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RESEARCH ARTICLE :

Evaluation of artificial neural network and regression PTFs in estimation soil hydraulic properties

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SUMMARY : Study of soil properties like field capacity (F.C.) and permanent wilting point (P.W.P.) play important roles in study of soil moisture retention curve. Although these parameters can be measured directly, their measurement is difficult and expensive. Pedotransfer functions (PTFs) provide an alternative by estimating soil parameters from more readily available soil data. Forty five different sampling locations in Sindapalli Uppodai were selected and undisturbed samples were taken to measure the water content at field capacity (FC), -33 kPa, and permanent wilting point (PWP), -1500 kPa. Measured soil variables included texture, organic carbon, water percentage at field capacity and wilting point, water saturation percentage, Bulk density were also determined for each soil sample at each location. Three different techniques including pattern recognition approach Artificial Neural Network (ANN), pedo transfer functions (PTF) and field measurement were used to predict the soil water at each sampling location. Root mean square error (RMSE), mean error (ME) and co-efficient of determination (R^2) were used to evaluate the performance of all the three approaches. Our results showed that field measurement and PTF performed better than ANN in prediction of water content at both FC and PWP matric potential. Various statistics criteria for simulation performance also indicated that between field measurement and PTF, the former, predicted water content at PWP more accurate than PTF; however, both approach showed a similar accuracy to predict water content at FC.

KEY WORDS :
Artificial neural network, Field capacity, Permanent wilting point, Pedotransfer functions

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BACKGROUND AND OBJECTIVES

Field capacity is defined as the maximum water content in a soil two to three days after being wetted and free drainage is negligible. Wilting point is defined as the soil water content where leaves of sunflower plants wilt continuously. Soil water contents at field capacity and wilting point are used to calculate the water depth that should be applied by irrigation and to determine water availability, which is a crucial factor in assessing the suitability of a land area for producing a given crop.

Contamination of surface water and groundwater due to point and non-point sources such as landfills and agricultural practices has motivated the development of complicated simulation models. Recently, application of simulation models for water flow and solute transport processes in the vadose zone has increased significantly. However, crop models such as the SWAT often use the upper (field capacity, FC) and lower (permanent wilting point, PWP) level of available water or available water capacity (AWC) of each soil horizon as a primary soil hydraulic property (Ritchie *et al.,* 1999). The FC and PWP are the soil water contents on the retention curve at soil water potentials of –33 and –1500 kPa, respectively and AWC refers to the difference between the FC and PWP. Since soil hydraulic properties are time consuming and expensive to measure directly, utilizing pedo transfer functions (PTFs) for the indirect estimation of these properties from more easily measured or widely available soil properties like sand (S), silt (Si), and clay (C) fractions, bulk density (BD) and organic matter (OM) has received considerable attention (Bell and Kerulen, 1995; Tomasella *et al.*, 2008 and Borgesen and Schaap, 2005).

Field measurement and PTFs have been developed for estimation of points on the water retention curve at known pressure heads like FC, PWP, or AWC and *Ks*. They have also been developed to predict the parameters of soil water retention models such as those of Vangenuchten (1980). PTFs have also been utilized in joint estimation of both point and parametric estimations (Pachepsky *et al.*, 1996). The relationships between these hydraulic properties (point or parametric) and basic soil properties are most often constructed using either traditional multiple linear regression (MLR) Mayr *et al*. (1999), or artificial neural network (ANN) approach Borgesen and Schaap, 2005).

Several attempts have been made to estimate indirectly these properties from more easily measurable and more readily available soil properties such as particle-size distribution (sand, silt and clay content), organic matter or organic C content, bulk density, porosity, etc. Such relationships are referred to as pedo-transfer functions (PTFs) Mermoud and Xu (2006). The two common methods used to develop PTFs are multiple-linear regression method and ANN. One of the advantages of neural networks compared to traditional regression PTFs is that they do not require a priori regression model, which relates input and output data and in general is difficult because these models are not known Schaap and Leij (1998). The objective of this paper is to evaluate the general applicability of field measurement, artificial neural network and multivariate regression in estimating FC and PWP in the soils of Sindapalli Uppodai.

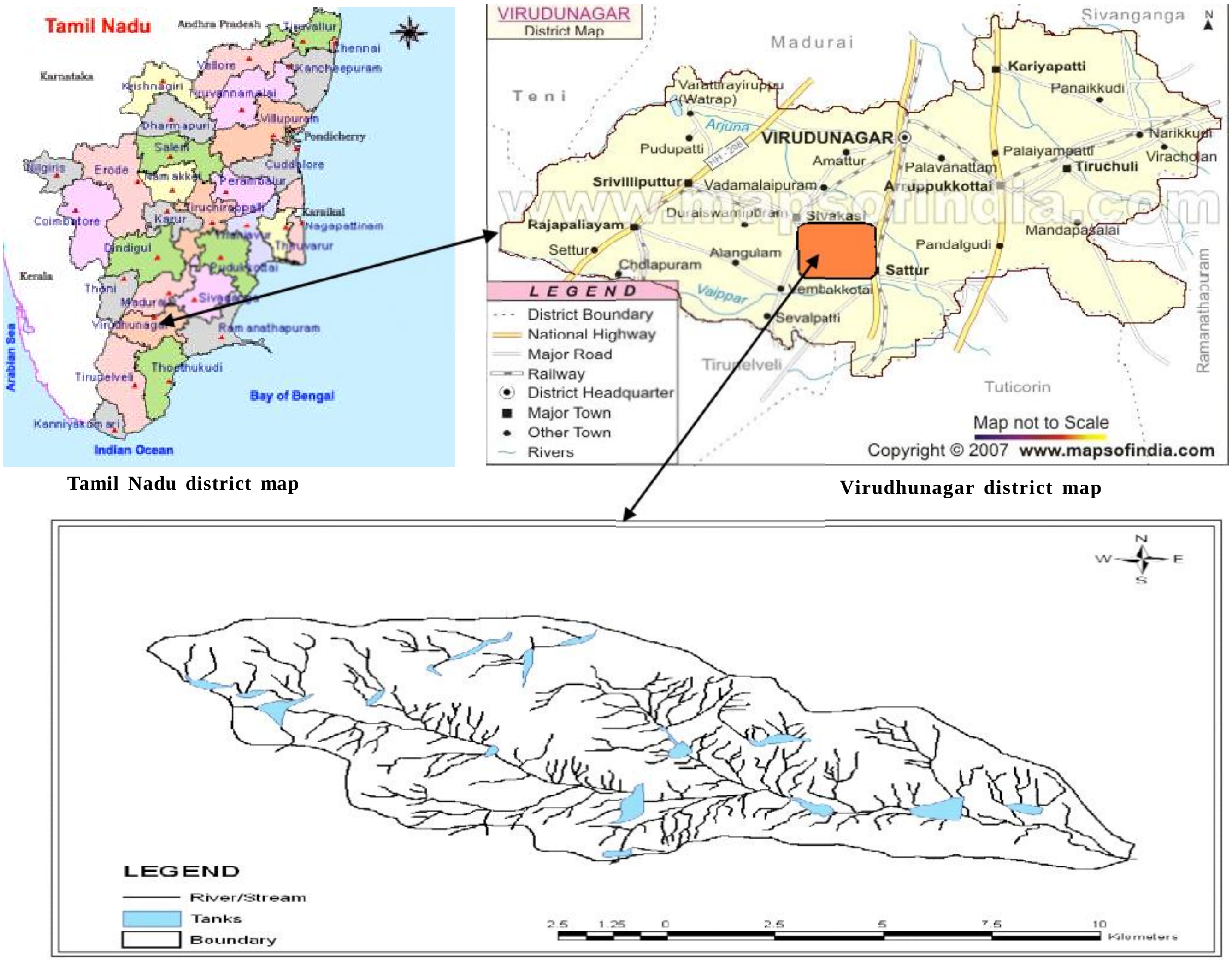
RESOURCES AND METHODS

Study area :

The surface water storage bodies termed as tanks are commonly adopted in the Tamil Nadu state located in the south eastern part of India. Sindapalli Uppodai sub basin, situated in Tamil Nadu, consists of many tanks forming cascade type and some are isolated. The maximum amount of rainfall is collected and stored in these 15 tanks and utilized for the irrigation and drinking water demands through directly as well as by recharging ground water aquifers. In the sub basin, tank irrigation is followed in the vicinity of tanks and well irrigation is practiced in other areas. Sindapalli Uppodai sub basin of Vaippar river basin, receives drainage from its own catchment. It originates from the plain terrain near by Duraiswamypuram village of Sivakasi taluk, runs for a distance of 26 km and it joins in Arjunanadhi at the downstream of Allampatti Village. The location of the basin is at latitude of 9° 25’00"N to 9° 30’00" N and longitude 77° 45’00"E to 77° 55’00"E situated in taluks of Sivakasi and Sattur in Virudhunagar district of Tamilnadu. Normally subtropical climate prevails over district without any sharp variation. The temperature rise slowly to maximum in summer months upto may and after which it drops slowly. The mean maximum temperature is 33.95 ºC to the mean minimum temperature is 23.78ºC. The seventy years average annual rainfall is 799.8 mm from three distinct seasons that is South West monsoon, North East monsoon and transitional period. There are seven rain gauge stations spread over the district and maintained by different organisation. In this, Sindapalli Uppodai is influenced by 3 rain gauge stations namely Vembakottai, Sathur and Sivakasi.

Field measurement in soil hydraulic parameters :

After preliminary studies of geological (1:100000, 1:250000) and topographic maps, using GPS, studying locations were appointed. 45 soil samples were collected from different horizons of soil profiles located in Sindapalli Uppodai. Particle-size distribution was determined after dissolution of $CaCO_3$ with 2 N HCl and decomposition of organic matter with 30% H_2O_2. After repeated washing to remove salts, samples were dispersed using sodium hexametaphosphate for determination of sand, silt and clay fractions by the international pipette method



Tamil Nadu district map

Virudhunagar district map

Fig. A: Sindhapalli uppodai sub basin

(Day, 1965). Organic carbon (O.C) was determined by Walkley-Black method Nelson and Sommers (1982). The maximum, minimum and average value of physical properties for three types of soil were found out and shown in the Table 1.

Methods to fit PTFs:

Multiple linear regressions equation:

Therefore, the soil hydraulic parameters, field capacity and permanent wilting point were substituted by linear equations relating these parameters with soil properties in a physically meaningful way: field capacity (Fc) = f (bulk density, clay, sand, silt), permanent wilting point (pwp) = f (clay, bulk density, silt, sand).

The most accurate PTF for the water content at the soil water potential of field capacity (-33 kPa) and per- manent wilting point (-1500 kPa), multiple regressions using step wise approach. The pedo transfer functions proposed by Hutson and Wagenet (1992) are based on a two-parameter soil hydraulic function of the above Hutson model. The following regression equations were proposed by Hutson and Wagenet (1992).

$\bar{}_{J33}$=0.3486-0.0018(S~)+0.0039(Cl)+0.0228(Om)-0.0728($°_d$) ....(1)

$\bar{}_{-1500}$=0.0854-0.0004(S~)+0.0044(Cl)+0.0122(Om)-0.0182($°_d$) ...(2)

where, $°_d$ is the bulk density (g /cm^3), C the carbon content (%), Cl the clay content (%) and *S~* the sand content (%), Si is the silt content (%) Hutson and Wagenet (1992).

Artificial neural network :

An artificial neural network is a highly interconnected network of many simple processing units called neurons, which are analogous to the biological neurons in the human brain. Neurons having similar characteristics in an ANN are arranged in groups called layers. The neurons in one layer are connected to those in the adjacent layers, but not to those in the same layer. The strength of connection between the two neurons in adjacent layers is represented by what is known as a >connection strength= or >weight=. An ANN normally consists of three layers, an input layer, a hidden layer, and an output layer. In a feed forward network, the weighted connections feed activations only in the forward direction from an input layer to the output layer. On the other hand, in a recurrent network additional weighted connections are used to feed previous activations back into the network. The lines joining the neurons represent weights; the inputs are represented by X=s; Y represents the output; Vji and Wkj represent the weights between input and hidden and hidden and output layers, respectively. An important step in developing an ANN model is the training of its weight matrix. The weights are initialized randomly between a suitable range and then updated using certain training mechanism Jain and Kumar (2006) and Minasny and McBratney (2002).

Neuro Solutions 5.0 software was used for the design and testing of ANN models. Soil parameters including clay, sand, silt, O.C and B.D were input data for prediction of the two outputs (F.C and P.W.P.). In this study, the ANN structures were all consisted of one hidden layer, a sigmoid activation function in hidden layer, and a linear activation function in output layer and LM algorithm was used to train the networks due to efficiency, simplicity and high speed. To develop a statistically sound model, the networks were trained three times and the best values were recorded for each parameter Omid *et al.* (2009). The network weights and biases are then adapted and employed for validation in order to determine the neural network model overall performance. The RMSE and R^2 of the ANN models on test sets are then calculated and compared with multivariate regression model.

Evaluation criteria :

At different stages of the PTF development, it is required to quantify the amount by which an estimated value differs from the 'true' value of the quantity being estimated. Such quantification describes how well the estimator describes the 'true' values. In this research, such differences between estimated values and the 'true' values are quantified using the following performance criterion: (i) root mean square error (RMSE), (ii) mean error (ME) and (iii) co-efficient of determination (R^2).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}((Z_S - Z_0)^2)} \quad .....(3)$$

$$ME = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Z_S - Z_0)} \quad .....(4)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}((Z_S - Z_0)^2)}{\sum_{i=1}^{N}((Z_S - \bar{Z}_0)^2)} \quad ....(5)$$

Where n is the number of observations, Z_s is the pre- dicted value, Z_o is the observed data and $\bar{Z}_0$ is the mean of observations.

OBSERVATIONS AND ANALYSIS

The results obtained from the present study as well as discussions have been summarized under following heads:

Developing PTFs using multivariate regression and artificial neural network :

Results showed that artificial neural network with two neurons in hidden layer had better performance in predicting all soil properties (FC and PWP) than multivariate regression which is in line with the work done by Amini *et al.* (2005); Minasny and McBratney (2002) and Schaap and Leij (1998). Amini *et al.* (2005) found that the neural network-based models provided more reliable predictions than the regression-based PTFs. Schaap and Leij (1998) confirmed applicability of ANNs and concluded that accuracy of these models depend on number of inputs.

Soil particle distribution, bulk density, organic carbon content is used in Pedo Transfer Function to obtain field capacity and wilting point. Hutson model for F.C and W.P were used according to Eq. (1) and (2). The maximum, minimum and average value of field capacity and wilting point for three types of soil and two methods were found out and shown in the Table 2.

The scatter plots of the measured against predicted FC and WP for the test data set are given in Fig. 1, 2 ,3 and 4 for the multivariate regression and artificial neural network model, which we identified as being the best model for artificial neural network model predicting soil parameters. So that according to these diagrams, the best fitted line has the angle of near to 45° that shows the high accuracy of estimation by the ANN model. The result of correlation co-efficient (R^2), Mean Error (ME) and root Mean Square Error (RMSE) values related to studied soil parameters for multivariable linear regression method and artificial neural network method are presented in Table 3. The reason of this superior efficiency of ANN is models compared with the basic regression equations are probably because; the PTFs that have been derived from various areas have different efficiencies. On the other hand, according to the hypothesis of Schaap and Leij (1998), for designing of a neural network we do not need a special equation. However, they believe that with creation of a suitable equation between input and output data we are able to achieve to the best results. Also, due to the inherent nonlinearity between the exploratory variables and predicting variables, the neural networks have the better efficiency compared with the basic regression equations.

Similar results have been reported by the Tamari *et al.* (1996) as well. They found that using ANN leads to less RMSE values than the multivariable linear regression. They also reported that the neural network has not better efficiency than linear regression models in occasion of high stability of data. However, the high accuracy of data leads to more efficiency of neural network and also, shows the proper selection of testing and training data. As Fig. 3 and 4 showed ANN predicted soil properties with relatively high accuracy (R^2 = 0.86 and 0.89).

In practice, it is extremely difficult to saturate a soil with water because of air trapping Mermoud and Xu (2006). Tamari *et al.* (1996) poorly predicted K values at matric potentials of -10 and -25 kPa with both methods ANN and regression and they suggested that soil

Table 1: Physical properties of soil

	Physical properties of soil				
	Sand (%)	Silt (%)	Clay (%)	Bulk density (gram/cm$_3$)	Organic carbon (%)
Soil type			Sandy loam		
Maximum	68.50	40.50	10.00	1.76	0.9357
Minimum	51.50	21.50	6.00	1.37	0.3235
Average	57.35	34.59	7.94	1.52	0.5257
Soil type			Silty loam		
Maximum	40.55	57.27	9.00	1.41	0.7527
Minimum	35.73	52.95	6.00	1.08	0.2956
Average	37.80	54.74	7.56	1.28	0.4601
Soil type			Loam		
Maximum	51.35	43.83	9.20	1.72	0.8757
Minimum	48.17	40.35	7.00	1.42	0.3167
Average	50.03	41.96	8.00	1.54	0.5365

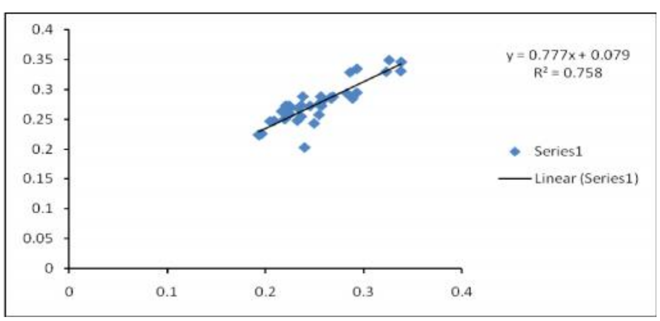


Fig. 1: The scatter plot of the measured versus predicted field capacity in multivariate linear regression

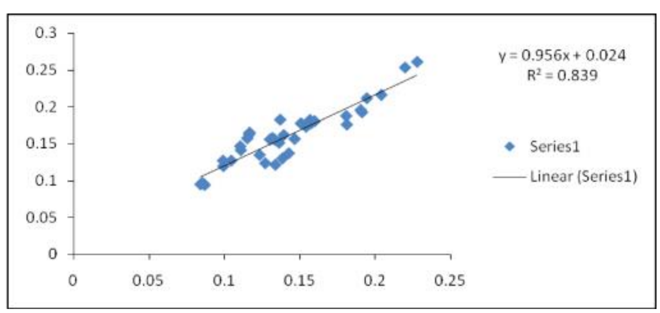


Fig. 2: The scatter plot of the measured versus predicted wilting point in multivariate linear regression

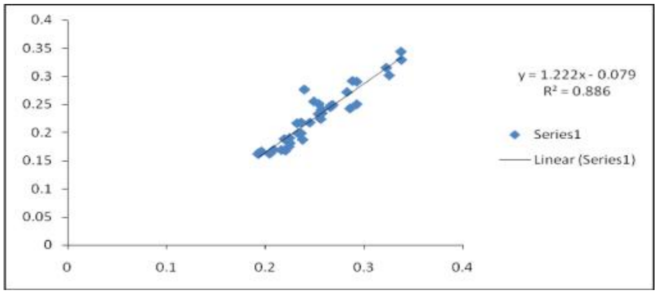


Fig. 3: The scatter plot of the measured versus predicted field capacity in artificial neural network

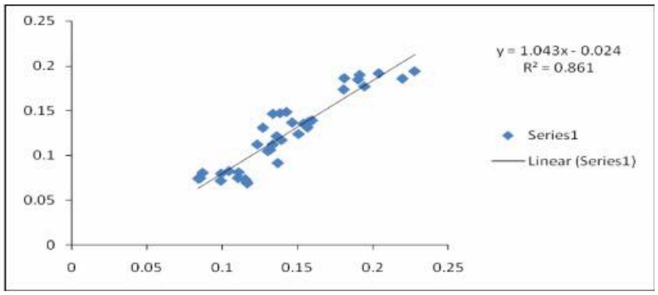


Fig. 4: The scatter plot of the measured versus predicted wilting point in artificial neural network

samples should be classified based on their texture as coarse, medium and fine. Therefore, difficulty in measuring soil hydraulic properties in heterogeneous soils might cause this relatively poor prediction. Analysis of the ANN parameters suggested that more input variables were necessary to improve the prediction of unsaturated hydraulic conductivity Tamari *et al.* (1996). The differences between the field and laboratory determination of water retention data might be associated to the insufficient representation of large pores in the laboratory, sample disturbance and spatial variation, hysteresis and scale effects related to the sample size (Field *et al.*, 1984 and Shuh *et al.*, 1988). Pachepsky *et al.* (2003) found significant differences between the field and laboratory volumetric water contents for coarse-, intermediate and fine-textured soil horizons. Therefore, measurement errors might cause the poor prediction of the parameters.

Conclusion:

In this study, multivariate linear regression and neural network model (feed-forward back-propagation network) were employed to develop a Pedotransfer function for predicting soil F.C and W.P by using available soil properties. For predicting the soil property by means of PTFs, the input data were consisted of clay, sand, silt,

Table 2 : The result of linear regression and neural network based pedo transfer function

	Multivariate regression method		Artificial neural network method	
	Field capacity	Wilting point	Field capacity	Wilting point
Soil type	Sandy loam		Sandy loam	
Maximum	0.2731	0.1647	0.2771	0.1483
Minimum	0.2023	0.0936	0.1622	0.0685
Average	0.2499	0.1338	0.1981	0.0961
Soil type	Silty loam		Silty loam	
Maximum	0.3492	0.2957	0.3444	0.1938
Minimum	0.2849	0.1510	0.1879	0.0913
Average	0.3134	0.2094	0.2740	0.1551
Soil type	Loam		Loam	
Maximum	0.2876	0.1820	0.2496	0.1371
Minimum	0.2475	0.1232	0.2172	0.1169
Average	0.2730	0.1598	0.2362	0.1302

Table 3 : Evaluation of linear regression and neural network based pedo transfer function estimating field capacity and permanent wilting point

Statistical parameters	Multivariate linear regression (F.C)	Multivariate linear regression (P.W.P)	Artificial neural network (F.C)	Artificial neural network (P.W.P)
ME	-0.313	-0.253	-0.233	-0.214
RMSE	0.0235	0.0195	0.0174	0.0164
R^2	0.76	0.84	0.89	0.86

O.C, and B.D for F.C and W.P. The performance of the multivariate linear regression and neural network model was evaluated using a test data set. Results showed that ANN with five neurons in hidden layer had better performance in predicting soil F.C and P.W.P than multivariate regression. The network model for these parameters was more suitable for capturing the nonlinearity of the relationship between variables. ANN can model non-linear functions and have been shown to perform better than linear regression.

However, due to difficulties of direct measurement of soil parameters, we recommend using of neuron-fuzzy models such as ANFIS in the future studies for obtaining the logical equations of other soil parameters, especially soil hydraulic properties, in each area. ANFIS is more tolerant to noisy or missing data and has a good generalization capability. ANN posses a number of properties for modelling PTFs: universal function approximation capability, learning from experimental data, tolerance to noisy or missing data and good generalization capability. When function approximation is the goal, the ANN model will often deliver close to the best fit. The present work was motivated in this direction. Apart from model accuracy and generalization capability, other important issues such as computational time, credibility, tactical issues and replicating the results have to be considered when comparing multivariate linear regression vs. ANN to predict soil F.C and W.P Although outperforming the empirical modelling techniques, ANN has one big offset – it is hard to draw any physical information out of it, *i.e.* no information from the neurons' weights and biases can be drawn about the weights of each predictor in the final score Omid *et al.* (2009). Nevertheless, because of their better results, ANNs are commonly used during the past 10 years to solve non-linear problems of high complexity.

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