Cancellation Rate Prediction of Auto Insurance Policy

Shuaimin Kang, Yubing Yao

University of Massachusetts Amherst

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Data Exploration

Prediction Models

Summary

Discussion

Data Exploration

Data:

- 7578 records, 16 features, 105 NAs, 25 cancel$== -1$, 40 age $<$ len.at.res, 8 age $>$ 100.

High Cancellation population:

- Low credit, Virginia, 2014(mainly caused by Virginia and Washington), Single + young + Online + New customer + Higher premium, Coverage type B + Tenant, Tenant + (n.adults > 3), Male + high n.adults, House + White color

Interactive visualization details:

- `https://visualplot1.herokuapp.com/`

Prediction Models

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- **Other models**: Neural Network, k-nearest neighbor (knn)

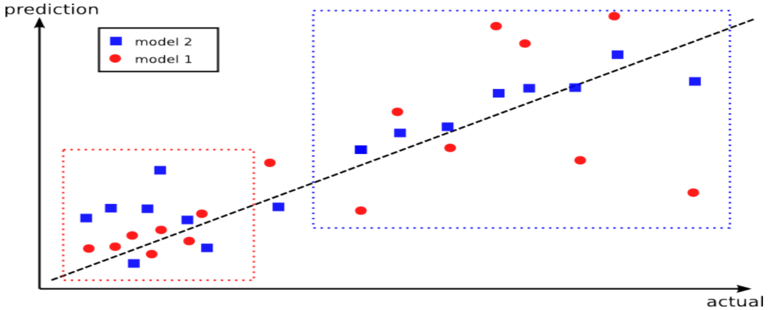
Important features in prediction models

We identify most important features for predicting cancellation rate based on two tree based models-**Decision Tree** and **Extreme Gradient Boosting (Xgboost)** and regression coefficients of the features in **logistic regression** with Lasso method.

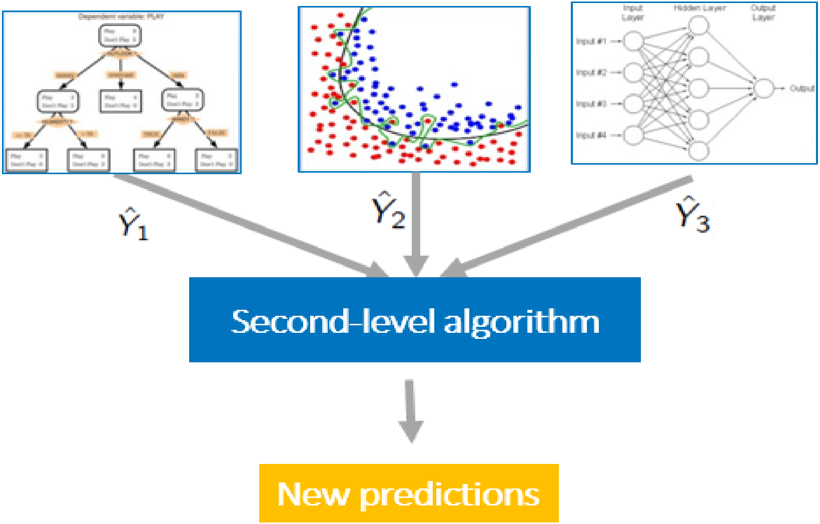
`https://dhn6zvu0qoinq.cloudfront.net/`

Stacking models-Motivation

Data is quite heterogeneous and one single model can only capture partial information in the data. Combining multiple diverse models through stacking we could improve prediction accuracy.



Stacking multiple base models-an illustration



$\hat{Y}_1$ $\hat{Y}_2$ $\hat{Y}_3$

Second-level algorithm

New predictions

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3. Generally speaking stacking models has better prediction performance using more diverse base models.

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2. We used lasso logistic regression and decision tree models to extract important features and interactions, such as credit level, claim indication, Virginia, young and Online buyers.

3. We applied advanced modeling techniques, such as bagging, boosting and stacking, to reach a robust prediction.

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4. Tracking and modeling policyholders’ features and cancellation behaviors dynamically.
5. Direct/indirect causal effect? Confounder?

Thank You!