Making Smart Contracts Predict and Scale Syed Badruddoja, Ram Dantu, Yanyan He, Mark Thompson, Kritagya Upadhyay, Abiola Salau University of North Texas

The machine learning algorithms can predict events based on the trained models and datasets. However, a reliable prediction requires the model to be trusted, tamper-resistant and free from poisoning attack. Blockchain technology provides trusted output with consensus-based transactions and an immutable distributed ledger. The machine learning algorithms can be trained on blockchain smart contracts to produce trusted models for reliable prediction. But most smart contracts in the blockchain do not support floating-point data type, limiting computations for classification, which can affect the prediction accuracy.



A model can be poisoned by training wrong images as shown above to falsify prediction. As a result, the prediction is falsified and unreliable.

Blockchain Properties



Blockchain is a distributed ledger of transaction with consensus-based validation which is highly trusted for immutable records in a decentralized network.

Purpose

- Identify limitations of blockchain to predict classes or events using machine learning algorithm
- Derive numerical methods to overcome limitation and allow prediction in blockchain using machine learning algorithm





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Smart contracts are used by blockchain network for transactions. Solidity is one of the popular smart contract languages that is highly used by developers. The above limitations prohibits smart contracts to predict using machine learning algorithms.

Solution: Integer-based Probability

We have devised a numerical method based on Taylor's series expansion for converting the fixed-point calculations to integer-based estimation and facilitate smart contracts to classify and predict based on estimated probability. We have chosen naive Bayes algorithm to estimate the probability of a class using only integer operation.

Naive Bayes Formula

Conditional Probability

$$P(c \mid x) = \frac{P(x \mid c) * P(c)}{P(x)}$$

Expanding conditional probability for all x features

$$P(x \mid c) * P(c) = (P(x_1 \mid c) * P(x_2 \mid c) * \dots * P(x_n)) * P(c)$$

ssian Probability :
$$P(x | c) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{1}{\sigma}}$$

c is class, x is feature, P is the probability, σ is the variance of features for particular class c, μ is the mean of features for a particular class c.

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Comparing Integer Outputs

Derived probability estimation for two classes C_k and C_l

 $\frac{p(C_k)^2}{p(C_l)^2} = \frac{\frac{Ak}{Bk}e^{-\frac{Ck}{Dk}}(p(C_k))^2}{\frac{Al}{Bl}e^{-\frac{Cl}{Dl}}(p(C_l))^2}\dots\dots eqn(1)$

$$\frac{p(C_k)^2}{p(C_l)^2} = \frac{A}{B} \cdot e^{-Q} \cdot e^{-\frac{R}{D}} \cdot \frac{(p(C_k))^2}{(p(C_l))^2} \dots \dots eqn(2)$$

Final two equations of derivations are shown above. From equation (2) we compare probability estimations in integers between individual classes of C_k and C_1 to identify the higher probable classes between them. For more classes, similar comparisons are performed until higher probable class is found which will be the predicted class for the input data with unknown class.

Dataset			
et	Features	Training Samples	Testing Samples
Diabetes	8	614	154
Note Authentication	4	1097	278
Block Detection	10	4378	1095



Comparable Prediction Accuracy of Smart Contracts against Python Libraries

Reference