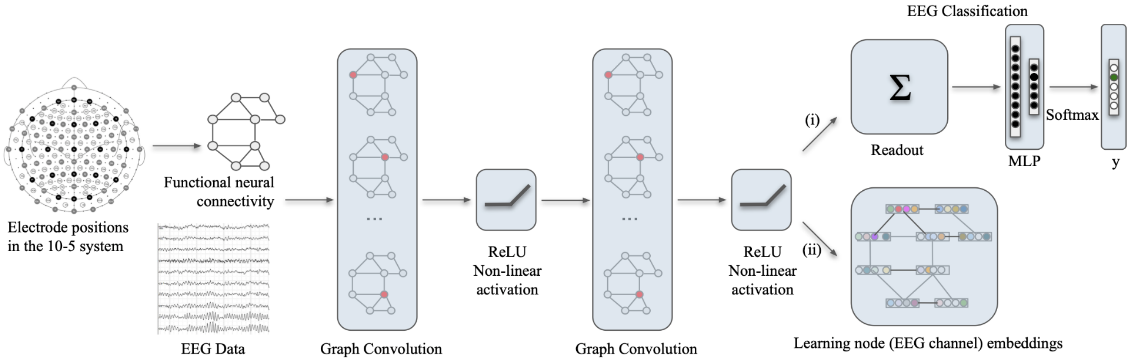
Graph representation of BCI signal
https://arxiv.org/pdf/2106.09135.pdf



Идея: представить многоканальный сигнал в виде графа, где вершины это электроды со значениями сигнала в конкретный момент времени (связность, веса ребер, методы анализа предстоит исследовать: попробовать разные разные методы определения ребер (порог на расстояние, корреляция сигналов, k-ближайших соседей и т.д.), учесть нейробиологические представления о распространении сигнала при конкретной задаче, для учета временной зависимости можно попробовать как сверточные архитектуры так и рекуррентные)

Adjacency matrix of this graph can be constructed flexibly, e.g., i) every pair of nodes is connected by an unweighted edge, ii) every pair of nodes is connected by an edge weighted by the functional neural connectivity factor, which is the Pearson correlation coefficient between the feature vectors of the two nodes, iii) a sparse adjacency matrix can be designed under the constraint only nodes that are closer than a heuristic distance are connected, or iv) a sparse adjacency matrix can be constructed via k-nearest neighbors (k-NNG).

Это позволит
- исследовать более сложную функциональную связь между различными участками электродов
- получить нейробиологическую интерпретацию функциональных связей мозга

One of the major drawbacks to using CNNs to classify EEG data is they fail to provide a brain connectivity mapping by identifying Regions of Interests (ROIs), whereas EEG-GNN can learn and visualize the connectivity between salient nodes, which addresses a critical issue of neuroscientific interpretability.
- оценить применимость подхода к отбору каналов для снижения вычислительной эффективности и проектирования портативных гарнитур для снятия сигналов

В этой статье производится обзор набора GNN и их стратерий агрегирования, продемонстрировано преимущество в производительности классификации над CNN

Обзор стандартов размещения электродов:
https://robertoostenveld.nl/electrode/#oostenveld2001

https://ru.wikipedia.org/wiki/%D0%94%D0%B8%D1%81%D0%BA%D1%80%D0%B5%D1%82%D0%BD%D1%8B%D0%B9_%D0%BE%D0%BF%D0%B5%D1%80%D0%B0%D1%82%D0%BE%D1%80_%D0%9B%D0%B0%D0%BF%D0%BB%D0%B0%D1%81%D0%B0 - дискретный оператор лапласа

https://arxiv.org/pdf/2002.01038.pdf - graph rnn для извлечения графовой пространственной структуры и временной зависимости в данных, в предположении фиксированной структуры графа по всем итерациям времени.

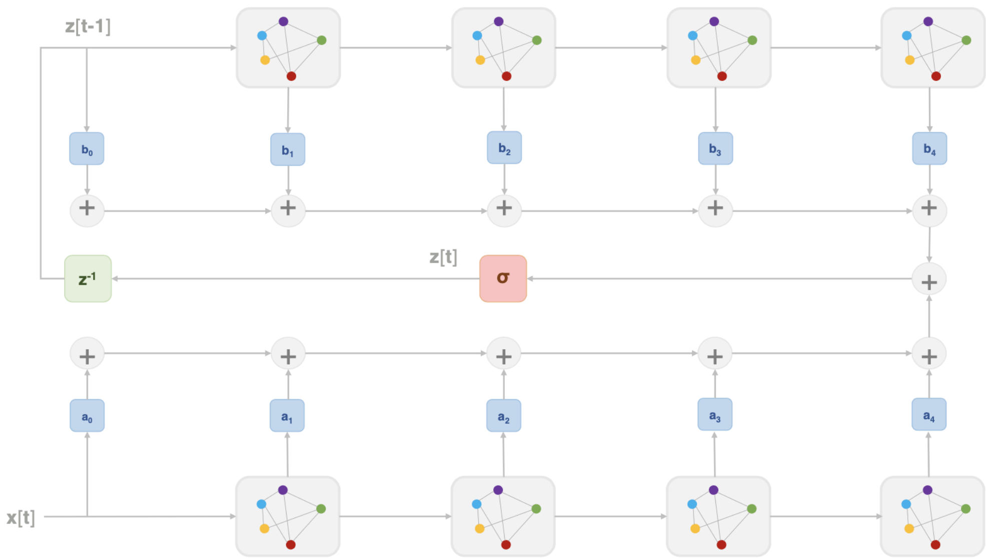


Figure 1. State computation in a graph recurrent neural network with $K = 5$. Gray blocks with graphs on the inside stand for graph shifts, blue blocks for linear weights, the red block for a pointwise nonlinearity and the green block for a time delay.

The notion of *graph shifts* can be used to define *graph convolutions* analogous to *time* convolutions. Formally, we define the graph convolution as a weighted sum of shifted versions of the signal [31], [32],

$$\mathbf{A}(\mathbf{S})\mathbf{x} = \sum_{k=0}^{K-1} a_k \mathbf{S}^k \mathbf{x}. \qquad (4)$$

$$\mathbf{z}_t = \sigma\big(\mathbf{A}(\mathbf{S})\mathbf{x}_t + \mathbf{B}(\mathbf{S})\mathbf{z}_{t-1}\big)$$

https://downloads.hindawi.com/journals/jhe/2010/707290.pdf - про различные метрики на графах, которые можно включить в описание каждой вершины как доп структурная информация, плюс описаны оценки взаимосвязи, подбирая порог на которые можно определять связность вершин графа eeg каналов

Magnitude squared coherence (MSC)

MSC (or simply coherence) has been a well-established and traditionally used tool to investigate the linear relation between two signals or EEG channels. Let us suppose that we have two simultaneously measured discrete time series x_i and y_i, $i = 1 \ldots N$. MSC is the cross spectral density function $S_{xy}(f)$, which is simply derived via the FFT of the cross-correlation, normalized by their individual autospectral density functions. Hence, MSC is calculated using the Welch's method as:

$$\gamma_{xy}(f) = \frac{\left|\left\langle S_{xy}(f)\right\rangle\right|^2}{\left|\left\langle S_{xx}(f)\right\rangle\right|\left|\left\langle S_{yy}(f)\right\rangle\right|} \tag{11}$$

where <·> indicates window averaging. The estimated MSC for a given frequency f ranges between 0 (no coupling) and 1 (maximum linear interdependence).

Partial Directed Coherence (PDC)

The main advantage of this linear method is that it is able to derive additional information on the "driver and response" relationship between observations. The concept of Granger-causality [81] is based on the commonsense idea that causes precede their effects in time and is formulated in terms of predictability. In a linear framework, Granger-causality is commonly evaluated by fitting Vector Autoregressive Models. Suppose that a set of n simultaneously observed time series $\mathbf{x}(t) = \left[x_1(t), \ldots, x_N(t)\right]^T$ is adequately represented by a Vector Autoregressive Model of order p (MVAR(p)):

$$\mathbf{x}(t) = \sum_{k=1}^{p} A_k \mathbf{x}(t-k) + \mathbf{w}(t) \tag{12}$$

where $\mathbf{A}_k = \begin{bmatrix} a_{11}(k) & \cdots & a_{1n}(k) \\ \vdots & \ddots & \vdots \\ a_{n1}(k) & \cdots & a_{nn}(k) \end{bmatrix}$ is the coefficient matrix at time lag k, and

$\mathbf{w}(t) = [w_1(t), \ldots, w_n(t)]^T$ is the vector of model innovations having zero mean and covariance matrix Σ_w. The autoregressive coefficients $a_{ij}(k)$, $i, j = 1, \ldots, n$ represent the

linear interaction effect of $x_j(t\text{-}k)$ onto $x_i(t)$. In order to provide a frequency domain description of Granger-causality, Baccala and Sameshima [18] introduced the concept of Partial Directed Coherence (PDC) which has recently been generalized to the new PDC [82] as follows:

Let

$$A(\lambda) = \sum_{k=1}^{p} A_k e^{-i2\pi\lambda k} \tag{13}$$

be the Fourier transform of the coefficient matrices, where λ is the normalized frequency in the interval [–0.5, 0.5] and $i = \sqrt{-1}$. Then the new PDC is defined as [82]

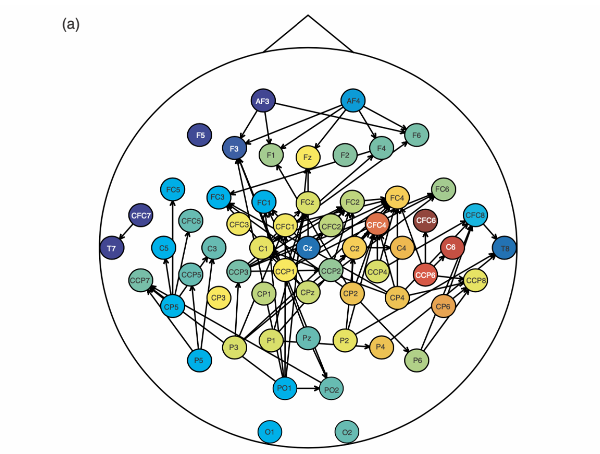
$$\left|\pi_{i\leftarrow j}(\lambda)\right| = \frac{\frac{1}{\sigma_i}\left|\bar{A}_{ij}(\lambda)\right|}{\sqrt{\sum_{m=1}^{p} \frac{1}{\sigma_m^2} \bar{A}_{mj}(\lambda) * \bar{A}_{mj}^H(\lambda)}} \tag{14}$$

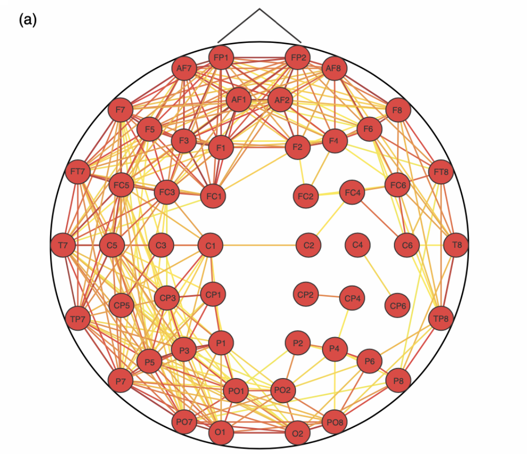
where $\bar{A}(\lambda) = I - A(\lambda)$ and σ_i^2 refers to the variance of the innovation processes $w_i(t)$. $\left|\pi_{i\leftarrow j}(\lambda)\right|$ ranges between 0 (indicating independence) and 1 (indicating maximum coherence).

Кроме них

Phase Locking Value (PLV) (It assumes that two dynamic systems may have their phases synchronized even if their amplitudes are zero correlated)

Nonlinear synchronization (state-space approach) (generalized synchronization (GS) concept and are based on analyzing the interdependence between the amplitudes of the signals in a





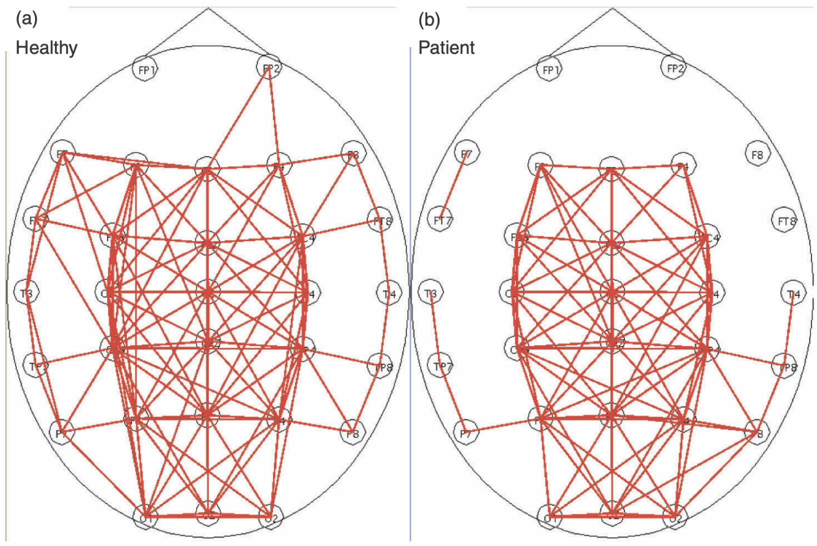


Figure 5. (a) A “healthy” brain network during a working memory task appears to have higher average degree K and clustering coefficient C, and lower average shortest path length L values compared to the “schizophrenic” one (b). These disturbances are more prominent for the connections of the frontal lobes as well as the temporal lobes.

<u>Summarization</u>. Our brain is a complex network in which information is continuously processed and transported between spatially distributed but functionally linked regions.Graph visualization reveals the hidden structure of the networks and enhances human understanding.

https://arxiv.org/pdf/2105.02786.pdf -local-global-graph representation of BCI

The brain is a complex network with a hierarchical spatial and functional organization at the level of neurons, local circuits, and functional areas. 1D convolutional kernels along the spatial dimension of EEG might not be able to capture the complex relations among different local and global brain functional areas. To address the above problems, we define the EEG data as a local-global graph whose local graphs belong to the different functional areas of the brain according to neurological knowledge. The nodes in each local graph are fully connected because they reflect the brain activities within each brain functional area. The edges of local graphs, or the global connections among local graphs, reflect the complex functional connections among different brain functional regions.

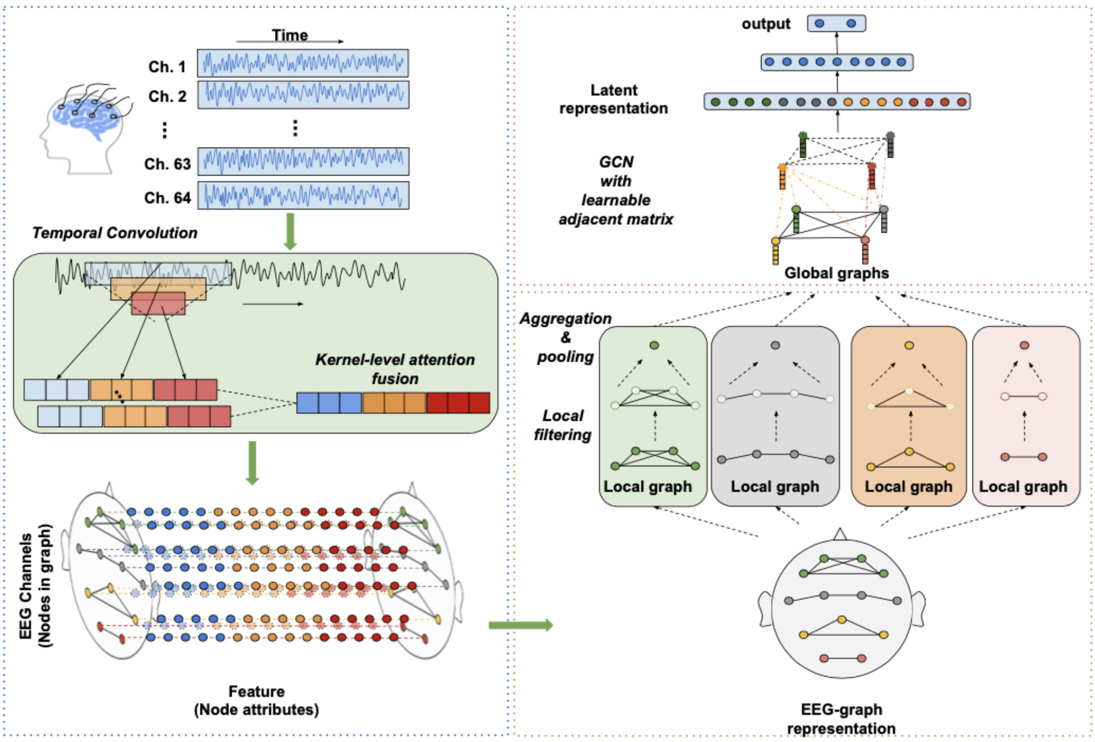
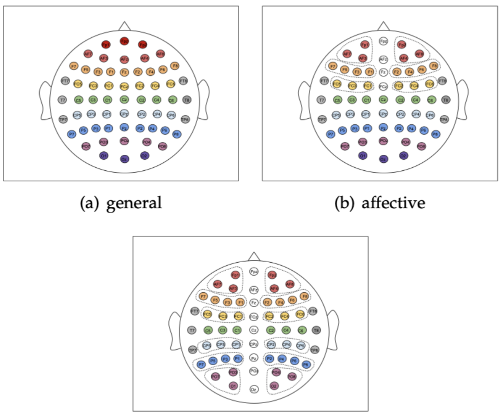


Fig. 1. Structure of LGG. LGG has three main parts, temporal convolutional layer, local graph-filtering layer, and global graph-filtering layer respectively. The temporal convolutional layer aims to learn dynamic frequency representations from EEG directly instead of human extracted features. The local graph-filtering layer learns the brain activities within each local region. Then the global graph-filtering layer with a trainable adjacency matrix will be applied to learn complex relations among different local regions. Four local graphs are shown in the figure for illustration purposes only, the detailed local-global-graph definitions are provided in subsection 'Local-Global-Graph Representation of EEG' of section III. Best viewed in color.



(a) general (b) affective

(c) hemisphere

Fig. 7. Different definitions of local-global graphs. (a) and (b) are the proposed general and affective local-global graphs, which are introduced in Section A of Chapter III. (c) is utilized in [40], which has subareas from frontal to occipital lobe. The subareas of (c) are symmetrically located on right and left hemisphere therefore it is named hemisphere.

Функциональная организация мозга: какие области за что отвечают
https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3222858/

- анализ эмоций: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2752702/
- карта связностей функциональных групп, которые активировались при эмоциональных реакциях(чем ближе точки тем сильнее ко-активация, длина ребер отвечает значимости связи между функциональными регионами)

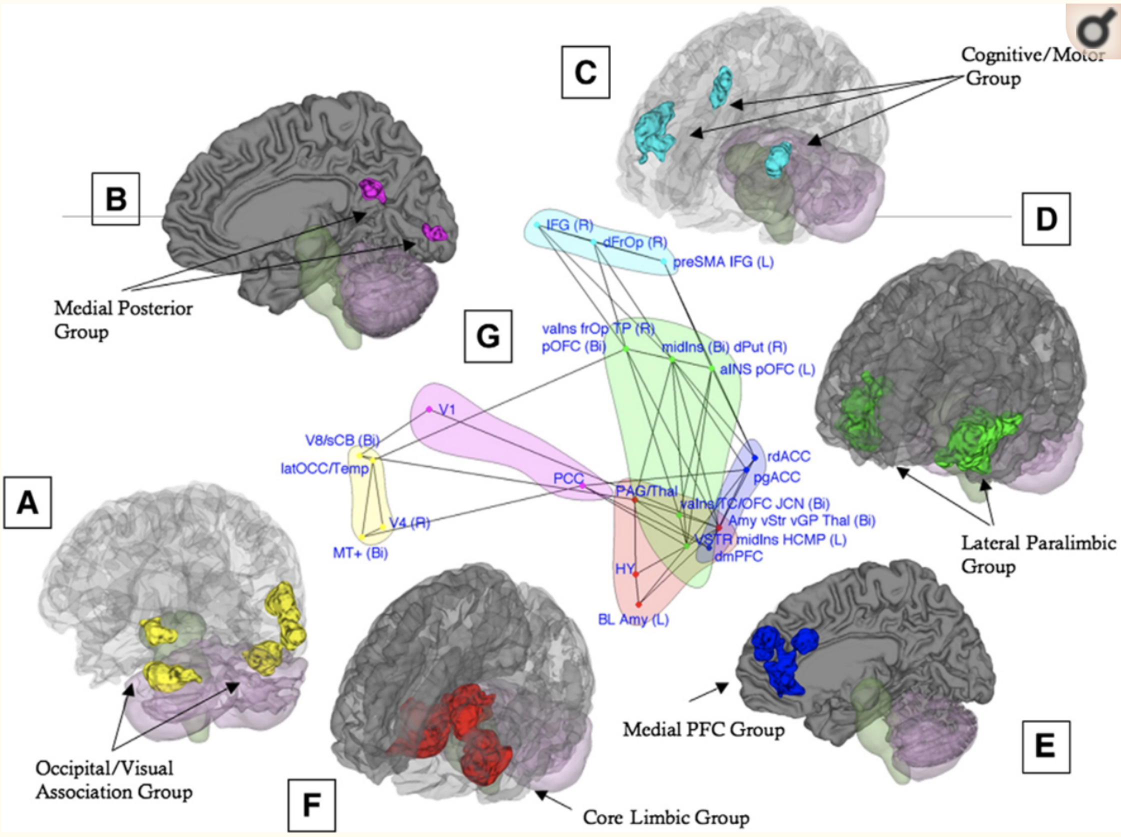


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Fig. 7

(A–F) The six functional groups revealed by our multivariate analysis are depicted in 3D rendering on the single-subject brain. Regions in each group are rendered in a unique color. (G) To visualize the relationships among the regions in each group, both regions and co-activation lines are displayed on a “flattened” map of the connectivity space along the first two dimensions determined by NMDS (see Methods). Colors correspond to those in panels A–F and identify each network. Points closer together on the graph tend to have stronger positive co-activation, and connected lines represent significant Tau-b (τ) association values between pairs of regions. The connectivity map has been “pruned” such that the relationships depicted are direct, meaning that they were not completely mediated by any other single intervening region. Direct relationships were assessed by mediation analyses considering each possible mediating region in turn, with 1000 bootstrap samples per analysis. See Table 1 for abbreviations.

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GraphSAGE

http://snap.stanford.edu/graphsage/#motivation

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Hierarchical Convolutional Neural Networks for EEG-Based Emotion Recognition

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GRAPH SIGNAL REPRESENTATION OF EEG FOR GRAPH CONVOLUTIONAL NEURAL NET- WORK (прро методы оценки связи-определение ребра) https://openreview.net/pdf?id=Bk6Y0RR8M

Exploring Structure-Adaptive Graph Learning for Robust Semi-Supervised Classification (MAP оценка)

https://arxiv.org/pdf/1904.10146.pdf

The Emerging Field of Signal Processing on Graphs (спектральный анализ графов)

https://arxiv.org/pdf/1211.0053.pdf

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Пояснения GNN

https://theaisummer.com/gnn-architectures/

GODE

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http://proceedings.mlr.press/v139/chamberlain21a/chamberlain21a.pdf

https://icml.cc/media/icml-2021/Slides/8889.pdf https://openreview.net/pdf?id=SJg9z6VFDr

https://github.com/Zymrael/gde/tree/master/torchgde

Datasets

DEAP: https://ieeexplore.ieee.org/document/5871728

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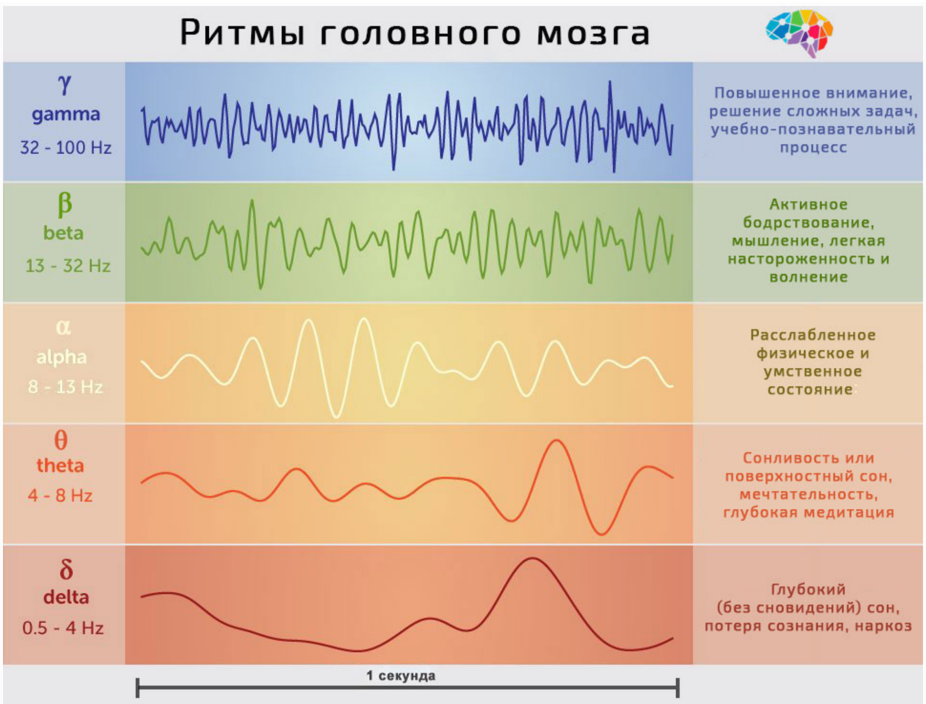

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метод галеркина

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VAR - https://www.machinelearningplus.com/time-series/vector-autoregression-examples-python/

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