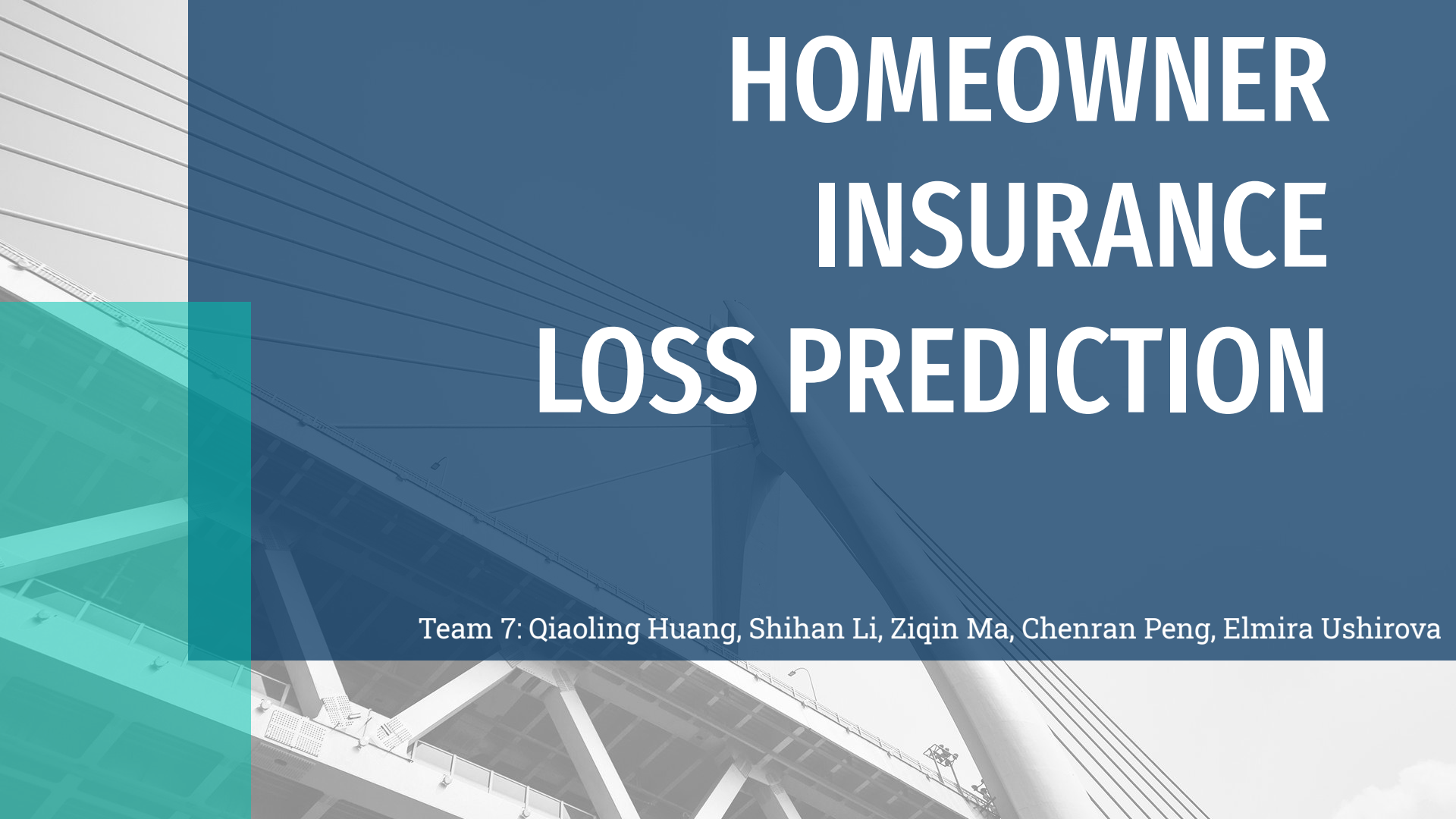

HOMEOWNER INSURANCE LOSS PREDICTION

Team 7: Qiaoling Huang, Shihan Li, Ziqin Ma, Chenran Peng, Elmira Ushirova

AGENDA

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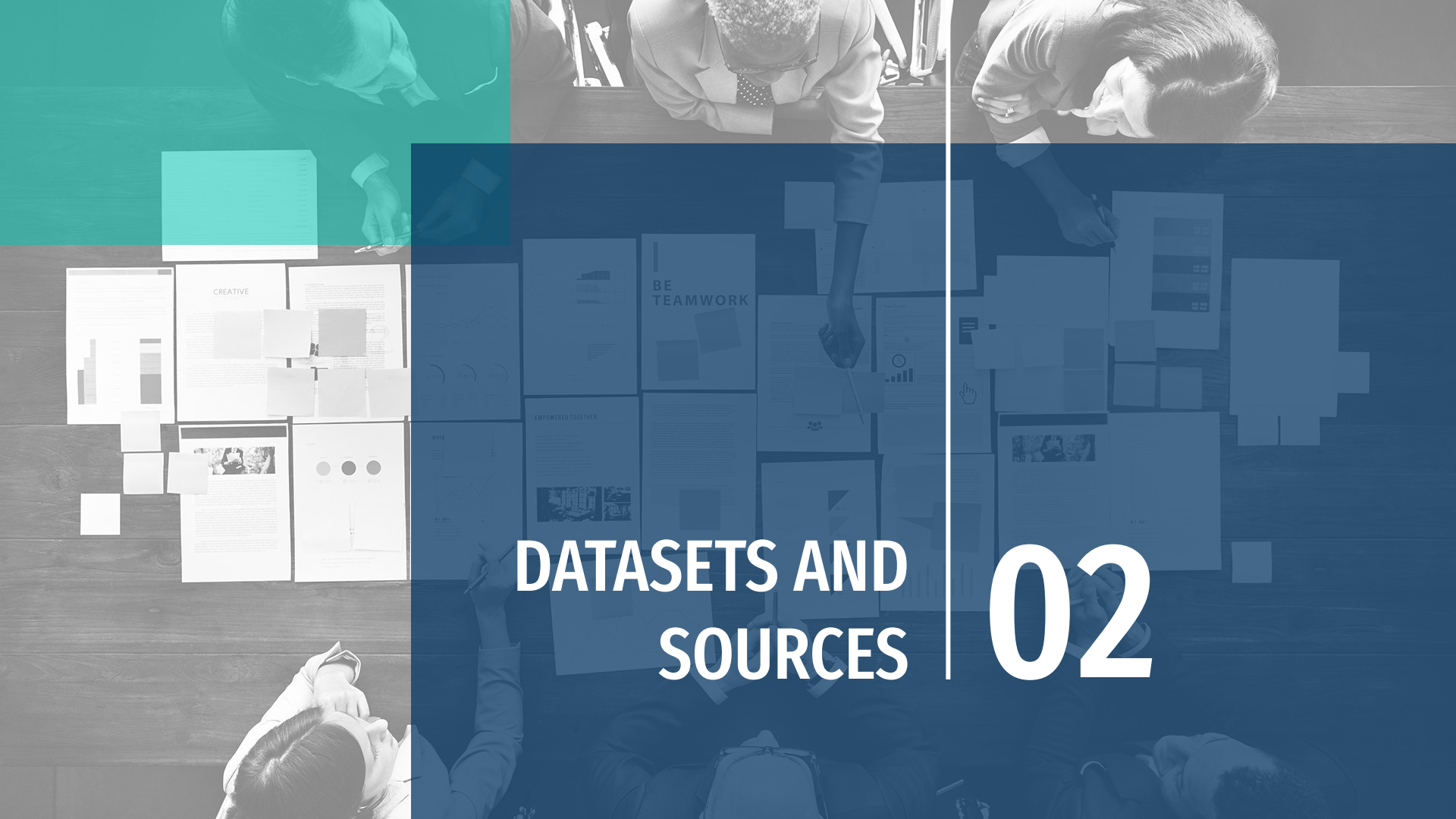
BUSINESS PROBLEM 01

Business Problem

We would like to explore different factors that are associated with risks of homeowner insurance and come up with new efficient **variables** and a precise **model** that can predict **house damage losses** at zip code level in the USA.



DATASETS AND SOURCES

02

Datasets: Company Data

For this project, we are working closely with a fast-growing home insurance company that provides services in the New England area.

This company has provided us with the anonymized data on a zip code level that has actual loss data for 5 years(2013 - 2018) and the predicted loss amounts by their existing models.

The provided data also includes an Earned Exposure information, which shows the proportion of the year that a certain address stayed with a certain insurance policy. Besides that, we also were provided with population, area, and the number of properties for each zip code.

Datasets: Crime from the FBI

Table 8
Offenses Known to Law Enforcement
by State by City, 2018

State	City	Population	**Violent crime**	Murder and nonnegligent manslaughter	Rape[1]	Robbery	Aggravated assault	**Property crime**	Burglary	Larceny-theft	Motor vehicle theft	Arson[2]
ALABAMA	Abbeville	2,551	18	0	2	0	16	49	14	33	2	
	Adamsville	4,323	19	0	1	4	14	289	42	230	17	
	Alabaster	33,501	92	0	2	10	80	579	56	497	26	
	Albertville	21,428	24	0	6	10	8	802	194	492	116	
	Alexander City	14,548	314	2	5	15	292	610	92	484	34	
	Aliceville	2,315	9	0	0	1	8	24	7	16	1	
	Andalusia	8,753	82	1	6	6	69	467	76	368	23	
	Anniston	21,592	646	7	43	68	528	1,696	413	1,131	152	
	Ardmore	1,428	5	0	0	1	4	35	15	18	2	
	Ashford	2,145	4	0	0	0	4	32	2	24	6	
	Ashland	1,918	52	0	0	1	51	57	16	35	6	
	Athens	26,177	13	3	0	8	2	768	110	630	28	
	Auburn	65,585	240	4	16	29	191	1,396	115	1,206	75	
	Bay Minette	9,304	73	0	3	3	67	250	35	196	19	
	Bayou La Batre	2,500	36	0	4	5	27	305	70	203	32	
	Birmingham	210,564	4,025	88	180	941	2,816	13,295	2,555	8,988	1,752	145
	Boaz	9,678	74	0	3	3	68	364	68	259	37	

FBI crime data includes numbers of different crime categories by State and city.

There are 20 separate excel tables, each table representing 1 year from 1999 to 2018.

Violent crime: Murder and nonnegligent manslaughter, Rape, Robbery, Aggravated assault

Property crime: Burglary, Larceny- theft, Motor vehicle theft, Arson.

Datasets: Lightning

Raw lightning data was obtained through the Google Cloud Platform's public datasets. The full dataset consists of 32 tables each representing one year from 1987 till 2019. For our analysis, we focused only on the recent 20 years (1999 - 2018).

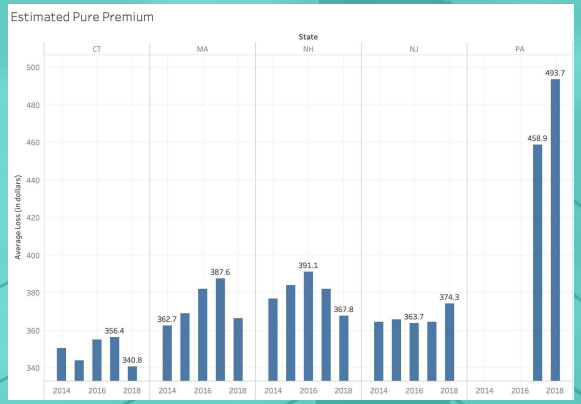
Each table represents daily information about the number of strikes and geo points (around US territory) for each year.

Source:
https://console.cloud.google.com/marketplace/details/noaa-public/lightning?filter=solution-type:dataset&filter=category:climate&id=d18e2712-bc50-471a-bf22-a2de3d9489d9&authuser=1

Row	day	number_of_strikes	center_point
54801	2019-12-31	6	POINT(-75.5 32.4)
54802	2019-12-31	6	POINT(-75.4 32.4)
54803	2019-12-31	6	POINT(-74.9 32.4)
54804	2019-12-31	6	POINT(-74.9 32.9)
54805	2019-12-31	6	POINT(-75.9 32.3)
54806	2019-12-31	6	POINT(-75 32.4)
54807	2019-12-31	7	POINT(-76.6 31.7)
54808	2019-12-31	7	POINT(-75.8 31.7)
54809	2019-12-31	7	POINT(-75.5 32)
54810	2019-12-31	7	POINT(-74.6 32)
54811	2019-12-31	8	POINT(-72.3 34)

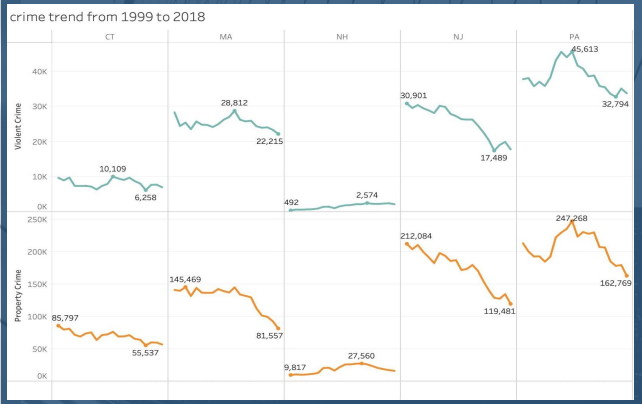
Exploratory Data Analysis

Company Data



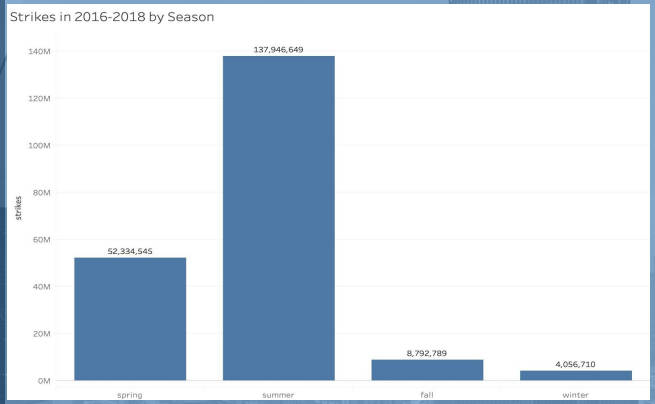
Based on the Company data, we have calculated Pure Premiums for each State and each year by dividing actual total loss by the total earned exposure. Pure Premium is usually used as a base for the insurance policy pricing.

Crime Data



We have summarized the number of violent and property crimes over the 1999-2018 period for 5 States in focus on the graph above.

Lightning Data



For our analysis, we have grouped the lightning tables by geo points and summarized the total number of strikes, number of events (count of days) and the name of seasons during which the lightning happened.

03 METHODOLOGY

NAs imputation

Crime

We replaced NAs in the original data by computing the mean of each State and multiply by the population ratio of the missing city.

For those population that we don't have, we assume that we replaced with mean population with other cities without any crime record.

Lightning

We matched geocodes of strikes with a unique zip code based on distance. If lightning data is missing under certain zip code, we assumed that 0 strikes occurred in that area.

Create New Variables

1 year	3 years	5 years	10 years	20 years
Sum of Original				
State Level				
Nation Level				
Violent Crime/Total Crime Property Crime/Total Crime				
Each Type of Violent Crime/Violent Crime Each Type of Property Crime/Property Crime				

Total: 205 New Variables

Crime

1 year	3 years	5 years	10 years	20 years
Group by Each Season				
Sum of Original				
State Level				
Nation Level				
Strikes and Events/Area				
Strikes and Events/Population				
Strikes and Events/Property				

Total: 315 New Variables

Lightning

Sample Design

In Time and Out of time

2016 to 2018 as our in-time sample

2014 and 2015 as our out of time sample

CAP

99.3 percentile on losses as our Y

We divided losses into 4 levels: 0, low, medium, high.

Stratify

By year, State and loss level.

70% Train
30% Test

Considering our data shape, we did downsampling, randomly dropped 50% of zero loss from the in-time sample to balance zero and non-zero losses. We ended up with 5 samples: Train_reduced, Test_reduced, Train_full, Test_full and Validation.

Feature Selection

We used wrapper method (backward elimination) for the feature selection, we ended up with 33 variables in total.

After the feature selection, the result showed that crime data have more predicting power than lightning.

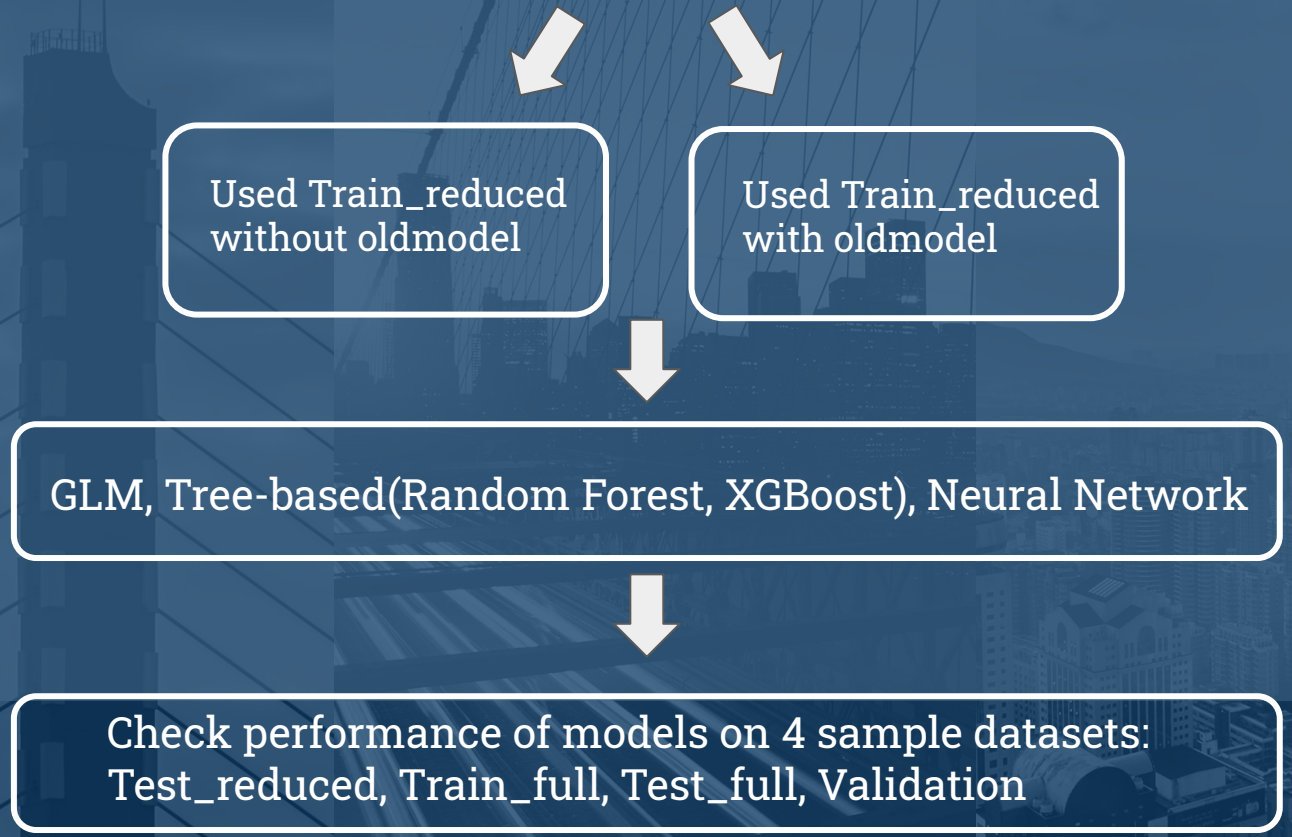
Selected Variables

Crime (Total 23 variables)			
Robbery at State level for 1 year	Larceny-theft /Property crime at 20 years level	Murder/Property crime at 10 years level	Motor vehicle theft at State level 10 years
Motor vehicle theft/Property crime 3 years level	Aggravated assault /Total Violent crime 1 year level	Motor vehicle theft /Property crime at 20 years level	Larceny-theft /Property crime at 10 years level
Property crime at State level 10 years	Robbery at State level 5 years	Motor vehicle theft at State level 3 years	Burglary at State level 5 years
Property crime /Total crime 10 years level	Burglary at State level 10 years	Property crime at State level 5 years	Burglary/Property crime 3 years level
Aggravated assault /Total Violent crime 5 year level	Property crime at nation level 10 years	Burglary at State level 20 years	Larceny-theft/Property crime 3 years level
Larceny-theft at State level 5 years	Violent crime/Total crime 10 years level	Larceny-theft at State level 20 years	

Selected Variables

Lightning (Total 10 variables)			
Total strikes for 5 years	Event number in fall for 3 years	Strikes in winter for 5 years	Event number in winter for 5 years
Total strikes for 10 years	Total events in 10 years	To total strikes in fall for 10 years	Strikes in winter for 10 years
Event number at nation level for 10 years	Event number in summer for 3 years		

Model Design



04 RESULTS

Results - without oldmodel

Our selected features do have predictive power on losses.

Model	Train_reduced AUC	Test_reduced AUC	Train_full AUC	Test_full AUC	Validation AUC
Benchmark	0.5	0.5	0.5	0.5	0.5
Simple GLM	0.631	0.516	0.6	0.606	0.480
Random Forest	0.834	0.481	0.719	0.759	0.523
XGBoost	0.777	0.605	0.668	0.672	0.554
Neural Network	0.551	0.526	0.528	0.579	0.54

Important Variables – without oldmodel

Motor vehicle theft/Property crime 3 years level	56%
Larceny-theft/Property crime 3 years level	14%
Larceny-theft at State level 5 years	7%
Strikes in winter for 5 years	6%
Robbery at State level for 1 year	4%
Total strikes for 5 years	3%

Results - with oldmodel

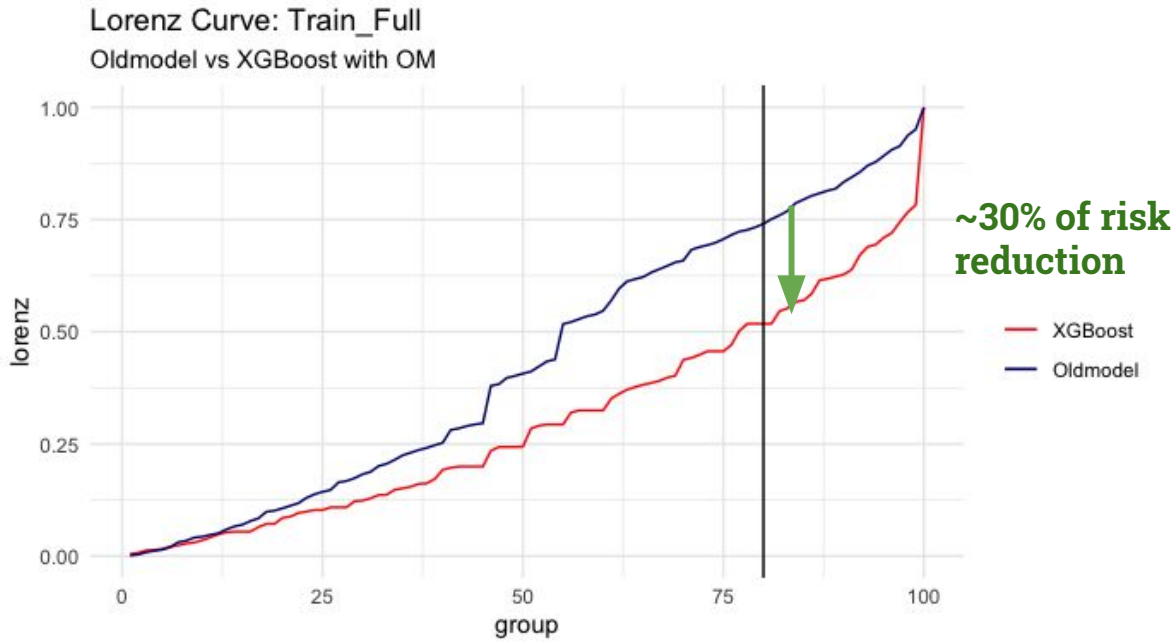
Our variables have additional predictive power on the oldmodel.

Model	Train_reduced AUC	Test_reduced AUC	Train_full AUC	Test_full AUC	Validation AUC
Benchmark (oldmodel)	0.572	0.61	0.598	0.554	0.641
Simple GLM	0.649	0.619	0.643	0.651	0.600
Random Forest	0.931	0.538	0.808	0.802	0.592
XGBoost	0.735	0.607	0.699	0.679	0.608
Neural Network	0.607	0.552	0.582	0.621	0.547

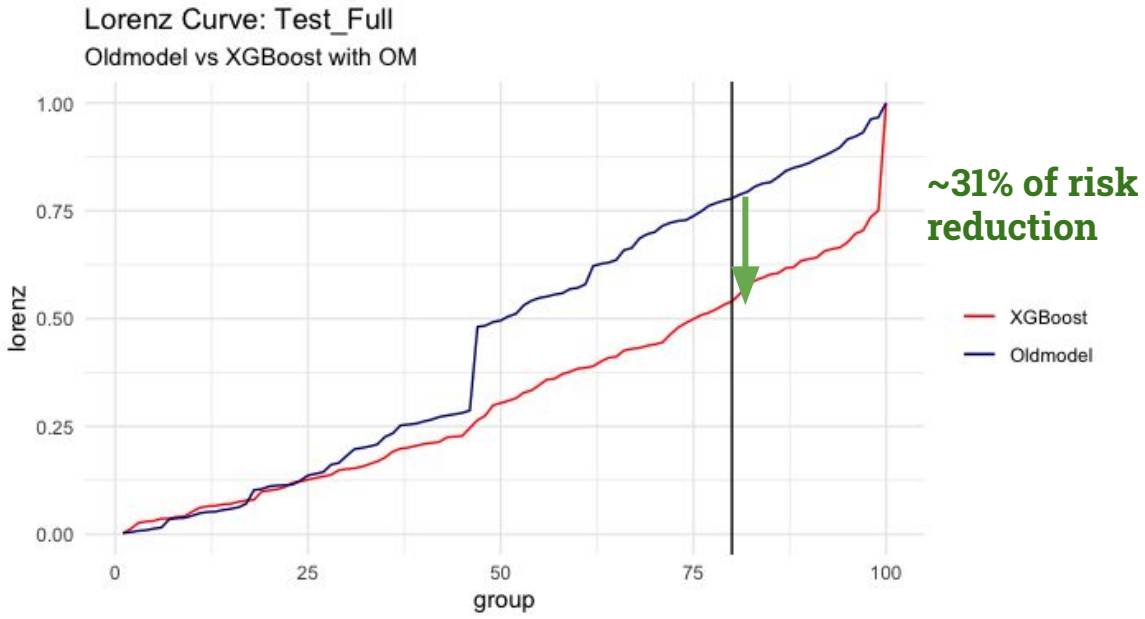
Important Variables - with oldmodel

Oldmodel	81%
Number of strikes for recent 5 years	14%
Violent crime /Total crime ratio for recent 10 years	1%

Lorenz Curve Comparison - Train



Lorenz Curve Comparison - Test



~31% of risk reduction

CRITICISM OF THE RESULTS AND FUTURE WORK

05

Criticism of the results and future work

The company data was a sample from a bigger dataset. Adding the same variables to that bigger dataset may result in different AUC scores

More features can be introduced to the model: earthquake, solar radiation, gas leak, etc.

Adjusting some parameters (i.e. distribution) might give better results.

Different methods of feature selection might bring different sets of variables; Re-train the model with only important ones can improve the performance.

CONCLUSION AND ACKNOWLEDGMENT

06

Conclusion

Some new have predictive power by themselves, as well as with existing model predictions.

In terms of business application, our variables can reduce the risk of loss payment by 30%.

Thank you!