**Empirical Orthogonal Functions (EOFs) analysis**

In order to gain insight in understanding the dynamical behaviour of the system, and not to blur your vision with large time and space datasets with several variables, there have been developed some methods to extract the main features of large time and space datasets, being Empirical Orthogonal Functions (EOFs) one of them.

EOFs decompose a space-time field into spatial patterns and associated time indices. Typically, the EOFs are found by computing the eigenvalues and eigenvectors of a spatially weighted anomaly covariance matrix of a field (REFs1). This analysis is often used to study possible spatial modes (i.e., patterns) of variability and how they change with time.

For our purposes, we will use EOFs to study the different water masses present in our study zone and observe their principal patterns of variability. This would help us determine how many water masses are in our study zone, so we can make then, an optimum multiparametric analysis (OMPA) to estimate the contributions of the different water masses in the different transects studied.

This approach used in our data will allow us to determine where the different water masses contacts are as (one of the) EOFs should show where the zones where the variability is the most (water masses contacts) are. (?) To accomplish this, we would compute the EOFs over the different transects of our study zone. This should give a perspective of how the water masses change along the different transects. To compute the EOFs of our dataset we used the “eofs” python library.

The data matrix where we compute the EOFs analysis should contain the whole values of the dataset standardized to be able to compare the different variables. The dimensions should be the following: (1) nº of variables, (2) nº of transects, (3) nº of stations of the transects and (4) nº of depths of the stations. Since the nº of depths of each station is different we will have to adjust the matrix size to obtain an eventual regular matrix.

Data Matrix creation:

To create the data matrix and make it regular (or squared), we classified the stations according to its relative depth position. All our transects are formed by four stations ordered from deeper to shallower. As the different stations of a same group (i.e., the deeper stations) will not have the same depths each one, we have limited the stations of a same group to the depth of the shallower station of the group. Thus, all the stations of a same group will have the same depth. For example, if the deeper stations group is composed by the following station bottom depths: 1700, 1750, 1600 and 1800; we would limit this group of stations to 1600 as it is the shallower bottom depth. We would repeat this process for each group of stations. Then, as we need to have a regular matrix that includes all the stations, we stablished the depth of the deeper group of stations as the length of the data matrix nº of depths dimension (if we selected the depth of the shallower group, we would not be able to include all the values of the deeper stations). The remaining empty spots for the shallower stations (those spots located between the depth of the station and the depth stablished for the whole data matrix) will be filled with Not a Numbers (NaN).

The final step is the data matrix standardization. The standardization is needed to compare the different variable values, as they have different units and scales. The data matrix standardization consisted in the rest of the matrix values from the data matrix mean and then divide it by the data matrix standard deviation. By doing this, we obtain a data matrix with values that have a mean of 0 and a standard deviation of 1. This will be the final data matrix where we will compute the EOFs.

No weighting matrix has been applied to compute the EOFs of the data matrix. For further approaches we should consider applying a weighting matrix of the latitudes or distances between transects.

We have approached this EOFs analysis in two main perspectives. One first approach where we applied the EOFs to just one variable and a second approach where we applied the EOFs to multiple variables (i.e., temperature, salinity and oxygen). The EOFs are computed along the transects dimension. Thus, we will be able to see the main modes of variability of the water masses along the transects.

We added a third approach where we compute the EOF analysis along the variable’s dimensions. Thus, we obtain the main modes of variability of the variables for each transect of our study zone, instead of obtaining the main modes of a variable along the whole set of transects (first two approaches).

**First Approach: Computing EOFs for one specific variable**

**Second Approach: Computing EOFs for multiple variables**

**Third Approach: Computing EOFs along the variable’s dimension**

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EOFs decompose a space-time field into spatial patterns and associated time indices. Typically, the EOFs are found by computing the eigenvalues and eigenvectors of a spatially weighted anomaly covariance matrix of a field (REFs1). This analysis is often used to study possible spatial modes (ie, patterns) of variability and how they change with time.

For our purposes, we will use an EOFs analysis to study how water masses change and interact. To accomplish that, we will compute the EOFs over the different transects of our study zone. This should give us a perspective of how the water masses included in the transects change along the study zone.

To compute the EOF analysis, we have used the “eofs” python library. To use its EOFs analysis function, we will just have to create the data matrix and the weighting matrix.

The dataset where we compute the EOFs analysis should contain the variables values standardized. The dimensions should be the following: (1) nº of variables, (2) nº of transects, (3) nº of stations of the transects and (4) nº of depths of the stations. Since the nº of depths of each station is different we will have to adjust the matrix size to obtain an eventual regular(?) matrix. We have developed this issue in our different approaches.

## Approach 1

In this first approach,

The ocean system, such as the atmospheric one, is the result of highly complex interactions between many degrees of freedom or modes. In order to gain insight in understanding the dynamical and physical behaviour involved, there have been developed statistical methods to extract the main features of large time and space datasets, being the Empirical Orthogonal Functions (EOFs) one of them.

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The ocean, such as climate or weather, is a system where high dimensional and complex phenomena meet. In order to get a simplified

This method decomposes a space-time field into spatial patterns and associated time indices.

The method is in essence an exploratory (i.e. non-modelorientated) tool, which allows a time display and a spacedisplay of the space-time field that may be useful tothe atmospheric scientist

Given any space-time meteorological field, EOF anal-ysis finds a set of orthogonal spatial patterns along witha set of associated uncorrelated time series or principalcomponents (PCs)

EOF analysis is often used to study possible spatial modes (ie, patterns) of variability and how they change with time (e.g., the [**North Atlantic Oscilliation**](https://climatedataguide.ucar.edu/guidance/hurrell-north-atlantic-oscillation-nao-index-pc-based)).

Typically, the EOFs are found by computing the eigenvalues and eigenvectors of a spatially weighted anomaly covariance matrix of a field.

REFS:

National Center for Atmospheric Research Staff (Eds). Last modified 22 Jul 2013. **"The Climate Data Guide: Empirical Orthogonal Function (EOF) Analysis and Rotated EOF Analysis."** Retrieved from https://climatedataguide.ucar.edu/climate-data-tools-and-analysis/empirical-orthogonal-function-eof-analysis-and-rotated-eof-analysis.