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The analysis of current neural network configuration used to predict the critical foF2 frequency in the ionosphere

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Introduction

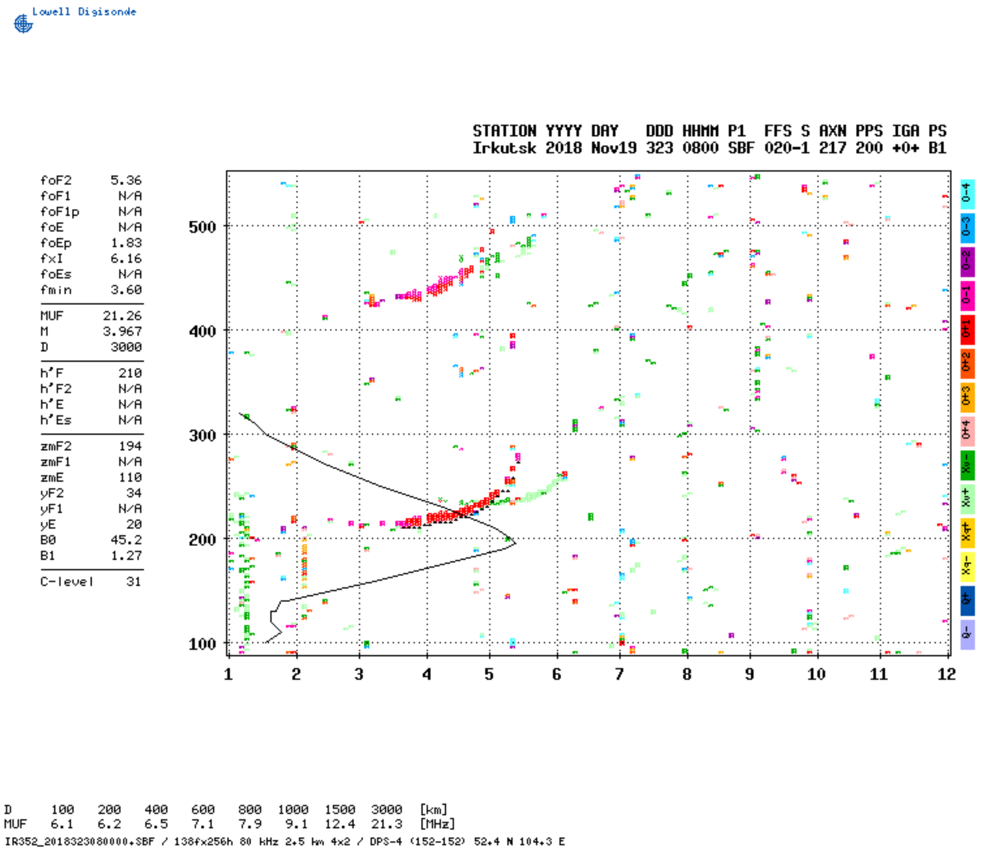
The characteristics of the ionosphere are of significant practical importance for radio communications. Predicting these values allows to operate with greater radio communication and navigation hardware. In turn, the accumulated measurement data and computational capabilities that have increased in recent decades allow the use of various empirical prediction models, such as, for example, artificial neural networks.

The aim of this work

The aim of this work — is the train and analyze artificial neural network model based on solar and geomagnetic indicies to predict foF2 ionosphere frequency.

foF2 ionosphere frequency

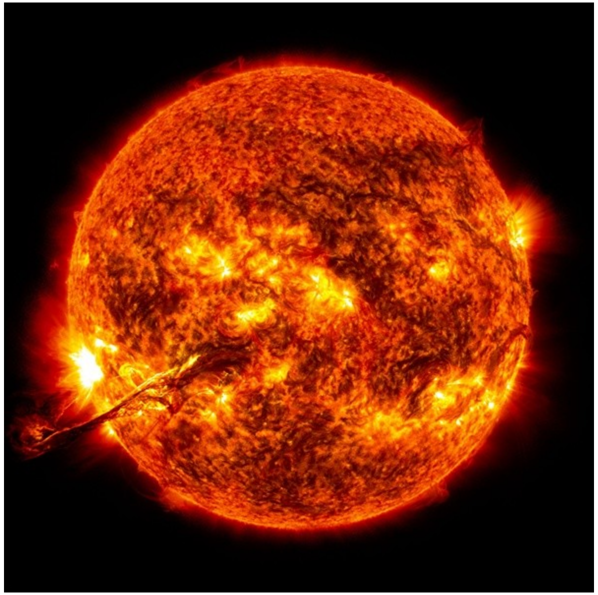
The critical frequency foF2 is the maximum frequency of the radio wave reflected from the ionosphere during a vertical fall. If the frequency of the radio wave exceeds the critical one, then the wave will penetrate the ionosphere.



Solar f10.7 index

f10.7 - solar radiation flux at a wavelength of 10.7 cm (2800 MHz frequency)

Solar flux correlates with solar activity, such as the number of sunspots and the total sunspot area.



Geomagnetic indices

Kp-index, characterizing the disturbance in the three-hour interval. The initial data for calculating the *Kp* index are the *K-index* data of twelve observatories located between 63 ° and 48 ° north and south geomagnetic latitudes. K-index is expressed in points and takes values from 0 to 9. Score 9 corresponds to a very strong geomagnetic disturbance.

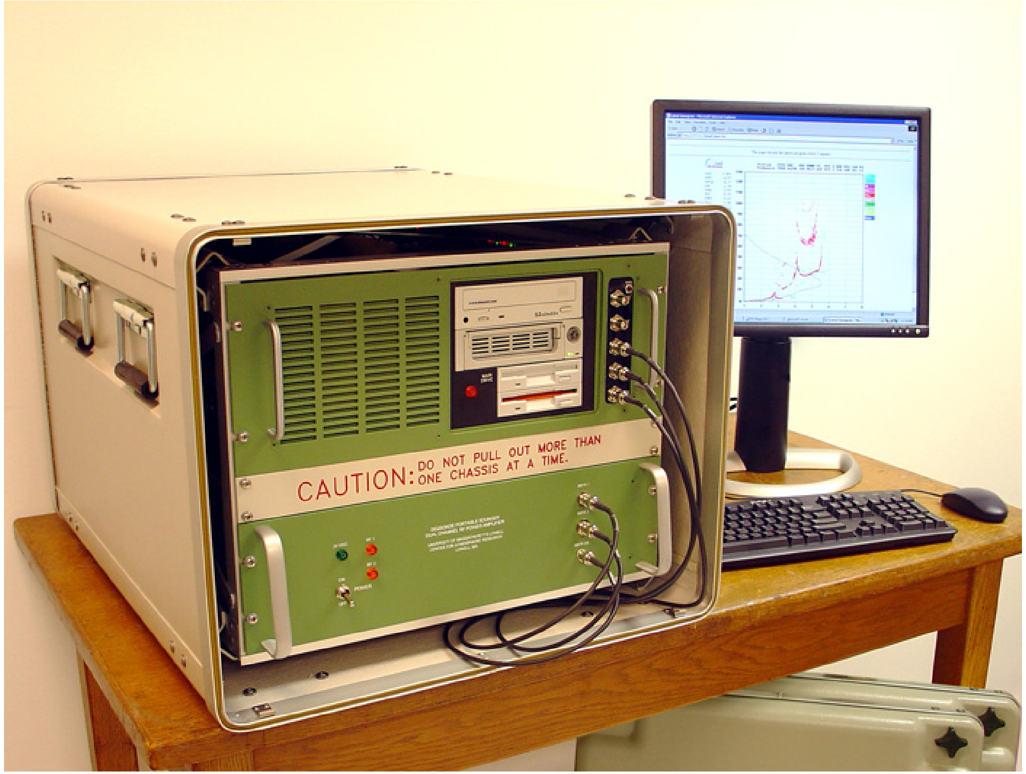
The index *ap* is calculated from the *Kp* index data and represents the change in the most perturbed magnetic element D (direction / inclination of the magnetic in the horizontal plane) or H (intensity of the horizontal component of the magnetic field) in the 3-hour time interval at mid-latitude stations, expressed in units of 2γ. The ap index is called the planetary amplitude in the 3-hour interval.

Dst-index have the clear physical meaning (it characterizes the intensity of a symmetrical ring current (current flowing in a polar oval at 100 km altitude), typical of the recovery phase of a magnetic storm), it quickly won well-deserved recognition. Dst-index is the average value of the disturbance in the hourly interval, calculated from the network data of low-latitude stations separated by longitude. The unit of measure for the *Dst-index* is gamma. To calculate the *Dst-index*, data from four stations are used.

Digisonde DPS-4 Data

The DPS-4 system consists of a digisonde with two 150 W transmitters, four receiving antennas and a “crossed vertical diamonds” transmitting antenna system. The Digisonde has the ability to simultaneously register in the automatic mode such radio signal parameters as amplitude, frequency, altitude (range), angles of arrival, phase, polarization, and Doppler frequency shift of the radio waves. Based on the obtained ionogram, the operator or the algorithm calculates the critical frequency ***foF2***.

We used data from a digisonde belonging to the ISTP SB RAS and located in Irkutsk.



Solar and geomagnetic indices data

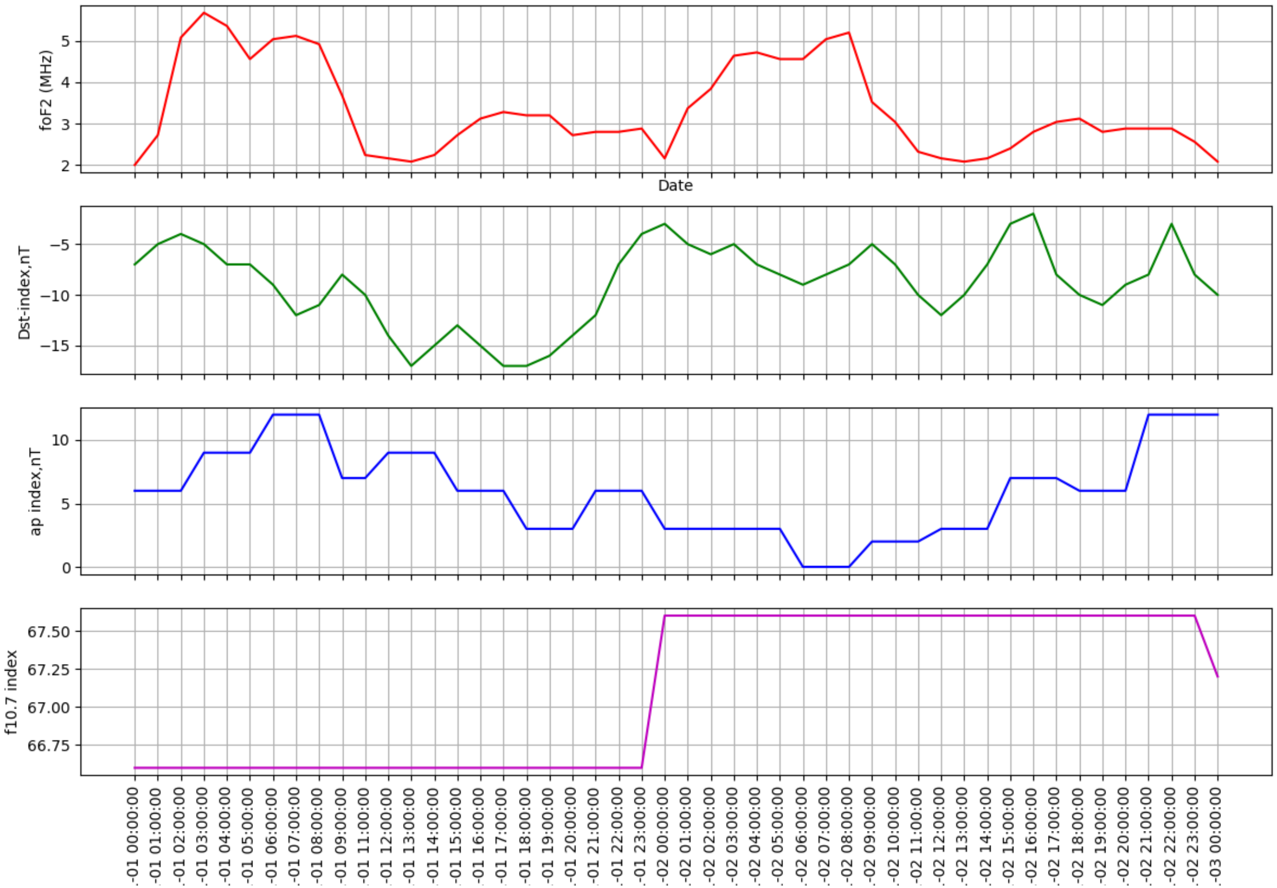
Daily variation of solar and geomagnetic indices and critical frequency.

foF2, MHz

Dst-index, nT

ap index, nT

F107 index



Merged input data

*Table. 1 Train and test dataset structure**

cos_HOD(LST)	*sin_HOD(LST)*	*cos_DOY(LST)*	*f10.7_index*	*Kp_index*	*ap_index,nT*	*Dst-index,nT*	*foF2*
...							

* Geomagnetic and solar indicies obtained from OMNI database (NASA)

Dataset consists 61675 rows.
Data range: 2009-2016

Artificial Neural Network

Artificial *neuron:*

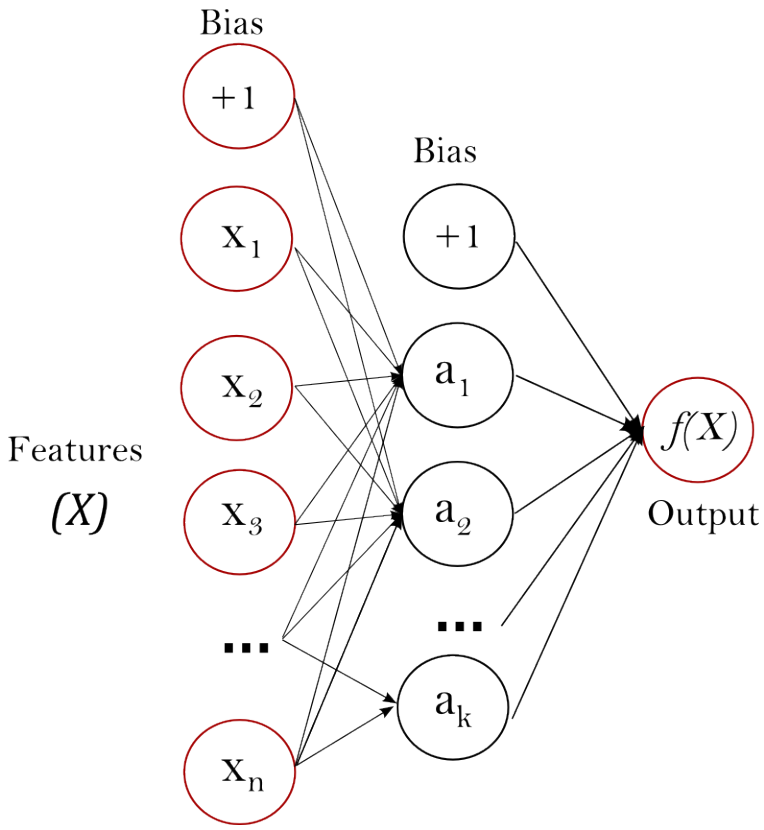
$$s(w,x)=w_1x_1+w_2x_2+w_mx_m+b \quad (1)$$

$$p(w,x)=sigmoid(s(w,x)) \quad (2)$$

The aim of training — loss function minimization:

$$Loss(\hat{y},y,W)=\frac{1}{2}\|\hat{y}-y\|_2^2+\left(\frac{\alpha}{2}\right)\|W\|_2^2 \quad (3)$$

$$W^{(i+1)}=W^i-\epsilon\nabla Loss_W^i \quad (4)$$



Neural network parameters

scikit-learn
Machine Learning in Python

```
MLPRegressor(activation='logistic', alpha=0.001, batch_size='auto',
       beta_1=0.9, beta_2=0.999, early_stopping=False, epsilon=1e-08,
       hidden_layer_sizes=(11, 5), learning_rate='constant',
       learning_rate_init=0.01, max_iter=500, momentum=0.9,
       nesterovs_momentum=True, power_t=0.5, random_state=None,
       shuffle=True, solver='adam', tol=0.0001, validation_fraction=0.1,
       verbose=True, warm_start=False)
```

- Solve algorithm — *adam*
- L2 regularization coefficient = *0.001*
- 2 layers : *11 and 5 neurons*
- Activation function - sigmoid

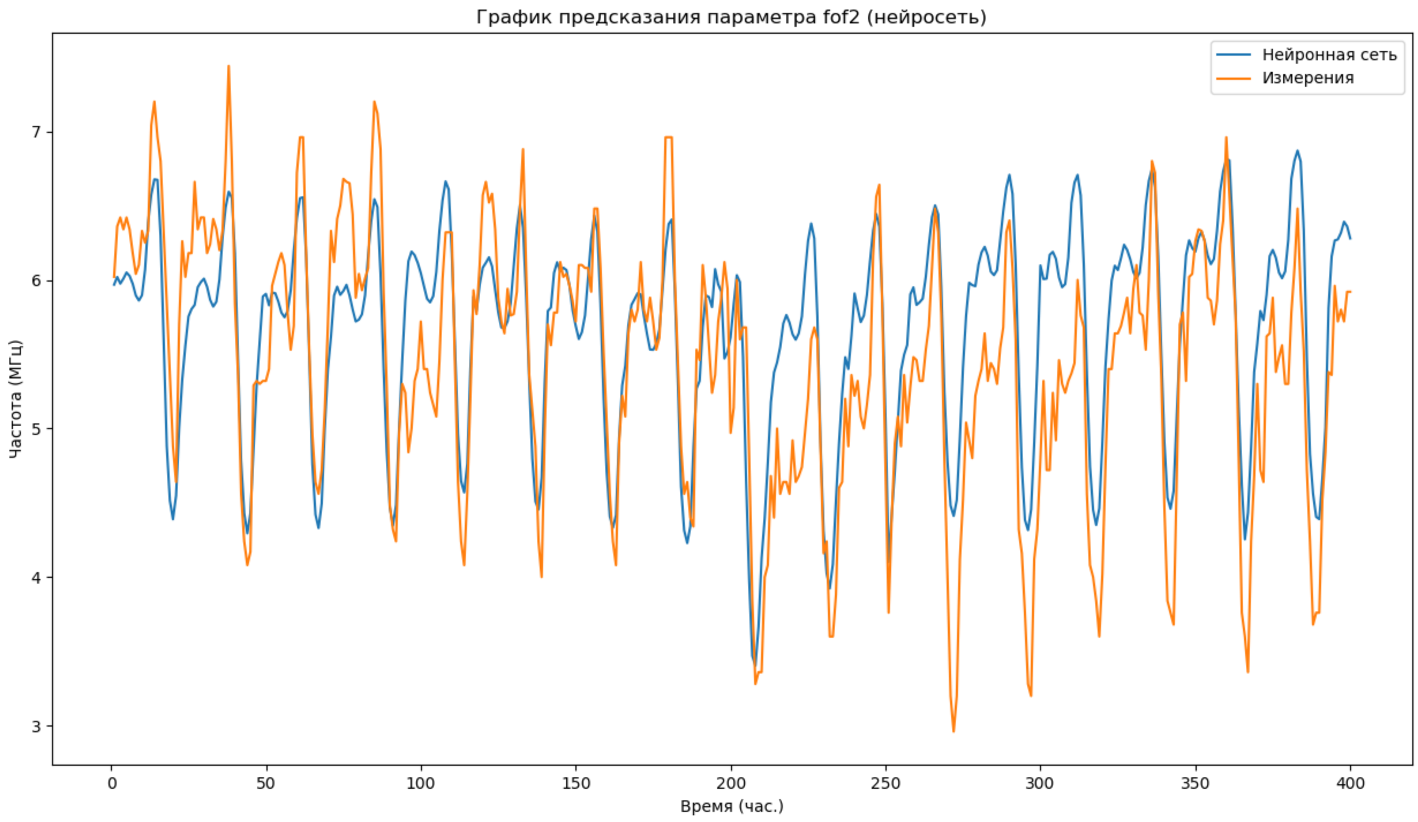
Training and checking model

The input data sample was divided into two subgroups: the training sample and the test sample in a ratio of 80 to 20%, respectively.

Table. 2. Compare experimental data with data ecaluated from NN model

r (Pearson coeff.)	RMSE	MAPE, %
0.89	0.84	14.74

Pearson correlation coefficient, mean square error, and mean absolute percentage error were measured. A high correlation coefficient and a small error indicate a good model quality for predicting the critical frequency in the ionosphere.



Compare NN prediction and experimental data

Analysis of the structure of the neural network

Weights before features in artificial neurons

Layer 1:

Neuron	Kp_index	Dst-index(nT)	ap_index(nT)	f10,7_index	cos_HOD(LST_simple)	sin_HOD(LST_simple)	cos_DOY(LST_simple)	SUM ABS
10	-0,054	-0,336	-0,083	0,088	-5,389	3,258	-2,847	12,055
11	0,069	-0,197	-0,049	0,324	-3,618	-1,991	-4,058	10,306
1	0,795	-0,106	-0,761	0,012	0,244	-2,911	-4,56	9,389
6	0,118	-0,21	-0,346	4,781	-1,968	0,669	-0,473	8,565
2	0,181	0,248	-0,027	-0,202	-3,496	-1,388	-2,874	8,416
9	-0,137	0,344	-0,23	-0,094	-2,171	3,1	-0,552	6,628
7	0,269	-0,022	-0,385	2,149	-0,01	-0,875	-2,329	6,039
3	0,286	-0,233	-0,142	-0,201	-3,436	-0,814	0,035	5,147
8	-0,026	-0,255	0,094	3,333	0,335	0,534	-0,282	4,859
4	0,131	-0,301	-0,137	-0,304	-0,737	0,426	-1,534	3,57
5	0,03	0,048	0,086	-0,305	0,774	0,607	-1,546	3,396

Layer 2:

Neuron	Neuron ou	Neuron out 2	Neuron out 3	Neuron out	Neuron out 5	Neuron out 6	Neuron out 7	Neuron out 8	Neuron out 9	Neuron out 10	Neuron out 11	SUM ABS
3	-1,522	1,016	-2,01	1,172	-4,614	1,944	1,508	1,437	1,493	-5,129	-3,106	24,951
4	-0,091	2,578	-0,416	-4,699	-3,057	2,292	-2,229	1,704	1,265	0,086	-0,098	18,515
2	0,173	-0,813	1,675	-1,246	3,007	2,07	4,023	-0,308	-1,337	1,815	0,556	17,023
5	0,069	2,653	0,942	-3,453	-0,784	-0,18	-0,639	2,541	1,847	0,511	0,376	13,995
1	0,75	-0,249	1,704	-3,85	0,529	-0,176	1,492	1,883	-0,402	-0,148	1,905	13,088

Output layer:

Neuron	Neuron ou	Neuron out 2	Neuron out 3	Neuron out 4	Neuron out 5
1	2,09	1,941	-3,122	3,378	4,599

Analysis of the structure of the neural network

Tables show neuron weights, according to the formula.[1] The last column of table indicates the sum of the absolute values of the coefficients for each neuron. Table rows are sorted in descending order by this parameter. If we analyze the first three most influential neurons of the first layer, then we can see a significant superiority of weights with time features (cos_HOD(LST), sin_HOD(LST), cos_DOY(LST)).

The first most influential neuron of the second layer contains large coefficients (-5.139 and 3.106) at the outputs of the tenth (10) and eleventh (11) neuron of the first layer (which are the most influential in the first layer).

At the same time, coefficients at the exit from the sixth (7) and eighth (8) neurons of the first layer are also significant (1.944 and 1.437). If we look at these neurons in the first layer, we will see that they have the largest weights belonging to the characteristic for the frequency f107 (solar radiation flux at a wavelength of 10.7 cm). The output layer contains coefficients of approximately the same order, which allows us to restrict ourselves to the analysis of the most influential neurons in the first two layers.

After the analysis, we can conclude that when using the neural network model to predict the frequency of foF2, the value of frequency f107 and the value of current local solar time have the greatest influence on its value.

Conclusion

In this work, we using the data of the Irkutsk Digisonde and data of geomagnetic indices from 2009 to 2016, for train the neural network model to predict the critical frequency foF2.

1. It is shown that the model has acceptable quality indicators.

2. The weight coefficients inside individual neurons were also analyzed and it was concluded that the critical frequency of foF2 most strongly depends on the solar radiation flux at a wavelength of 10.7 cm, as well as on the current local solar time.

Thanks for attention!

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