

# Traveler's 2020 modeling competition

Insurance modeling

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# Table of contents

- ① To handle the unbalanced data
- ② Combined model of frequency and severity
- ③ Tweedie regression
- ④ Sample based matching from the external data
- ⑤ Sufficient dimension reduction (SDR) and SDR with categorical data
- ⑥ Special Correlation measures
- ⑦ Thanks



## To handle the unbalanced data

- The failure of Accuracy. AUC or Gini index instead.

		Truth	
		0 majority	1 minority
Predict	0 majority	990	10
	1 minority	0	0

- Two general solution: Sampling or weighted loss.

$$\begin{aligned}1 : 100 &\rightarrow 100 : 100 \\ &\rightarrow 1 : 1\end{aligned}$$

$$\begin{aligned}\ell_T(x, y) &= w_0 \ell(x, y | y = 0) + w_1 \ell(x, y | y = 1) \\ w_0 : w_1 &= \# \{y = 1\} / \# \{y = 0\}\end{aligned}$$

# Combined model of frequency and severity

In the chapter 6 of the book

 Predictive modeling applications in actuarial science

author gives a modeling pattern for the cost:

$$\text{frequency} = \text{claim\_count} / \text{exposure}$$

$$\text{severity} = \text{loss} / \text{claim\_count}$$

$$\text{frequency} \sim P(\lambda) \quad \text{or} \quad \text{NB}(n, m, \mu)$$

$$\text{severity} \sim G(\alpha, \beta)$$

# Tweedie regression

In the article



An index which distinguishes between some important exponential families

by Maurice Tweedie, the author proposed a tweedie distribution constructed by

$$\begin{aligned} \text{Cost} &= X_1 + \cdots + X_N \\ X_i &\stackrel{iid}{\sim} G(\alpha, \beta) \\ N &\sim P(\lambda) \end{aligned}$$

Comparison between Freq-Severity and Tweedie:



Loss Cost Modeling vs. Frequency and Severity Modeling, Jun Yan

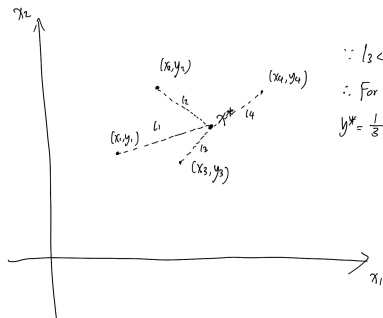
Link is here.

# Sample based matching from the external data

K-nearest-neighbor (KNN), with  $\{\vec{x}_i, y_i\}_1^n$  as the samples, for a new given  $\vec{x}^*$ , we set

$$y^* = \frac{1}{k} \sum_{j \in K} y_j$$

$$K = \arg \min_{T, |T|=k} \sum_{i \in T} \|\vec{x}_i - \vec{x}^*\|^2$$



$$\because l_3 < l_4 < l_2 < l_1$$

$\therefore$  For 3-NN,

$$y^* = \frac{1}{3} (y_2 + y_3 + y_4)$$

## Sample based matching from the external data

The data source: The dataset "dataCar" under the package "insuranceData".

Possible enhancement: Using kernel trick. In K-NN, the sample with different distance have same weights, while we can use the kernel function like Gaussian kernel to assign them with weights "proportional" to the distance.

$$\begin{aligned}y^* &= \sum_{j \in K} w_j y_j \\K &= \arg \min_{T, |T|=k} \sum_{i \in T} \left\| \vec{x}_i - \vec{x}^* \right\|^2 \\ \sum_j w_j &= 1 \\ w_j &\propto \exp \left( -\frac{\left\| \vec{x}_i - \vec{x}^* \right\|^2}{2\sigma^2} \right)\end{aligned}$$

# Sufficient dimension reduction (SDR) and SDR with categorical data



With the continuous  $x$ .

$$y \perp x \mid \beta^T x$$



Sliced inverse regression for dimension reduction, Li, Ker-Chau

With the continuous  $x$  and categorical  $W$ .

$$y \perp x \mid (\beta^T x, W)$$



Sufficient dimensions reduction in regressions with categorical predictors, Li, Bing



# Special Correlation measures

Distance correlation is hot topic in stats recently



Measuring and testing dependence by correlation of distances,  
Szekely, Gabor J

It is used to measure the distance between vector, so it can be adopted in the testing issue related to features and target. We test:

$$T^* = \frac{ndCov(X_i, Y)}{\frac{1}{n^2} \sum_{k,l=1}^n \|X_{ik} - X_{il}\|_p \frac{1}{n^2} \sum_{k,l=1}^n \|Y_k - Y_l\|_p} > (\Phi^{-1}(1 - \alpha/2))^2$$

Advantage: Regardless of the continuous or discrete type of variables

## Useful info



Git: [Git here](#).

Our department website is [Department of Statistics](#).

Our website for statistical data science lab at Uconn is Data Science Lab