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https://github.com/julianmak/academic-notes

The repository principally contains the compiled products rather than the source for size reasons.

- Associated Python code (as Jupyter notebooks mostly) will be held on the same repository. The source data however might be big, so I am going to be naughty and possibly just refer you to where you might get the data if that is the case (e.g. JRA-55 data). I know I should make properly reproducible binders etc., but I didn't...
- ▶ I do not claim the compiled products and/or code are completely mistake free (e.g. I know I don't write Pythonic code). Use the material however you like, but use it at your own risk.
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OCES 3301:

basic Data Analysis in ocean sciences

Session 10: fun with maps

Outline

(Just overview here; for actual content see Jupyter notebooks)

- actual fun with maps through cartopy
 - → map projections
 - examples with GEBCO and WOA13 data
- ► Fourier analysis (cf. 08 time-series analysis)
- Empirical Orthogonal Functions (EOFs)
 - \rightarrow basically PCA but with a spatial component (cf. 04 linear regression)

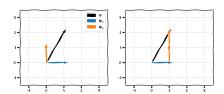


Figure: Demonstration of canonical basis in \mathbb{R}^2 .

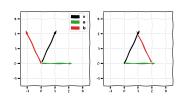


Figure: Demonstration of alternative basis in \mathbb{R}^2 .

$$\mathbf{v} = \begin{pmatrix} 1 \\ 2 \end{pmatrix} = 1 \begin{pmatrix} 1 \\ 0 \end{pmatrix} + 2 \begin{pmatrix} 0 \\ 1 \end{pmatrix} \qquad \mathbf{v} = \begin{pmatrix} 1 \\ 2 \end{pmatrix} = 1 \begin{pmatrix} 2 \\ 0 \end{pmatrix} + 1 \begin{pmatrix} -1 \\ 2 \end{pmatrix}$$
$$= 1\mathbf{e}_x + 2\mathbf{e}_y \qquad \qquad = 1\mathbf{a} + 1\mathbf{b}$$

- multiple choices in representation
 - \rightarrow vector representation depends on choice of basis



- location depends on choice of co-ordinates
- for the point x = (1,1) in standard Cartesian co-ordinates, we could have

$$x = 1, \quad y = 1$$

but we could also have it in polar co-ordinates

$$r = \sqrt{2}, \qquad \theta = \pi/4$$

with $x = r \cos \theta$, $y = r \sin \theta$

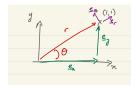


Figure: Polar co-ordinates schematic.

- some things more natural in polar co-ordinates
 - \rightarrow unit circle is the set of points with r=1 and $\theta \in [0,2\pi)$, compared to $y=\pm\sqrt{1-x^2}$ for $x\in [-1,1]$

- ▶ similarly, on a sphere, it is easier to consider spherical co-ordinates of (r, θ, ϕ) for radius, longitude and latitude
 - \rightarrow if on surface of Earth, take $r = R_{\text{Earth}}$, so now 2d data
 - ightarrow otherwise need a tuple (x,y,z) (raw satellite data do this actually)
- represent (lon, lat) data on 2d plane?

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- represent (lon, lat) data on 2d plane?
- !! problem: sphere is intrinsically 'curved' while a finite plane is intrinsically 'flat'
 - ightarrow unit sphere has Gaussian curvature $\kappa=1$, while plane has $\kappa=0$
 - \rightarrow Gauss–Bonnet theorem tells you κ is related to the Euler characteristic χ (cf. think of χ as the sum of angles of a triangle on the surface)

geometry ('local', from κ) \leftrightarrow **topology** ('global', from χ)



cursed cow

cursed doughnut

- topology studies global properties
 - \rightarrow e.g. how things are connected
 - \rightarrow cow is smoothly deformable into sphere
 - → cup is smoothly deformable into doughnut
- cow is not smooth deformable into doughnut
 - → difference in genus (cf. 'holes')

- ► to go from sphere to plane, need to introduce a 'tear' (actually just removing one point will do it)
- main upshot: no global isometry between sphere and plane
 - \rightarrow i.e. no distance preserving transformation possible

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A map projection assigns (lon, lat) to some (x, y) on the plane via some formula, but implication from above is that we can at best, for a global map projection:

- 1. preserve angles (conformal map)
- 2. preserve areas (area-preserving map)
- 3. do neither

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cartopy package does most of the heavy lifting for you



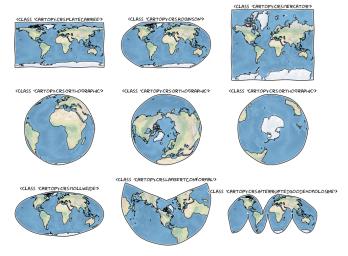


Figure: Sample projections available in cartopy. See notebook for cartopy usage and syntax.

Cartopy examples

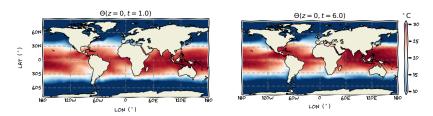
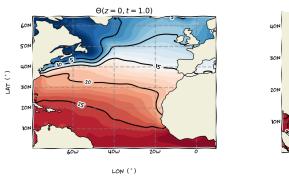
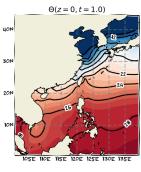


Figure: WOA13 data.

- WOA13 surface temperature from last time in Jan and Jul
 - \rightarrow xarray to read
 - → cartopy Plate Carree projection
 - \rightarrow land features from cartopy

Cartopy examples





LON (°)

Figure: WOA13 data with zooms.

- WOA13 surface temperature centered over two different regions
 - \rightarrow xarray to read and subset
 - \rightarrow contours overlaid onto the colour plots



Cartopy examples

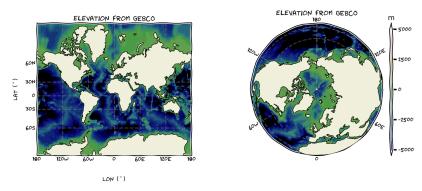


Figure: WOA13 data with zooms.

- GEBCO data using different projections
 - → Mercator (conformal but really messes area up)
 - → Northern Orthographic (does not show everything)



Fourier analysis (see 08)

Before for time-series we had

$$f(t) = a_0 + \sum_{k=1}^{N} a_k \cos(kt) + \sum_{j=1}^{N} b_j \sin(jt),$$

but there is no reason we can't do

$$f(x,t) = a_0(t) + \sum_{k=1}^{N} a_k(t) \cos(kx) + \sum_{j=1}^{N} b_j(t) \sin(jx)$$

- ► Fourier amplitudes now function of time
- k to be interpreted as wavenumber instead of angular frequency
 - \rightarrow the corresponding quantities will be wavelength instead of period (see 08 time series for conversion)
- !!! dodgy assumption that function is periodic in space!



time series revisited (fix space)

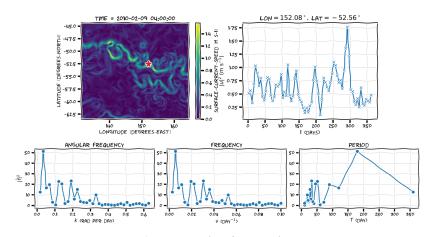


Figure: Fourier analysis of time-series data.

varying in **longitude** (fix latitude and time)

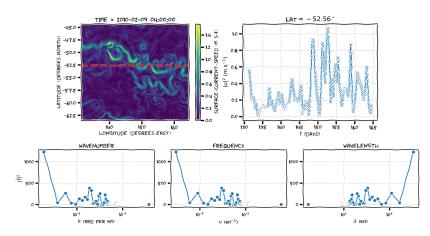


Figure: Fourier analysis of track data.

varying in space (fixed time)

Figure: Fourier analysis of horizontal data at fixed time.

▶ note here my data is not uniform in k_x and k_y because my data is not equally spaced as such

- 2d filtering in Fourier space
 - \rightarrow filtering here is uniform and based on a circle of some radius in **spectral space**

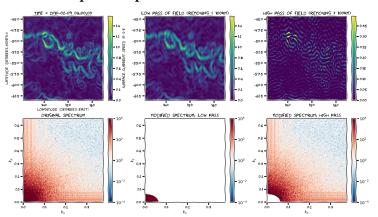


Figure: Filtering based on Fourier power spectrum.

EOFs

Want to do something like

$$f(t, x, y) = \sum_{k=1}^{N} PC_k(t) EOF_k(x, y)$$

to pick out spatial patterns that capture the most variability

sound familiar?

EOFs

Want to do something like

$$f(t, x, y) = \sum_{k=1}^{N} PC_k(t) EOF_k(x, y)$$

to pick out spatial patterns that capture the most variability

- ▶ sound familiar? basically like PCA! (04 regression)
 - \rightarrow EOF_k(x, y) the Empirical Orthogonal Function (EOF)
 - \rightarrow EOF tagged with a Principal Component PC_k(t)
- algorithm and methodology largely the same
 - → actually going to use the Singular Value Decomposition (SVD cf. diagonalisation of covariance matrix for PCA)
 - → going to leverage scikit-learn package again
- ► EOF analysis finds you a spatial basis via data, while Fourier analysis sets the spatial basis *a priori*

EOFs: work flow

- ▶ start with array containing f(t, x, y), flatten into f(t, space)
 - \rightarrow "space" is now the categorisation, and t contains the data points
 - \rightarrow cf. Iris sepal length vs. entries of Iris sepal length etc.
- preprocessing, but a few choices:
 - → de-mean, de-trend, Z-score standard scaling, others...
- throw into PCA algorithm (or your SVD algorithm if you want)
 - \rightarrow unflatten the resulting EOF(space) back to EOF(x, y)
 - → EOFs ranked in variance explained

EOFs: idealised example

Try first for (cf. data made for animation)

$$f(x,y) = \sin(x)\cos(y)\sin(t) + \frac{1}{2}\cos(2x)\cos(2t)$$

- ▶ 1st term as is, circular blobs
- 2nd term are 'rolls'
- Fourier analysis would definitively pick out two peaks (which ones? ignoring isolated values of t where individual parts of the function vanish)
- Q. what would the EOF analysis do?

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- Q. what would the EOF analysis do?
 - \rightarrow EOF₁ to be the 1st term, with PC₁ \sim sin(t)?

(because of imposed larger amplitude)

 \rightarrow EOF₂ to be the 2nd term, with PC₂ \sim cos(2*t*)?



EOFs: idealised example, no preprocessing

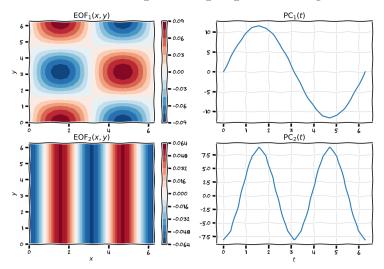


Figure: EOF of idealised data, no preprocessing.

EOFs: idealised example, demean

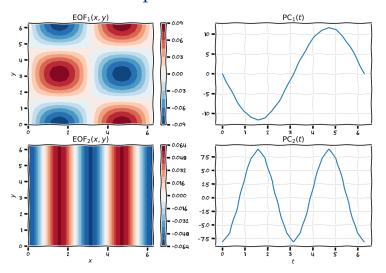


Figure: EOF of idealised data, remove time average per point. Notice a sign flip of EOF and PC 1, but that's ok.

EOFs: idealised example, detrend

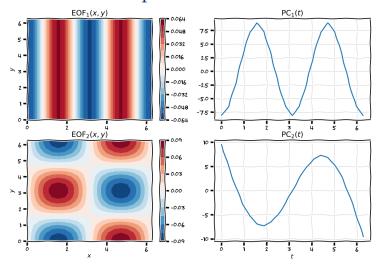


Figure: EOF of idealised data, remove linear trend per point (scipy.signal.detrend or use numpy.polyfit). Notice 'swapping' of EOF ordering relative to previous case, and PC 2 looks a bit weird.

EOFs: idealised example, Z-score standardisation

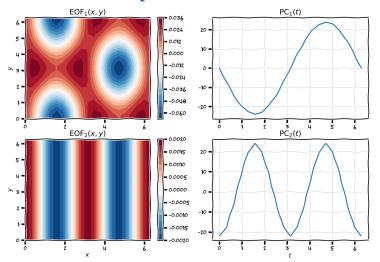


Figure: EOF of idealised data, using Z-score standardisation (StandardScaler in scikit-learn). Note that while EOF 1 no longer looks like circular blobs, and EOF 2 sign has changed, these are still valid choices of basis.

EOFs: 'real' example

- provided Extended Reconstructed SST data (full and anomaly version)
 - \rightarrow monthly, from mid 1800s to present day
 - \rightarrow global, 2° spatial resolution
 - \rightarrow already masked
 - \rightarrow anomaly relative to some climatology (!?)

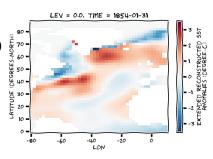


Figure: Raw data plot of SST anomalies over Atlantic. Using the anomalies file directly.

EOFs: 'real' example

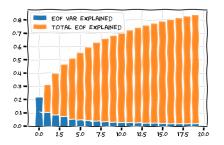
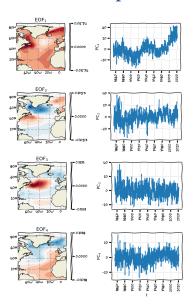


Figure: Percentage and cumulative percentage of variance explained by EOFs.

- ► EOF analysis as usual → using anomalies file directly, not detrending or demeaning here
- variance explained of EOFs are generally pretty low actually...

EOFs: 'real' example



- ► EOF 1 is probably global warming, maybe also bits of Atlantic Multi-decadal Variability (AMV)
- ► EOF 2 should be the SST equivalent of North Atlantic Oscillation (NAO see ENVS 3004 / OCES 4001)
- no idea what EOF 3 is but looks like EOF 2 of Fig. 3 in Buckley et al. 2013
- ► EOF 4 also looks a bit like the AMV?

Jupyter notebook

go to 10 Jupyter notebook to get some code practise

- exercises and code I haven't demonstrated here
 - \rightarrow EOFs with different locations and/or different pre-procesing
 - → analysis of PCs via Fourier analysis
 - → 1d isotropic power spectrum for surface current speed
 - \rightarrow time evolution of spatial power spectrum in time
 - $\rightarrow \dots$