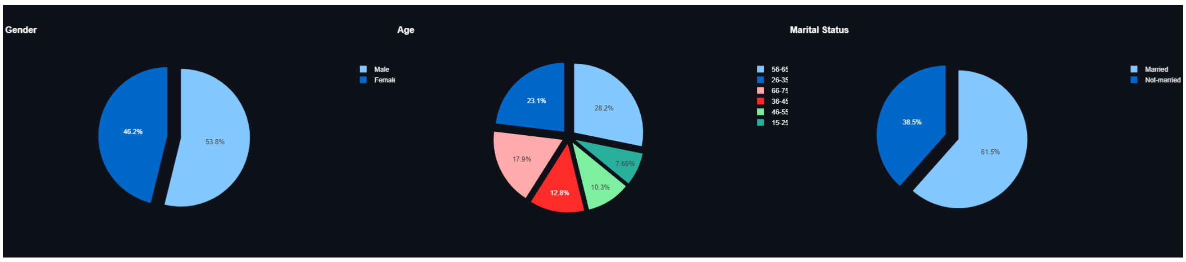


Sea bream ceviche with lemon cream and pickled fennel

Figure 8. Sample question results of the first survey

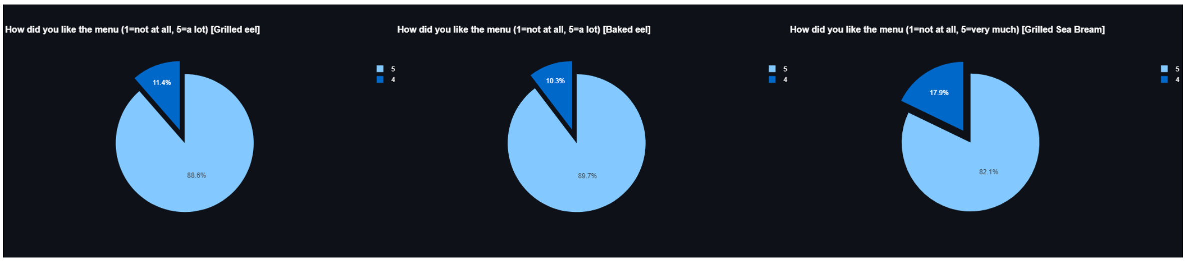
With this analysis we can observe the most liked product, including what they liked the most for that product. We can also observe the preferences of the mass by analyzing the data entries of the question "Do you like traditional or modern recipes?"

The data analysis results of the second survey are as follows.

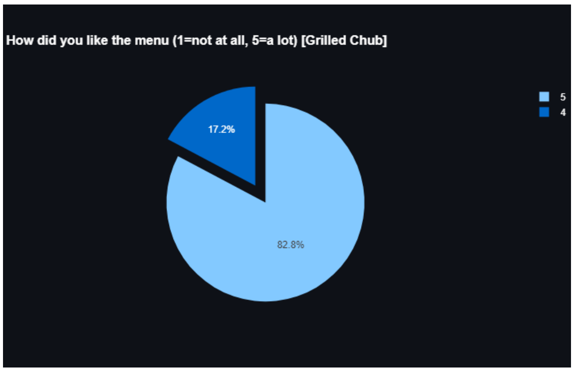


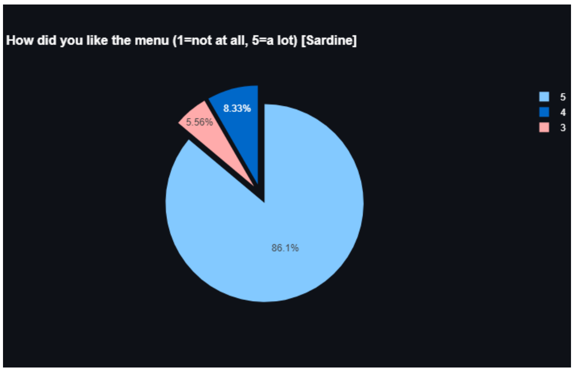
Gender Age Marital Status

Figure 9. Demographic question results of the second survey



Grilled Eel Baked eel Grilled sea bream





Grilled Chub Sardine

Figure 10. Second survey sample question results

5. Conclusions

AliAmbra focused on the promotion of the products produced by high-quality catches of the Amvrakikos Gulf, as a research team, we focused on a thorough analysis of the data retrieved from each exhibition. In addition, we developed a recommendation system to determine a person's preferences for the products displayed in the exhibitions, based on their demographic data.

Each experiment focused on the production of different results. In our model-driven analysis, we found a strong correlation between each customer with their demographic data and preferences for each product, as we can observe in the previous plotted results Figures 5 and 6. We determined that FC2 performed best compared to the rest of the models. In our data-driven analysis, we were able to observe the preferences of the mass for each individual question. We found that each analysis contributed to a different conclusion, in demand for the project.

Based on the analysis that was executed, it can be concluded that the best-fitting algorithm for the development of the project AliAmvra is FC2 [9]. FC2 performed best in both phases, where only the demographic data or all of the data, was used to recommend a customer a product they would consider.

In order to see more normalized data results in the model-driven analysis, we have determined to retrieve more data on the second survey

6. Future Work

To get more accurate results from our model-driven analysis, more data will need to be retrieved using the second survey with the demographic data. This can be achieved with future exhibitions that can take place with the AliAmvra project.

After our analysis, we have acknowledged that in order to improve the accuracy of our model-driven analysis, it is vital that we proceed to retrieve more data through the second survey. This can be accomplished by conducting future exhibitions as part of the AliAmvra project.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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