Instance-level explanations for fraud detection

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INSTANCE-LEVEL EXPLANATIONS FOR FRAUD DETECTION
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THE PROBLEM
Fraud detection is a difficult problem that can benefit from predictive modeling. However, the verification of a prediction is challenging; for a single insurance policy, the model only provides a prediction score.

FEATURE DASHBOARD
This dashboard shows bar charts (A) expressing the contribution of a feature to the prediction. Additionally, partial dependence plots (B) show the impact of changing the feature value indicated with a vertical line) on the prediction.

THE SOLUTION
We designed two novel dashboards combining various state-of-the-art explanation techniques.

Partial dependence

Local rule extraction
Synthetic pruning data set, uniform samples from an n-ball:

\[ n \text{-ball uniform distribution} = \frac{Y \cdot U}{\| Y \|} \]

with \( Y \sim N(0, 1) \) and \( U \sim U(0, 1) \).

All decision rules applicable to instance \( i \) are extracted and pruned.

A Regularized Random Forest is trained on binary matrix of applicability of rules on the pruning dataset. Feature importance constitutes a metric of importance of individual decision rules.

For the example on the right, 1,300,000 rules are reduced to only 4, while still retaining 94.1% of the local fidelity of the reference model.