How severe is an insurance claim?

Team Member

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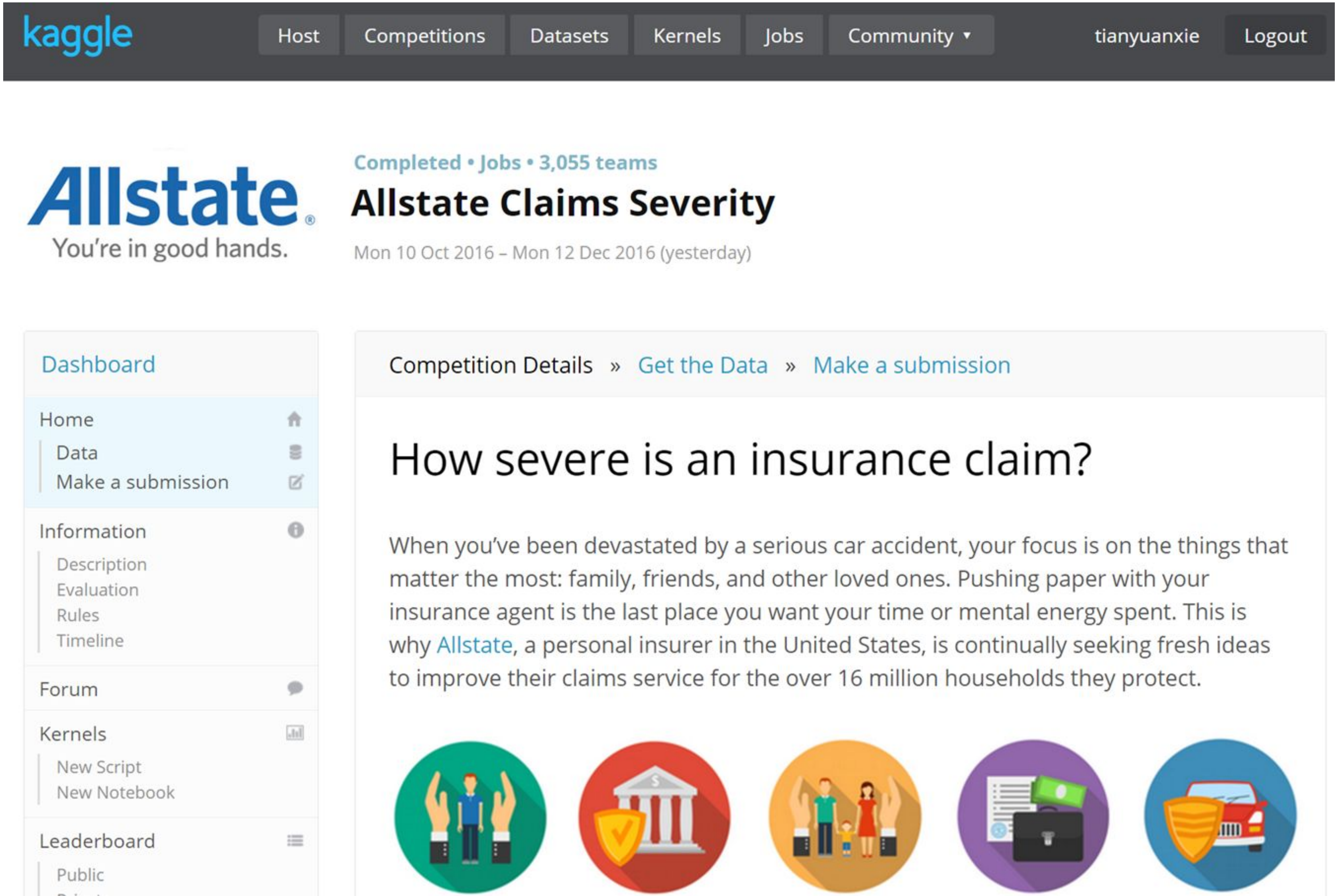
Project Objective



Data Overlook

	id	cat1	cat2	cat3	cat4	cat5	cat6	cat7	cat8	cat9	cat10	cat11	cat12	cat13
0	1	A	B	A	B	A	A	A	A	B	A	B	A	A
1	2	A	B	A	A	A	A	A	A	B	B	A	A	A
2	5	A	B	A	A	B	A	A	A	B	B	B	B	B
3	10	B	B	A	B	A	A	A	A	B	A	A	A	A
4	11	A	B	A	B	A	A	A	A	B	B	A	B	A

	cat14	cat15	cat16	cat17	cat18	cat19	cat20	cat21	cat22	cat23	cat24	cat25
0	A	A	A	A	A	A	A	A	A	B	A	A
1	A	A	A	A	A	A	A	A	A	A	A	A
2	A	A	A	A	A	A	A	A	A	A	A	A
3	A	A	A	A	A	A	A	A	A	B	A	A
4	A	A	A	A	A	A	A	A	A	B	A	A

⋮ **188318 * 132**

	cat109	cat110	cat111	cat112	cat113	cat114	cat115	cat116	cont1	cont2
0	BU	BC	C	AS	S	A	O	LB	0.726300	0.245921
1	BI	CQ	A	AV	BM	A	O	DP	0.330514	0.737068
2	AB	DK	A	C	AF	A	I	GK	0.261841	0.358319
3	BI	CS	C	N	AE	A	O	DJ	0.321594	0.555782
4	H	C	C	Y	BM	A	K	CK	0.273204	0.159990

	cont3	cont4	cont5	cont6	cont7	cont8	cont9
0	0.187583	0.789639	0.310061	0.718367	0.335060	0.30260	0.67135
1	0.592681	0.614134	0.885834	0.438917	0.436585	0.60087	0.35127
2	0.484196	0.236924	0.397069	0.289648	0.315545	0.27320	0.26076
3	0.527991	0.373816	0.422268	0.440945	0.391128	0.31796	0.32128
4	0.527991	0.473202	0.704268	0.178193	0.247408	0.24564	0.22089

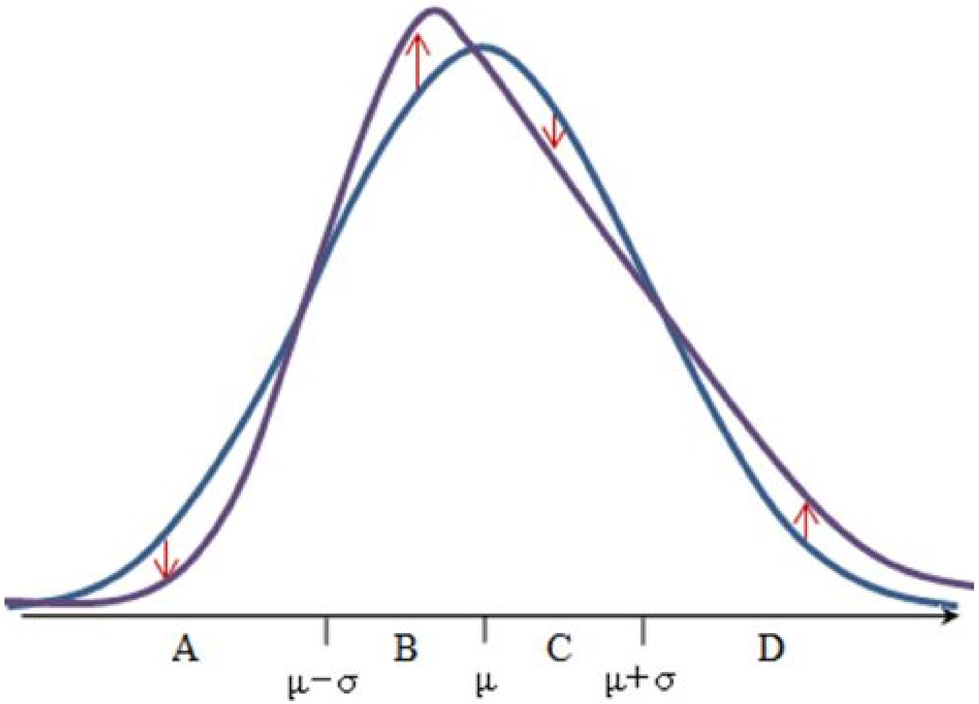
	cont10	cont11	cont12	cont13	cont14	loss
0	0.83510	0.569745	0.594646	0.822493	0.714843	2213.18
1	0.43919	0.338312	0.366307	0.611431	0.304496	1283.60
2	0.32446	0.381398	0.373424	0.195709	0.774425	3005.09
3	0.44467	0.327915	0.321570	0.605077	0.602642	939.85
4	0.21230	0.204687	0.202213	0.246011	0.432606	2763.85

Attributes?

Overview of Our Approaches

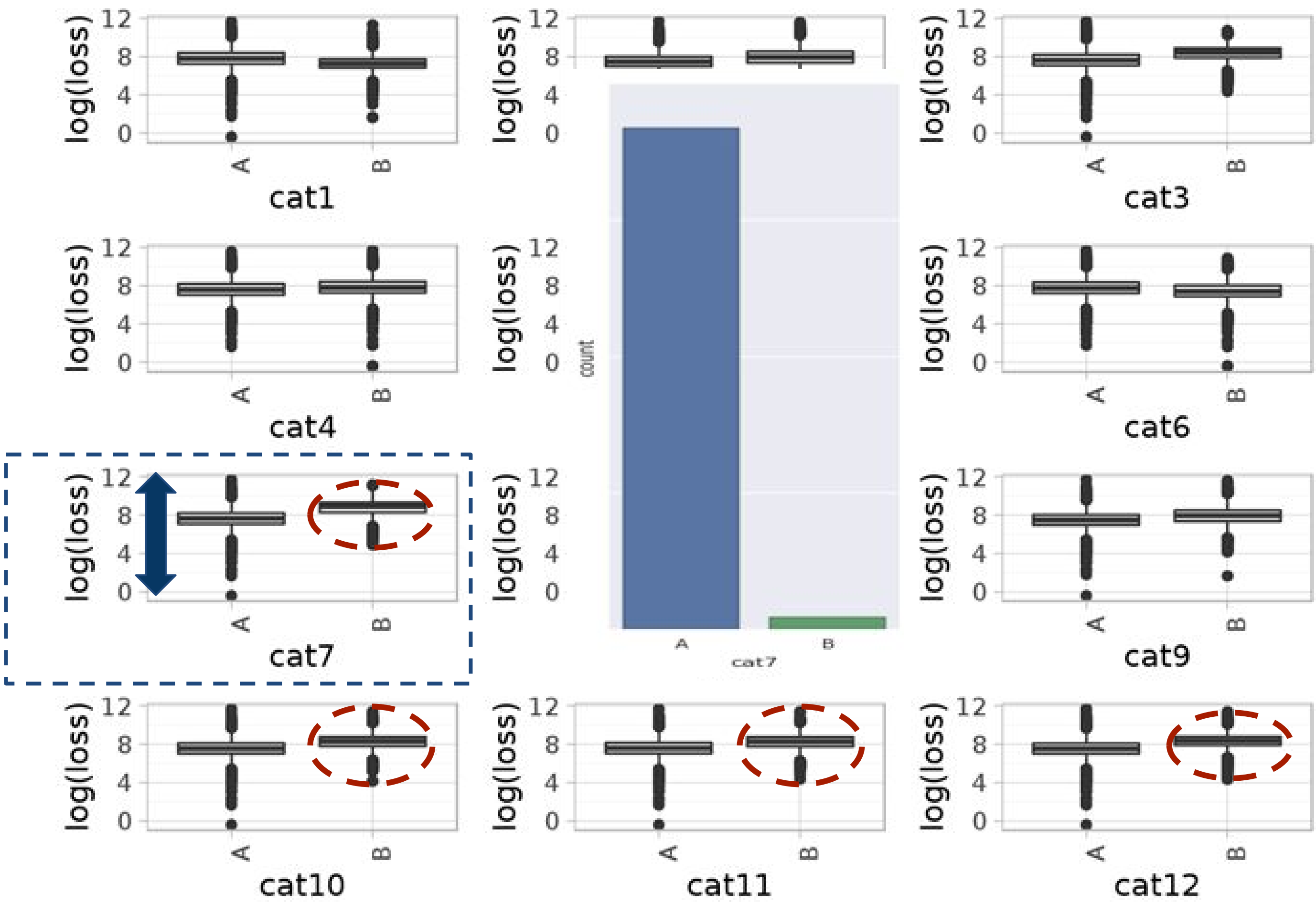
- Data Preprocessing
  - Categorical
  - Numerical
- Machine Learning Algorithm
  - Baseline: Linear Regression
  - Improvement
    - Linear Regression with l_1-loss objective function
    - Interaction between variables
    - XG-Boosting
    - Deep Learning
    - Neural Networks + XG-Boosting
- Result
- Conclusion

Data Preprocessing



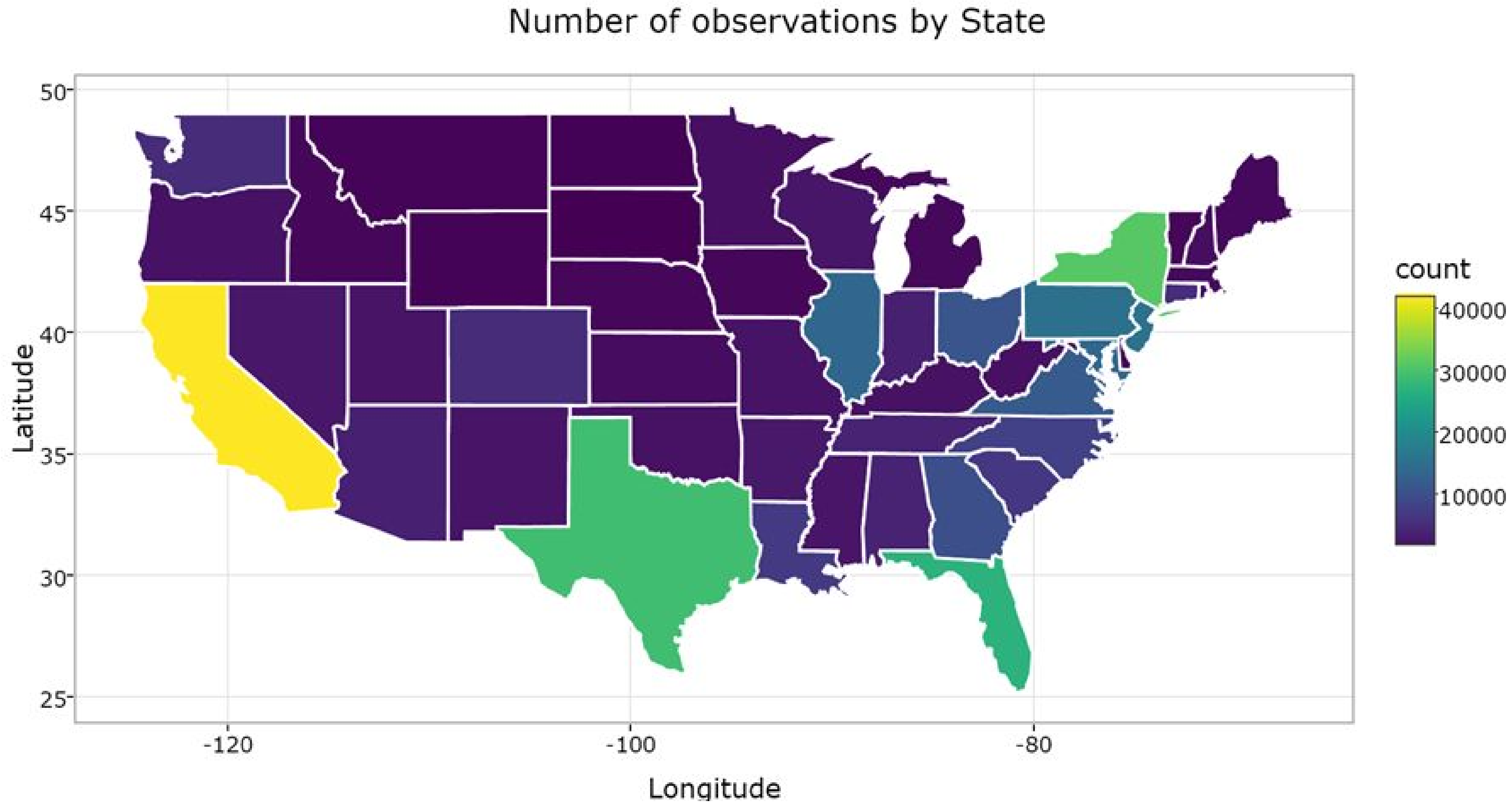
Categorical Feature Analysis

- *cat1 ~ cat72 have only two labels A and B. In most of the cases, B has very few entries*



Categorical Feature Analysis

- *cat73 ~ cat 116 have more than two labels*
- cat112 has 51 levels (50 + DC). California is well sampled, as well as some central states



Categorical Data Conversion: **One-Hot Encoding Technique**

Convert categorical to numerical data before doing linear regression, using Dummy variables.

Example: cat92 : [A, B, C, D, F, H, I]

- One way: A = 1, B = 2, …, F = 6,... I = 9
  - Confusing to algorithm
  - Meaningless, eg. location
- **One-Hot Encoding**

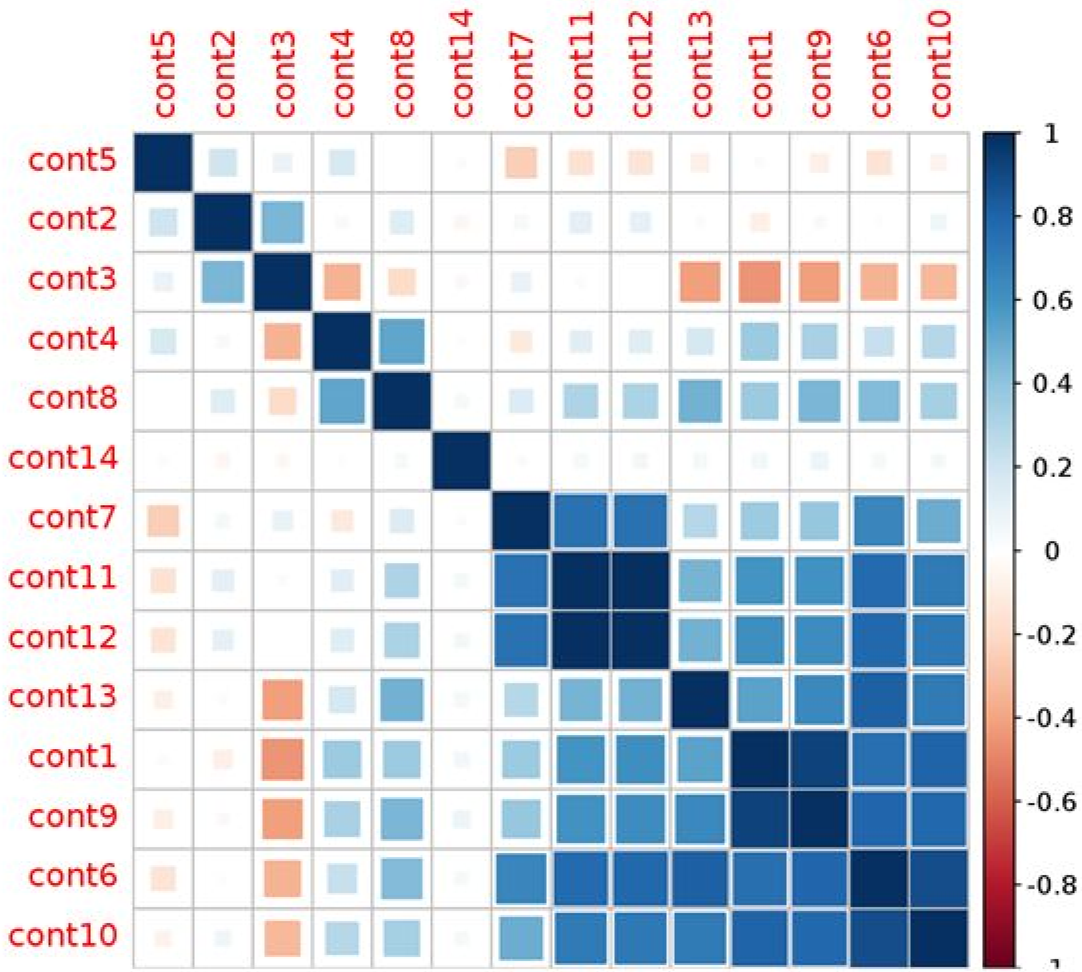
id	cat92
3	A
34	B

id	A	B	C	D	F	H	I
3	**1**	0	0	0	0	0	0
34	0	**1**	0	0	0	0	0

Number of features: 130 → 1176

cats are done

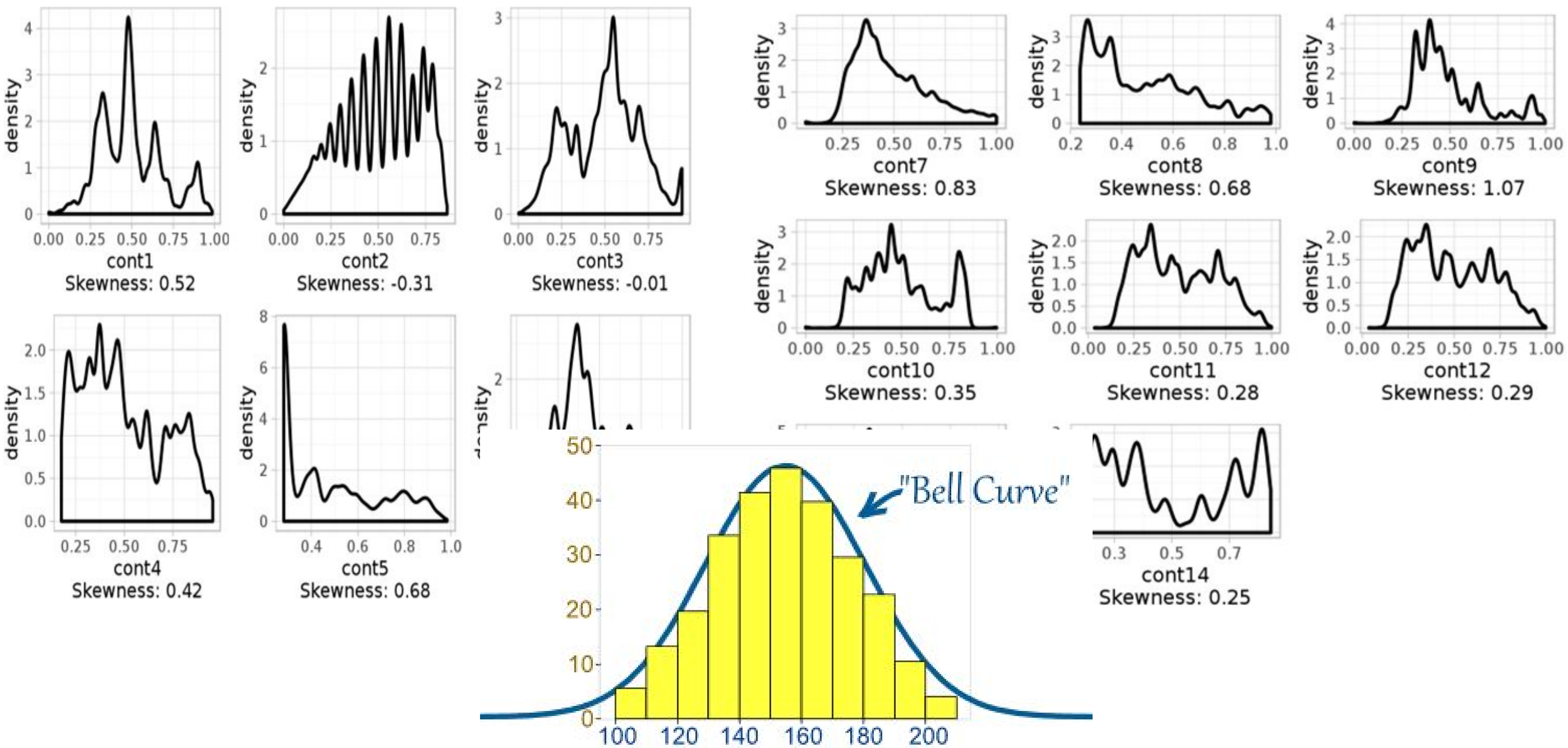
Continuous Feature Correlation



Highly correlated

cont11 and cont12 = 0.99
cont1 and cont9 = 0.93
cont6 and cont10 = 0.88
cont6 and cont13 = 0.82
cont1 and cont10 = 0.81
cont6 and cont9 = 0.80
cont9 and cont10 = 0.79
cont6 and cont12 = 0.79
cont6 and cont11 = 0.77
cont1 and cont6 = 0.76
cont7 and cont11 = 0.75
cont7 and cont12 = 0.74
cont10 and cont12 = 0.71
cont10 and cont13 = 0.71
cont10 and cont11 = 0.70
cont6 and cont7 = 0.66
cont9 and cont13 = 0.64
cont9 and cont12 = 0.63
cont1 and cont12 = 0.61
cont9 and cont11 = 0.61
cont1 and cont11 = 0.60
cont1 and cont13 = 0.53
cont4 and cont8 = 0.53

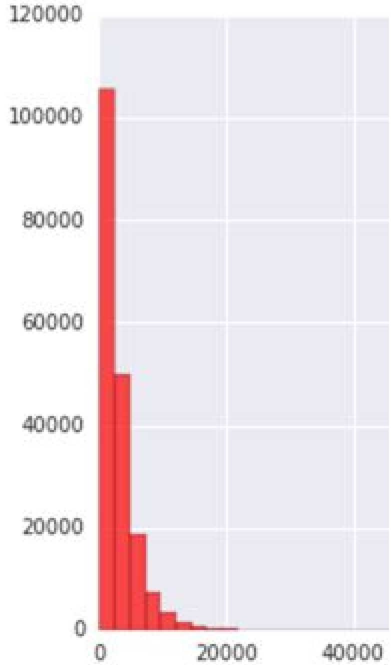
Continuous Feature Analysis -- Skewness

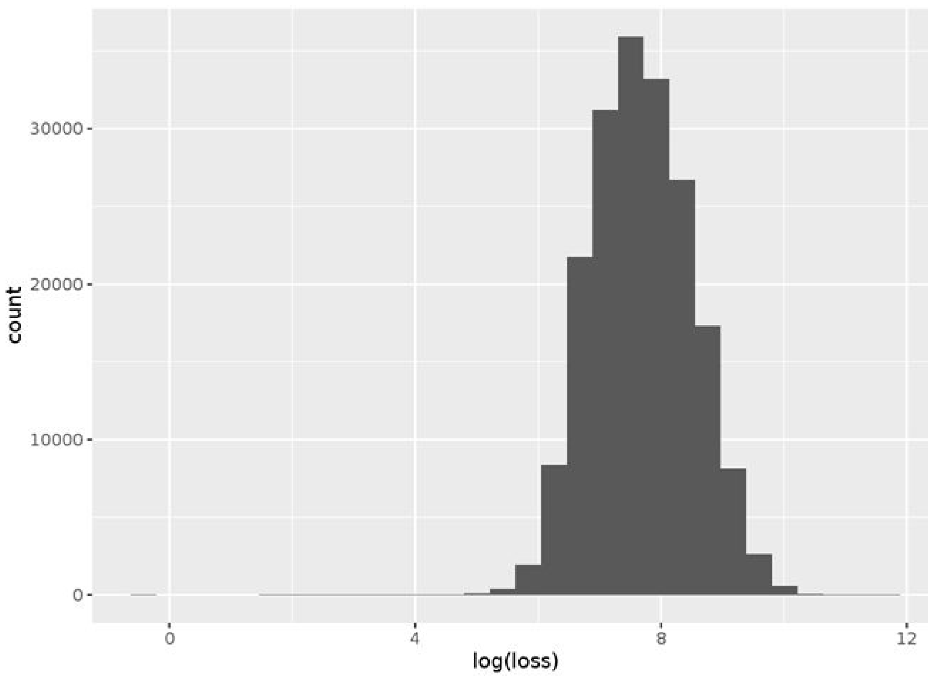


Continuous Feature Skewness Correction

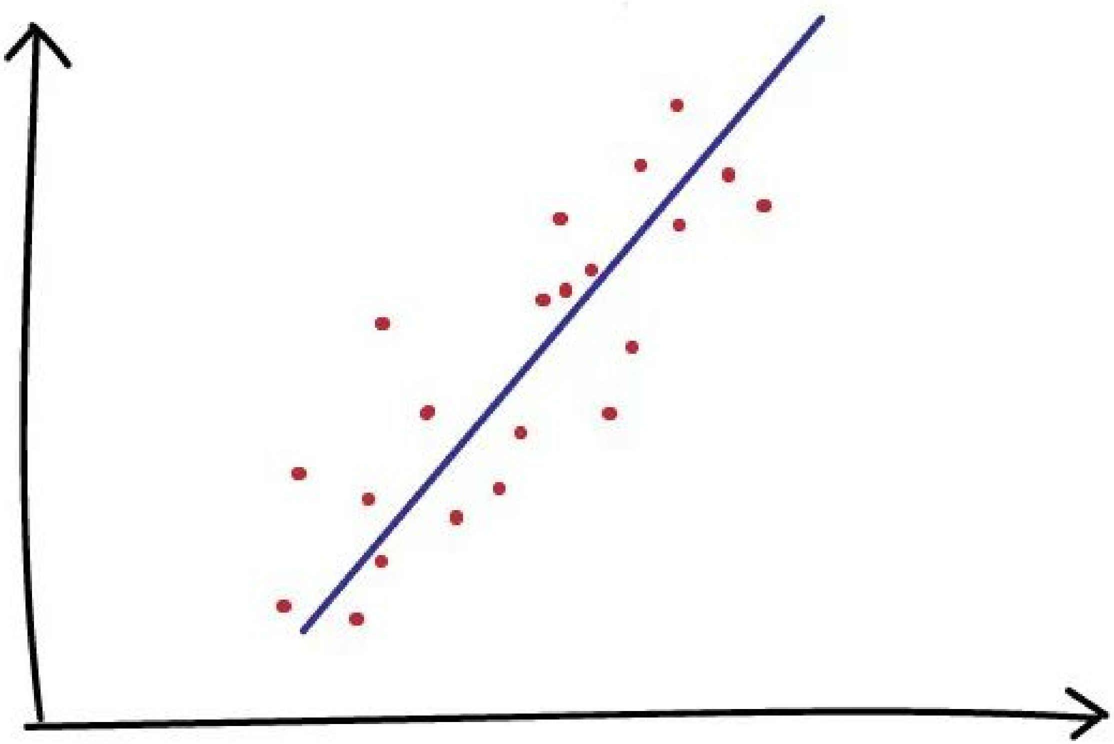
loss → log(loss + shift)

	skewness
cont1	0.516424
cont2	-0.310941
cont3	-0.010002
cont4	0.416096
cont5	0.681622
cont6	0.461214
cont7	0.826053
cont8	0.676634
cont9	1.072429
cont10	0.355001
cont11	0.280821
cont12	0.291992
cont13	0.380742
cont14	0.248674
loss	3.794958





Linear Algorithm



Baseline: Linear Regression

$$\min_{x \in R^{1176*1}} \frac{1}{2}||y - \hat{y}||^2$$

$$where \quad \hat{y} = Ax + b$$

$$Closed \quad form: x = (A^T A)^{-1} A^T (y - b)$$

- y: Real cost of insurance (188,318 x 1)
- A: Matrix we have (188,318 x 1176)
- x: Attribute vector (1176 x 1)

Mean Absolute Error: 1278

Other Attempts

LASSO:

$$\min_{x \in R^{1176*1}} \frac{1}{2}||y - \hat{y}||^2 + \lambda||x||_1$$

$$where \quad \hat{y} = Ax + b$$

Mean Absolute Error: 1262.5

Ridge Regression:

$$\min_{x \in R^{1176*1}} \frac{1}{2}||y - \hat{y}||^2 + \lambda||x||_2$$

$$where \quad \hat{y} = Ax + b$$

Mean Absolute Error: 1267

Elastic Net Regression:

$$\min_{x \in R^{1176*1}} \frac{1}{2}||y - \hat{y}||^2 + \lambda_1||x||_1 + \lambda_2||x||_2$$

$$where \quad \hat{y} = Ax + b$$

Mean Absolute Error: 1260

- y: Real cost of insurance (188,318 x 1)
- A: Matrix we have (188,318 x 1176)
- x: Attribute vector (1176 x 1)

Improvement:

Linear Regression with l_1-loss objective function

Objective Function:

$$\min_{x \in R^{1176*1}} ||y - \hat{y}||_1$$

where $\hat{y} = Ax + b$

Closed form by SGD: $$x = \begin{cases} x - \gamma A_i & when \quad y - A_i x - b < 0 \\ x + \gamma A_i & when \quad y - A_i x - b > 0 \\ [-A_i, \mathrm{A}_i] & when \quad y - A_i x - b = 0 \end{cases}$$

- y: Real cost of insurance (188,318 x 1)
- A: Matrix we have (188,318 x 1176)
- x: Attribute vector (1176 x 1)

Mean Absolute Error: 1239

Tree-based Method

Tree-based Methods

Single Tree (CART) MAE: **1741** (by Santhosh Sharma)

Tree Ensemble:

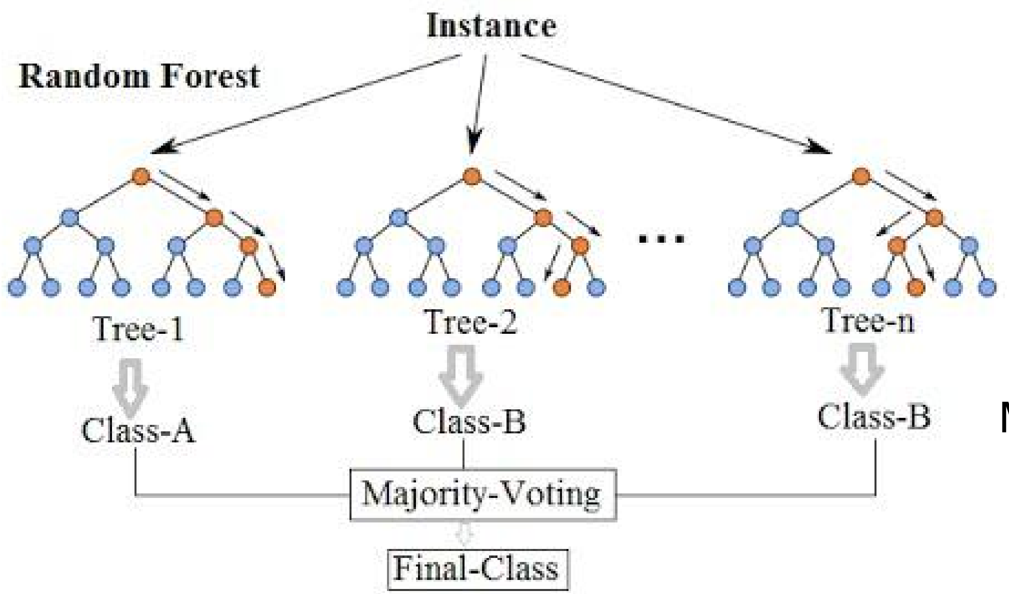
$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), f_k \in \mathcal{F}$$

f_k represents each tree

$\mathcal{F}$ represents the set of all possible trees

$$\text{obj}(\theta) = \sum_{i}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

Benchmark: **Random Forest with CART**



Mean Absolute Error: **1228**

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), f_k \in \mathcal{F}$$

$$\text{obj}(\theta) = \sum_{i}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

Dominating: **XG-Boosting**

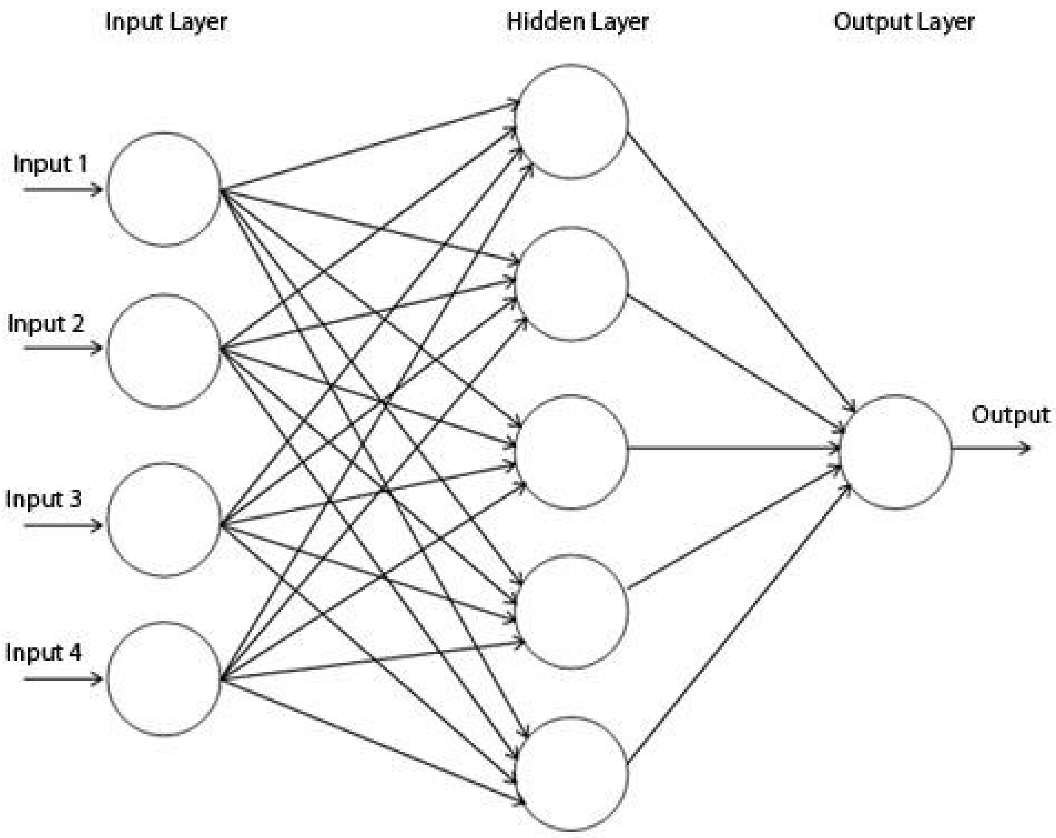
$$\hat{y}_i^{(0)} = 0$$
$$\hat{y}_i^{(1)} = f_1(x_i) = \hat{y}_i^{(0)} + f_1(x_i)$$
$$\hat{y}_i^{(2)} = f_1(x_i) + f_2(x_i) = \hat{y}_i^{(1)} + f_2(x_i)$$
$$\dots$$
$$\hat{y}_i^{(t)} = \sum_{k=1}^{t} f_k(x_i) = \hat{y}_i^{(t-1)} + f_t(x_i)$$

$$\text{obj}^{(t)} = \sum_{i=1}^{n} l(y_i, \hat{y}_i^{(t)}) + \sum_{i=1}^{t} \Omega(f_i)$$
$$= \sum_{i=1}^{n} l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) + \Omega(f_t) + constant$$

Mean Absolute Error: **1169**

Fine-tune + Cross-validation:
Score: **1106 (Our final result)**

Deep Learning: **Multi-layer Perceptron**



Different Structures:

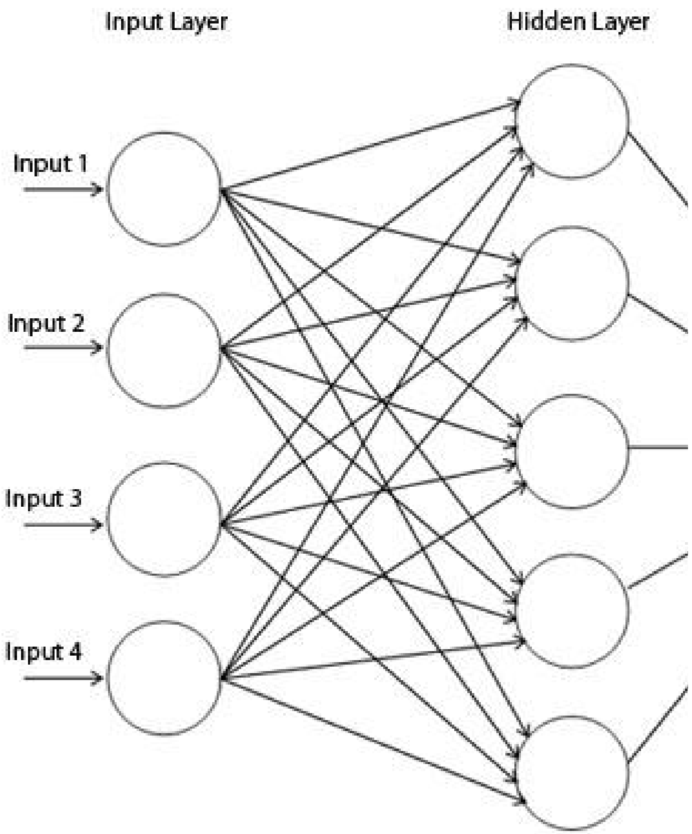
1024 - 2048 - 1
Relu Relu linear

1024 - 4096 - 1
Relu Relu linear

1024 - 4096 - 128 - 1
Relu Relu linear

Best achieve: **1168**

New Approach: **Neural Networks + XG-Boosting**



Used structure:

1024 - 2048 - 1
Relu Relu linear

To have 2048 outputs as the inputs for XG-Boosting

Best achieve: **1143**

Results

Algorithms	Resulting MAE
Linear Regression	1278 (Baseline)
LASSO	1262
Ridge Regression	1267
Elastic Net Regression	1260
Linear Regression (l_1 loss)	1239
CART	1741
Random Forest	1228 (Benchmark)
XG-Boosting (default)	1169
Multi-layer Perceptron	1168
NN+XG-Boosting	1143
Fine-tuned XG-Boosting	**1106** Ranking 533/3055 (18%)

Conclusion

1. It's important to choose a proper objective function. (Replace l_2 loss by l_1 loss in this case)
2. Tree-based methods performed better in this case, the data is not appropriate for the linear approaches.
3. Neural Network did give improvement on XG-Boosting, but not very much. Maybe deep learning structure is not very suitable for this case.

Future Work

- Multicollinearity
- Continuous value attribute processing

Thanks for your attention!

Questions?