Classify asteroid orbits using macl

Physics (https://www.neuraldesigner.com/tag/physics/)

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The central goal is to design a model that makes useful classifications for different orbit types.

NASA collected the data set for building the model. We use the data science and machine learning platform Neural Designer (https://www.neuraldesigner.com/) to build the model. You can use the free trial (https://www.neuraldesigner.com/free-trial) to follow the process step by step.

Contents:

1. Application type

This is a classification (https://www.neuraldesigner.com/learning/tutorials/neural-networks-applications#Classification) project since we want to predict a categorical variable, the orbit type (AMO, APO, ATE).

2. Data set

The first step is to prepare the data set (https://www.neuraldesigner.com/learning/tutorials/data-set), which is the source of information for the classification problem.

For that, we need to configure the following concepts:

- Data source.
- Variables.
- Instances.

Data source

The data source (https://www.neuraldesigner.com/learning/tutorials/data-set#DataSource) is the file orbit_class.csv (https://www.neuraldesigner.com/wp-content/uploads/2023/10/orbit_class.csv). It contains the data for this example in comma-separated values (CSV) format. The number of columns is 12, and the number of rows is 1722.

Variables

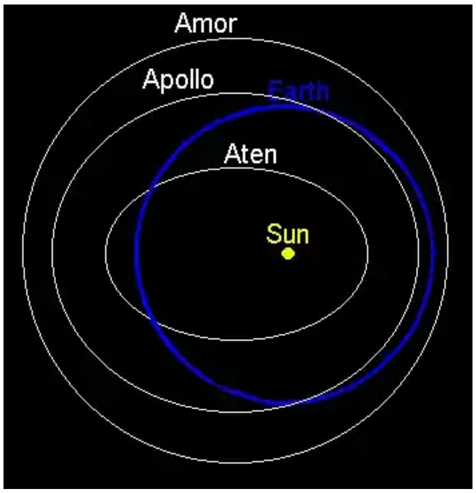
The variables are: (https://www.neuraldesigner.com/learning/tutorials/data-set#Variables)

- a: Semi-major axis of the orbit in AU.
- e: Eccentricity of the orbit.
- i: Inclination of the orbit concerning the ecliptic plane and the equinox of J2000 (J2000-Ecliptic) in degrees.
- w: Argument of perihelion (J2000-Ecliptic) in degrees.
- Node: Longitude of the ascending node (J2000-Ecliptic) in degrees.
- M: Mean anomaly at epoch in degrees.
- q: Perihelion distance of the orbit in AU.
- Q: Aphelion distance of the orbit in AU.
- P: Orbital period in Julian years.
- H: Absolute V-magnitude.
- MOID: Minimum orbit intersection distance (the minimum distance between the osculating orbits of the NEO and the Earth).
- class: AMO, APO, ATE used as the target.

The above target variables are asteroid orbits. AMO is referring to Amor asteroids: near-Earth asteroids. The orbital perihelion of these objects is close to, but greater than, the orbital aphelion of Earth (a > 1.0 AU and 1.017 AU < q < 1.3 AU).

ATE refers to Aten asteroids, a dynamic group of asteroids whose orbits bring them into proximity to Earth. By definition, Atens are Earth-crossing asteroids (a<1.0 AU and Q>0.983 AU).

These different asteroid orbits are shown in the following image:



Note that neural networks work with numbers. In this regard, the categorical variable “class” is transformed into three numerical variables as follows:

- AMO: 1 0 0.
- APO: 0 1 0.
- ATE: 0 0 1.

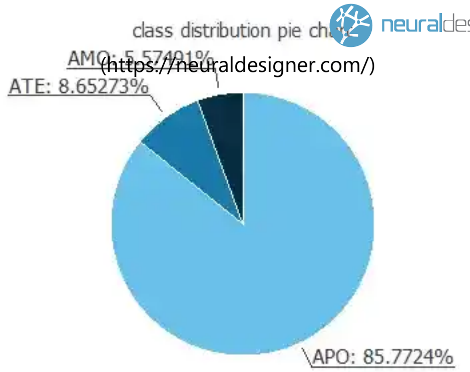
Instances

The instances (https://www.neuraldesigner.com/learning/tutorials/data-set#Instances) are divided into training, selection, and testing subsets. They represent 60% (1034), 20% (344), and 20% (344) of the original instances, respectively, and are split at random.

Variables distribution

We can calculate the distributions (https://www.neuraldesigner.com/learning/tutorials/data-set#Distributions) of all variables. The following figure is the pie chart for the orbit types.

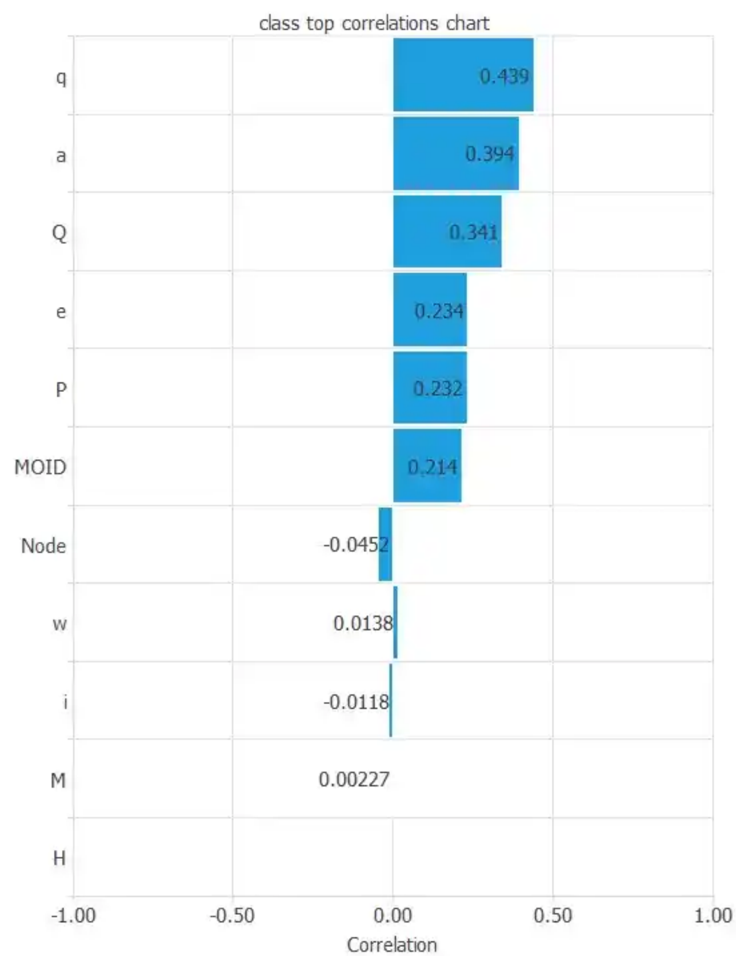
(https://neuraldesigner.com/)



As we can see, most of the samples are APO orbits.

Inputs-targets correlations

Finally, the inputs-targets correlations (https://www.neuraldesigner.com/learning/tutorials/data-set#InputsTargetsCorrelations) might indicate to us what factors most influence.



Here, the most correlated variables with the classification are a, q, and Q, the semi-major axis, perihelion distance, and aphelion distance of the orbit.

Also, there are variables with a small correlation, like M, mean anomaly, or H, absolute V-magnitude.

3. Neural network

The second step is to choose a neural network (https://www.neuraldesigner.com/learning/tutorials/neural-network) for classification, which is usually composed of the following:

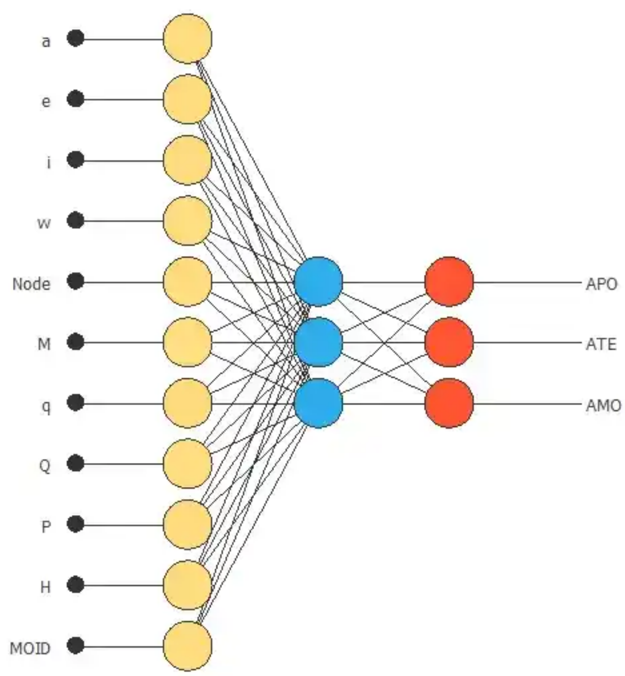
- A scaling layer.
- Two perceptron layers.
- A probabilistic layer.

The scaling layer (https://www.neuraldesigner.com/learning/tutorials/neural-network#ScalingLayer) contains the statistics on the inputs calculated from the data file and the method for scaling the input variables.

Here, the minimum and maximum method has been set. Nevertheless, the mean and standard deviation method would produce very similar results.

The number of perceptron layers (https://www.neuraldesigner.com/learning/tutorials/neural-network#PerceptronLayers) is 1. This perceptron layer has 11 inputs and 3 neurons. The probabilistic layer (https://www.neuraldesigner.com/learning/tutorials/neural-network#ProbabilisticLayer) allows the outputs to be interpreted as probabilities. All outputs are between 0 and 1, and their sum is 1.

The softmax probabilistic method (https://www.neuraldesigner.com/learning/tutorials/neural-network#SoftmaxProbabilisticMethod) is used here. The neural network has three outputs since the target variable contains 3 classes (AMO, APO, ATE). The following figure is a graphical representation of this classification neural network (https://www.neuraldesigner.com/learning/tutorials/neural-network#ClassificationNeuralNetworks):



Here, the yellow circles represent scaling neurons, the blue circles represent perceptron neurons, and the red circles represent probabilistic neurons. The number of inputs is 11, and the number of outputs is 3.

4. Training strategy

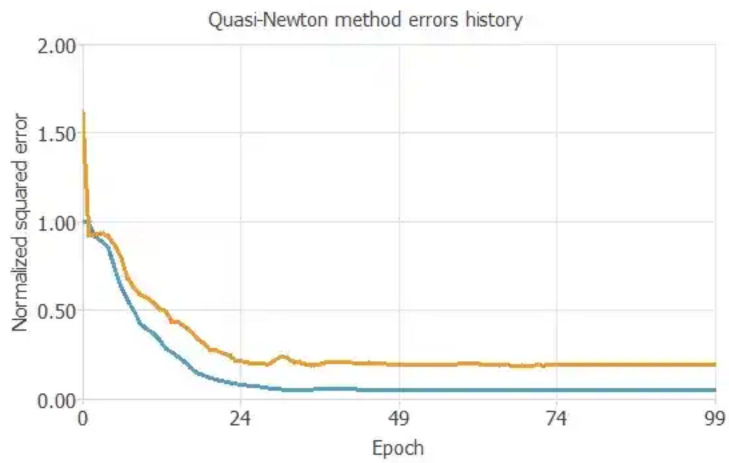
The fourth step is to set the training strategy (https://www.neuraldesigner.com/learning/tutorials/training-strategy), which is composed of:

- Loss index.
- Optimization algorithm.

The loss index (https://www.neuraldesigner.com/learning/tutorials/training-strategy#LossIndex) chosen for this application is the normalized squared error (https://www.neuraldesigner.com/learning/tutorials/training-strategy#NormalizedSquaredError) with L2 regularization (https://www.neuraldesigner.com/learning/tutorials/training-strategy#L2Regularization).

The error term (https://www.neuraldesigner.com/learning/tutorials/training-strategy#ErrorTerm) fits the neural network to the training instances (https://www.neuraldesigner.com/learning/tutorials/training-strategy#TrainingInstances) of the data set. The regularization term (https://www.neuraldesigner.com/learning/tutorials/training-strategy#RegularizationTerm) makes the model more stable and improves generalization. The optimization algorithm (https://www.neuraldesigner.com/learning/tutorials/training-strategy#OptimizationAlgorithm) searches for the neural network parameters that minimize the loss index. The quasi-Newton method (https://www.neuraldesigner.com/learning/tutorials/training-strategy#QuasiNewtonMethod) is chosen here.

The following chart shows how training and selection errors decrease with the epochs during training.



The final values are **training error = 0.0469 NSE** (blue) and **selection error = 0.189 NSE** (orange).

5. Model selection

The objective of model selection (https://www.neuraldesigner.com/learning/tutorials/model-selection) is to find the network architecture with the best generalization properties, which minimizes the error on the selected instances (https://www.neuraldesigner.com/learning/tutorials/data-set#SelectionInstances) of the data set.

Order selection (https://www.neuraldesigner.com/learning/tutorials/model-selection#OrderSelection) algorithms train several network architectures with a different number of neurons and select that with the smallest selection error.

The incremental order (https://www.neuraldesigner.com/learning/tutorials/model-selection#IncrementalOrder) method starts with a few neurons and increases the complexity at each iteration.

6. Testing analysis

The purpose of the testing analysis (https://www.neuraldesigner.com/learning/tutorials/testing-analysis) is to validate the generalization performance of the model.

Here, we compare the neural network outputs to the corresponding targets in the testing instances (https://www.neuraldesigner.com/learning/tutorials/data-set#TestingInstances) of the data set.

In the confusion matrix (https://www.neuraldesigner.com/learning/tutorials/testing-analysis#ConfusionMatrix), the rows represent the targets (or real values), and the columns represent the corresponding outputs (or predictive values).

The diagonal cells show the correctly classified cases, and the off-diagonal cells show the misclassified cases.

	Predicted APO	**Predicted ATE**	**Predicted AMO**
Real APO	283 (84.0%)	0 (0.0%)	1 (0.3%)
Real ATE	1 (0.3%)	30 (8.7%)	0 (0.0%)
Real AMO	7 (2.0%)	0 (0.0%)	16 (4.7%)

As we can see, the number of instances the model can correctly predict is 335 (97.4%), while it misclassifies 9 (2.6%).

This shows that our predictive model has a great classification accuracy.

(https://neuraldesigner.com/)

7. Model deployment

The neural network is now ready to predict outputs for inputs it has never seen. We call this process model deployment (https://www.neuraldesigner.com/learning/tutorials/model-deployment).

We calculate the neural network outputs (https://www.neuraldesigner.com/learning/tutorials/model-deployment#NeuralNetworkOutputs) from the different variables to classify a given orbit.

For instance:

- a: 1.75 AU.
- e: 0.53.
- i: 13.35 degrees.
- w: 180.46 degrees.
- Node: 172.25 degrees.
- M: 180.73 degrees.
- q: 0.76 AU.
- Q: 2.75 AU.
- P: 2.44 yr.
- H: 19.94.
- MOID: 0.02 AU.
- **Probability of APO: 99.9%.**
- **Probability of ATE: ~0.0%.**
- **Probability of AMO: ~0.0%.**

The neural network would classify the orbit as Apollo asteroid orbit for this case since it has the highest probability.

The mathematical expression (https://www.neuraldesigner.com/learning/tutorials/model-deployment#MathematicalExpression) of the trained neural network is listed below.

```
scaled_a = a*(1+1)/(17.81870079-(0.6369649768))-0.6369649768*(1+1)/(17.81870079-0.6369649768)-1;
scaled_e = e*(1+1)/(0.9560419917-(0.02542470023))-0.02542470023*(1+1)/(0.9560419917-0.02542470023)-1;
scaled_i = i*(1+1)/(75.41239929-(0.1460839957))-0.1460839957*(1+1)/(75.41239929-0.1460839957)-1;
scaled_w = w*(1+1)/(359.6629944-(0.5218380094))-0.5218380094*(1+1)/(359.6629944-0.5218380094)-1;
scaled_Node = Node*(1+1)/(359.855011-(0.1360419989))-0.1360419989*(1+1)/(359.855011-0.1360419989)-1;
scaled_M = M*(1+1)/(359.8250122-(0.05216519907))-0.05216519907*(1+1)/(359.8250122-0.05216519907)-1;
scaled_q = q*(1+1)/(1.060099959-(0.09279999882))-0.09279999882*(1+1)/(1.060099959-0.09279999882)-1;
scaled_Q = Q*(1+1)/(34.68000031-(0.9900000095))-0.9900000095*(1+1)/(34.68000031-0.9900000095)-1;
scaled_P = P*(1+1)/(75.22000122-(0.5099999905))-0.5099999905*(1+1)/(75.22000122-0.5099999905)-1;
scaled_H = H*(1+1)/(22-(14.10000038))-14.10000038*(1+1)/(22-14.10000038)-1;
scaled_MOID = MOID*(1+1)/(0.04998699948-(9.999999747e-06))-9.999999747e-06*(1+1)/(0.04998699948-9.999999747e-06)-1;
perceptron_layer_0_output_0 = tanh[ 0.998564 + (scaled_a*0.483063)+ (scaled_e*4.23015)+ (scaled_i*0.033193)+
(scaled_w*0.00368636)+ (scaled_Node*-0.0750109)+ (scaled_M*0.0156837)+ (scaled_q*4.51185)+ (scaled_Q*0.387602)+
(scaled_P*-0.48082)+ (scaled_H*-0.124104)+ (scaled_MOID*0.0301184) ];
perceptron_layer_0_output_1 = tanh[ 0.378967 + (scaled_a*0.0679598)+ (scaled_e*2.29236)+ (scaled_i*-0.259866)+
(scaled_w*-0.415081)+ (scaled_Node*-0.00389391)+ (scaled_M*-0.0223087)+ (scaled_q*-1.3599)+ (scaled_Q*0.12361)+
(scaled_P*-0.168758)+ (scaled_H*0.596372)+ (scaled_MOID*-0.376615) ];
perceptron_layer_0_output_2 = tanh[ -2.16292 + (scaled_a*1.04587)+ (scaled_e*0.149125)+ (scaled_i*0.107164)+
(scaled_w*-0.0590388)+ (scaled_Node*0.0606977)+ (scaled_M*-0.0259366)+ (scaled_q*5.8545)+ (scaled_Q*0.931787)+ (scaled_P*1.49335)+
(scaled_H*0.115587)+ (scaled_MOID*0.0850156) ];
probabilistic_layer_combinations_0 = -0.922149 +3.8602*perceptron_layer_0_output_0 +1.09178*perceptron_layer_0_output_1
-3.9471*perceptron_layer_0_output_2
probabilistic_layer_combinations_1 = 1.00764 -4.69034*perceptron_layer_0_output_0 +1.0006*perceptron_layer_0_output_1
-1.231*perceptron_layer_0_output_2
probabilistic_layer_combinations_2 = -0.0237251 +0.837826*perceptron_layer_0_output_0 -2.09368*perceptron_layer_0_output_1
+5.1967*perceptron_layer_0_output_2
sum_ = exp(probabilistic_layer_combinations_0 + exp(probabilistic_layer_combinations_1 + exp(probabilistic_layer_combinations_2;
APO = exp(probabilistic_layer_combinations_0)/sum_;
ATE = exp(probabilistic_layer_combinations_1)/sum_;
AMO = exp(probabilistic_layer_combinations_2)/sum_;
```

Conclusions

We have just built a predictive model to determine the possible asteroid orbit type.

References:

- Kaggle. Orbit Classification For Prediction (https://www.kaggle.com/brsdincer/orbitclassification).

Related posts:

- Star type classification (https://www.neuraldesigner.com/learning/examples/star-type).

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