# MULTIVARIATE ANALYSIS OF TASTE COMPOUNDS AND SPECTROSCOPIC PROPERTIES FOR ANIMAL ORIGIN FOOD PRODUCTS

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**Abstract:** UMAMI taste compound represented in the biggest amount by monosodium glutamate, was determined for four types of cheese, and also in goat and salmon meat.Monosodium glutamate content was quantificated using an enzyme linked assay (ELISA). The content of proteins, lipids, carbohydrates and ash were also determined using AOAC methods. An exploratory analysis of the hybrid database was performed using Principal Component Analysis (PCA) in order to identify the similarities among the analyzed products from the point of view of their chemical, molecular and sensorial properties. The variables contributing to the cluster discrimination are also related to the raw material of the assortments and to the characteristic features of technological process.
**Keywords:** Parmesan cheese, Goat meat, Monosodium glutamate, hybrid database, Principal Component Analysis.

## 1. Introduction

Parmesan cheese, Gouda cheese, Ementhal cheese is used not only for usual consumption but also widely as food ingredient, due to theirs delicate taste, flavor and taste - flavor compatibility [1, 2].

Milk quality plays a very important role on cheese yield and characteristics [3]. Also the region, the diet [4], the season [5], the time of the day (morning or evening) when the milk was collected, the refrigeration temperature [6] and the technological aspects [7,8] can influence the overall quality of cheese and in particular the sensorial aspects of these.

The Italian tradition in cheese making is very old and put on the table around 400 types of cheeses. The Pecorino Romano cheese is one of the most ancient cheeses – a description of cheese making process is pointed out before Christ. The Pecorino cheese has a taste typically strong. The Parmigiano Regiano cheese is an extra –hard cheese with a light straw-yellow color, a friable structure and a fragrant and delicate aroma. It is the representative cheese product for the umami taste. Gouda cheese is a cheese traditional from Netherlands, a hard cheese with relative low water content and with

relatively shiny openings. The flavor is creamy and mild. Emmenthal is a Swiss type cheese, is a large dimension cheese, hard pressed, with eyes with a soft and nutty flavor.

All these types of cheeses are produced all over the world. The purpose of the study is to evaluate the physico-chemical composition of these cheeses produced in Italy and Romania respectively. To evaluate the monosodium glutamate content the principal responsible for umami taste and to put the basis of a hybrid data base for dairy products.

## 2. Materials and methods

To create data base were selected four cheese assortments Parmesan cheese, Emmenthal cheese, Gouda cheese and Pecorino cheese. Te tests were extended also to two types of meat (being in animal origin food product area), very well known for their power

of umami taste young goat meat and salmon. For each product were analyzed 10 samples. – Parmigiano Regiano from Italy (PRIx) Parmesan Napolact from Romania (PNRx), Emmenthal Swizzera Italia (ESIx), Ementhal Dalia Romania (EDRx), Pecorino – Italy (PCIx), Gouda Gold Natural – Romania (GGNx), Cacciota con Peperoncino – Italy (CPIx) , Gouda Gold Picant – Romania (GGPx), young goat meat (CIRx) and salmon (SOMx) (x = 1…..10).

### 2.1. Physico-chemical analysis

The water, proteins, lipids content were evaluated using AOAC methods.

The monosodium glutamate content using Glutamate Assay kit (Bio Vision). The BioVision's Glutamate Assay Kit provides a sensitive detection method of the glutamate in a variety of samples. The glutamate Enzyme Mix recognizes glutamate as a specific substrate leading to proportional color development. The glutamate standard curve was obtained by a dilution of 10 µl of 0.1M Glutamamte Standard with 990 µl Assay Buffer. The tissue was homogenized and incubated at $37^0$C for 3 min. The amount of glutamate can therefore be easily quantified by colorimetric (spectrophotometry at $\lambda$ = 450 nm) methods. Spectrophotometer Sunrise Tecan with Magellan soft was used. The glutamate concentrations of the test samples were calculated:

$C=S_u/S_v$ nmol.$\mu L^{-1}$

where:

-$S_u$ is the sample amount of unknown (in nmol) from standard curve;

-$S_v$ is the sample volume (µL) added into wells.

### 2.2. Spectral analysis

The spectra of 100 samples have been registered between 190.3387 and 1099.992 nm (spectrophotometer UV-VIS Cintral) 0.426829 nm apart. These measurements have resulted in a spectral database representing a matrix with 100 x 2132 entries. In order to evaluate if the samples resent significant variations (and thus a chemometrical approach is necessary for the multivariate analysis of the data), the spectra were first inspected visually.

This initial evaluation aims to identify those variables that contribute obviously to the (similarity) modelling power or to the discrimination power of the data. The conclusions of this evaluation are expected to help us eliminate those variables that obviously do not have any discrimination power. In other words, their elimination from the database avoids the redundant information, and thus allows a much quicker chemometric data processing.

### 2.3. Statistical analysis

Principal Component Analysis (PCA) was applied to a hybrid data base composed by mean components of cheese values (water content, proteins, fat and MSG) and also to spectral database. The validation method has been full cross-validation.

## 3. Results and discutions

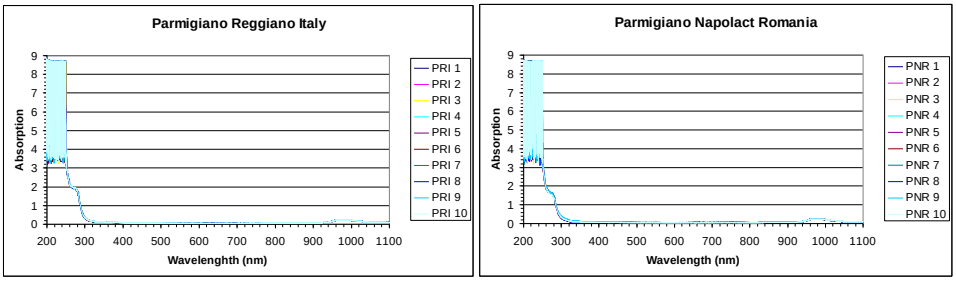
### 3.1. Principal Component Analysis

A first observation has been the fact that the absorptions of all spectra record systematically very large variations under 200 nm, probably because of the lower stability of the spectral source in this domain. For this reason, these absorptions have been

eliminated from the database and the evaluation has continued for the rest of the wavelengths.

Figure 1a shows that in the case of PRI, the most important absorptions show between 200 - 340 nm, and 940 - 1040 nm. The absorptions are characterized by a remarkable stability, the variations recorded for different samples being practically insignificant. The absorptions of PNR are presented in figure 1b. As the spectral data quality is low for wave numbers smaller than 250 nm for both PRI and PNR samples, the spectral window 200-250 nm has been eliminated from the database.

In order to assess if the intracategory variations may help discriminate between the two types of cheese based solely on their spectral behavior, the mean spectrum of the PRI and of Parmigiano Napolact –Romania (sample code PNR), mean spectra have been computed. Te spectra for all the samples were nearly identical. Small differences can be noticed in the intensities of the absorptions in the 256-278 nm spectral window, PRI presenting slightly stronger absorptions than PNR. We can draw the conclusion that the absorptions between 200 – 340 nm have the most important modelling power for Parmigiano cheese, including the 256-278 nm spectral window, which may serve for intracategory discrimination purposes according to the geographical region of origin. The rest of the spectrum can be eliminated, as it represents redundant information.A similar behavior is encountered for the Emmenthal cheese.




a b

***Fig. 1***. Spectral analysis of Parmigiano a) Parmigiano Reggiano Italy b) Parmigiano Napolact Romania

The same selection procedure has been applied to the absorptions recorded in the spectra of 10 samples of each of the following types of cheese: Pecorino (sample code PCI) and Caciotta con peperoncino (sample code CPI) produced in Italy and Gouda Gold Natural (sample code GGN) and Gouda Gold Picant (sample code GGP) produced in Romania. The region where the absorptions with important modeling and discrimination power for all cheese assortments has been determined to be between 250-340 nm. As a result, these absorptions have been included, besides the MOIST, PROT, LIP and MSG, variables, into the optimized database. The same variables, measured for 10 samples of young goat meat of Romanian origin (sample code CIR) and of 10 samples of salmon meat (sample code SOM) have also been included in the database, in order to allow a comparison with other alimentary products of animal origin. The final optimized database represented a matrix of 100 x 215 entries.

No weighting was used in the modeling process (i.e. all weights were set to 1.0). The validation method has been full cross-validation. The analysis has been done initially with a number of 20 principal Components (PCs). Data was centered on the mean. The

analysis of the residual variance has indicated that it decreases significantly only up to the first 3 PCs, which correspond to an explained variance of 99.26% (and a corresponding explained variance of 99.93% for calibration).

The score plot PC2 vs. PC1 (figure 2.) shows the formation of six well-defined clusters: 1) the cluster formed by the samples of Parmigiano Reggiano Italia (PRI), characterized by large positive PC1 scores and relatively small positive PC2 scores; 2) the cluster formed by the samples of young goat meat (CIR), characterized of small negative PC1 scores and large positive PC2 scores; 3) the cluster formed by the samples of salmon (SOM), characterized of large negative PC1 scores and large positive PC2 scores; 4) the cluster formed by the samples of Cacciota con Peperoncino - Italy (CPI), characterized of large negative PC1 and PC2 scores; 5) the cluster formed by the samples of Gouda Gold Picant (GGP), characterized by large negative PC1 and PC2 scores, but smaller than in the case of CPI samples; the cluster formed by the samples of Parmegiano Napolact Romania (PNR), characterized by small negative PC1 scores and medium negative PC2 scores.

The variables leading to the formation of these clusters have been identified by analyzing the loading plot presented in Figure 3. It shows that the MSG content of the samples is the main variable responsible for the large positive PC1 scores. The MOIST variable and the spectral absorptions are mainly responsible for the formation of the clusters characterized of large positive PC2 scores, while PROT and LIP are responsible of the clusters with large negative PC1 scores.

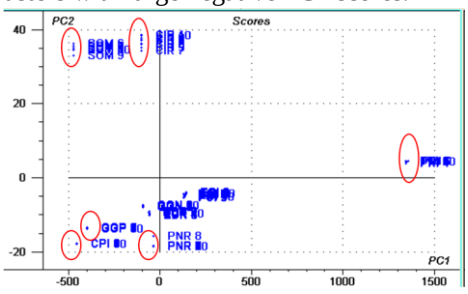



***Fig. 2.*** Score plot PC2 vs. PC1

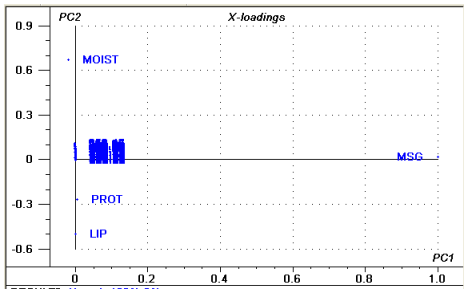



***Fig.3.*** Loading plot PC2 vs. PC1

The new model, built with only 3 PCs, was characterized by an explained variance of 99.953% (and a corresponding explained variance of 99.957% for calibration), which confirms that the selected number of PCs was correct.

The variables leading to the formation of these clusters have been identified by analyzing the loading plot presented in Figure 3. It shows that the MSG content of the samples is the main variable responsible for the large positive PC1 scores. The MOIST variable and the spectral absorptions are mainly responsible for the formation of the clusters characterized of large positive PC2 scores, while PROT and LIP are responsible of the clusters with large negative PC1 scores.

Analyzing all the variables for all the samples the image created is: 1) the cluster formed by the samples of Pecorino cheese from Italy (PCI) is characterized of small positive PC1 scores and large negative PC2 scores; 2) the cluster formed by the samples of Swizzera Italia (cod ESIx), characterized by small positive PC1 scores and small negative PC3 scores; 3) the cluster formed by the samples of Gouda Gold Natural (GGN) characterized by small negative PC1 and large positive PC2 scores. On the other hand, the samples of Ementhal Dalia Romania (EDR), are characterized by medium negative PC1

scores and medium positive PC2 scores are confounded in this plot with the samples of young goat meat samples, so the PC3 vs. PC1 score plot is not well suited for their identification or discrimination.

The variables which lead to the formation of these last three clusters (PCI, ESI and GG)it is a large negative PC3 scores characteristic to the PCI samples are due to the spectral absorptions, the large positive PC3 scores specific to the GGN cluster are due to the MOIST, PROT and LIP variables. The ESI cluster lays near the origin of the PC3 vs PC1 score plot, which is probably due to the balance of the two tendencies (strong absorptions on one hand and large MOIST, PROT and LIP values on another ).

Finally, the cluster formed by the samples of Ementhal Dalia cheese (EDR), which could not be well identified until now, is clearly defined in the PC3 vs PC2 score plot. The cluster is characterized by medium negative PC2 scores and small negative PC3 scores. The cluster formation is due mainly to the PROT and LIP content of these samples.

## 4. Conclusions

- An exploratory analysis of the hybrid database was performed using Principal Component Analysis (PCA) in order to identify the similarities among the analyzed products from the point of view of their chemical and molecular properties.
- The variables identified as being the main contributors to the formation of these clusters were discussed.
- The variables contributing to the cluster discrimination are also related to the origin (raw material) of the assortments and to the characteristic features of technological process.
- The conclusions of this study aim to stress the most important ways in which the results may be used for the optimization of the taste of the final product.

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