

ASSIGNMENT 1

1. (5) Consider the matrix $H(v) = \hat{1} - 2vv^T$, where v is a unit column vector. What is the rank of the matrix $H(v)$? Prove that it is orthogonal.

Solution 1 Let's prove that $A = A^T$

$$A^T = (I_n - 2vv^T)^T = I_n - 2(vv^T)^T = I_n - 2vv^T$$

So $A^T = A$. Calculating AA^T

$$AA^T = A^2 = (I_n - 2vv^T)(I_n - 2vv^T) = I_n - 4vv^T + 4vv^Tvv^T = |v^Tv = 1| = I_n$$

from which we conclude that A is both orthogonal and indepotent matrix.

For indepotent matrices following statement is true:

$$\begin{aligned} \text{tr } A &= \text{rank } A \\ \text{tr } A &= n - 2v^Tv = n - 2 \\ \text{rank } A &= n - 2 \end{aligned}$$

Solution 2

$$Hv = -v$$

So v is an eigenvector with eigenvalue $\lambda = -1$. If we take any another vector u such that $u \perp v$, we get $Hu = u$. So there are only two eigenvalues $\lambda_1 = -1$ and $\lambda_2 = 1$. It means that there exists some transformation V which makes H diagonal matrix $\text{diag}(-1, 1, \dots, 1)$. This matrix is it's own inverse hence orthogonal. Beside that it is indepotent matrix so $\text{rank } A = n - 2$

2. (10) Prove the following inequalities and provide examples of x and A when they turn into equalities:

- $\|x\|_2 \leq \sqrt{m} \|x\|_\infty$
- $\|A\|_\infty \leq \sqrt{n} \|A\|_2$

where x is a vector of m components and A is $m \times n$ matrix.

Solution 3 •

$$\begin{aligned} |x_i| &\leq \sup_j |x_j| := \|x\|_\infty \Rightarrow x_i^2 \leq \|x\|_\infty^2 \\ \|x\|_2 &= \sqrt{\sum_i x_i^2} \leq \sqrt{\sum_i \|x\|_\infty^2} = \sqrt{m \|x\|_\infty^2} = \sqrt{m} \|x\|_\infty \end{aligned}$$

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$$\|A\|_2 = \sup_{x \neq 0} \frac{\|Ax\|_2}{\|x\|_2} \leq \sup_{x \neq 0} \frac{\sqrt{m} \|Ax\|_\infty}{\|x\|_2} \leq \frac{\sqrt{m} \|Ax\|_\infty}{\|x\|_\infty} = \sqrt{m} \|A\|_\infty$$

$$\|Ax\|_\infty \leq \|Ax\|_2 \leq \|A\|_2 \|x\|_2 \leq \|A\|_2 \sqrt{n} \|x\|_\infty \Rightarrow \|A\|_\infty \leq \sqrt{n} \|A\|_2$$

$$\begin{aligned} \|x\|_\infty &\leq \|x\|_2 \leq \sqrt{m} \|x\|_\infty \\ \|A\|_2 &= \frac{\|Ax\|_2}{\|x\|_2} \leq \frac{\sqrt{n} \|Ax\|_\infty}{\|x\|_\infty} = \sqrt{n} \|A\|_\infty \\ \|A\|_\infty &= \frac{\|Ax\|_\infty}{\|x\|_\infty} \leq \frac{\sqrt{m} \|Ax\|_2}{\|x\|_2} = \sqrt{m} \|A\|_2 \end{aligned}$$

3. (5) Assuming u and v are m -vectors, consider the matrix $A = 1 + uv^T$ which is a rank-one perturbation of identity. Can it be singular? Assuming it is not, compute its inverse. You may look for it in a form of $A^{-1} = 1 + \alpha uv^T$ for some scalar α and evaluate α .
4. (5) Prove that for any unitary matrix U one has $\|UA\|_F = \|AU\|_F = \|A\|_F$.
5. (10) In this exercise your goal will be to study and speed up an implementation of [K-means algorithm](#). In the notebook `kmeans.ipynb`, you can find a naive implementation. Explore the code, make sure you understand it. You will find there two functions `dist_i` and `dist_ij` which are (on purpose) implemented in a rather inefficient way. Improve them by getting rid of the loops in the favor of a proper numpy vectorized implementation and measure the speed-up of the full algorithm for $N = 10000$.
6. (10) Some things just can not be vectorized but still can be sped up compared to naive implementation. For example, consider computation of the [Hofstadter-Conway sequence](#) $a(n)$ such that $a(1) = 1$, $a(2) = 1$ and

$$a(n) = a(a(n-1)) + a(n - a(n-1)), \quad n > 2 \quad (1)$$

Write three functions, computing the sequence up to n -th element in three ways: i) pre-allocating `numpy` array and filling it using `for` loop, ii) cumulatively appending `python` list and converting it to `numpy` array, iii) same as i) but compiled (`jit`) version. Time the resulting implementations and conclude which is preferable. With the optimal one, compute $a(10^8)$.

7. (15*) Consider a function mapping six tensors to one tensor: $Z(\lambda^{(1)}, \lambda^{(2)}, \lambda^{(3)}, \Gamma^{(1)}, \Gamma^{(2)}, U)$, with

$$Z_{ahij} = \sum_{bcdefg} \lambda^{(1)}_{ab} \Gamma^{(1)}_{cd} \lambda^{(2)}_{de} \Gamma^{(2)}_{fg} \lambda^{(3)}_{gh} U_{ijcf}. \quad (2)$$

Assume that all indices of the tensors appearing above take values from 1 to χ . Running the numerical experiments, explore the values of χ in the range 3–50 (from slowest to fastest implementation).

- In the notebook `convolution.ipynb` you may find implemented a *stupid* way to compute this convolution, which takes $\chi^4 \times \chi^6 = \chi^{10}$ flops. In fact, this can be computed much faster!
- Using the function `numpy.einsum` (its crucial to use the `optimize` argument), you can actually achieve a much faster implementation. In order to understand what it is doing under the hood, explore the function `numpy.einsum_path`. What is the minimal number of flops required for computation of Z ?
- Using the understanding of the output of `numpy.einsum_path`, implement an algorithm to compute Z , which is as effective as `numpy.einsum`, but relying only on more elementary `numpy.dot` and `numpy.tensor_dot`.