UNIVERSITY OF TORONTO
SCHOOL OF CONTINUING STUDIES

Toronto Fire Incident

Feature Engineering for Machine Learning & AI

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Our goal is to improve a classifier performance using feature engineering

We used the Toronto Fire Incidents data set

to predict if an incident had a civilian casualty or not

Data sets

Toronto Fire Incidents

contains information about the incidents itself, alarm system and sprinklers on the premises, type of building/business, and impact each incident

Stations

each Toronto information with latitude and longitude information. Used to get the nearest station from the incident site

Hydrants

similar to the station data set, contains geographic information. Used to get the nearest hydrant from the incident site

Ward profile

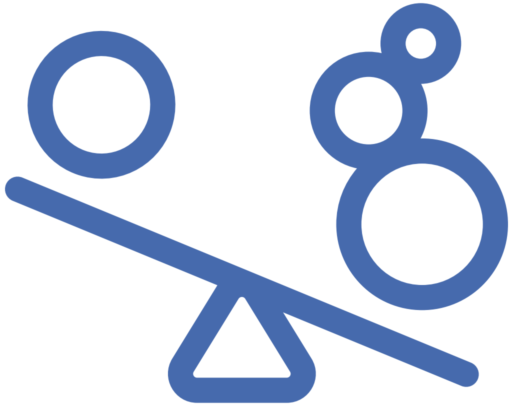
used to get information on population density and number of building by type

Several issues were identified during the EDA

Missing Values

- **~70%** of the features had missing values
- **How was it solved?** deleting features with more than 50% of missing values, filling NA's on categorical and numerical values based on *initial event type*

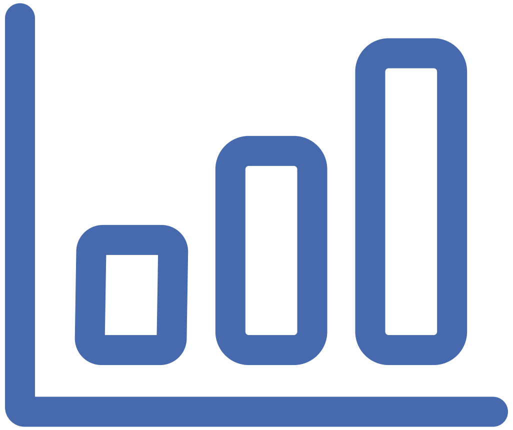
Several issues were identified during the EDA



Imbalanced data

- **What?** only **6%** of the incidents had causalities
- **How was it solved?** using **class-weight** parameter

Several issues were identified during the EDA



Categorical data

- **What?** most of the features on the Toronto Incidents data set were categorical
- **How was it solved?** applying Weight of Evidence (WOE)

New features added were added to improve the model score

Response time

Incident day of the week

Population density on the ward

Minutes until the fire was under control

Month when the incident happened

Distance to the nearest Fire Station

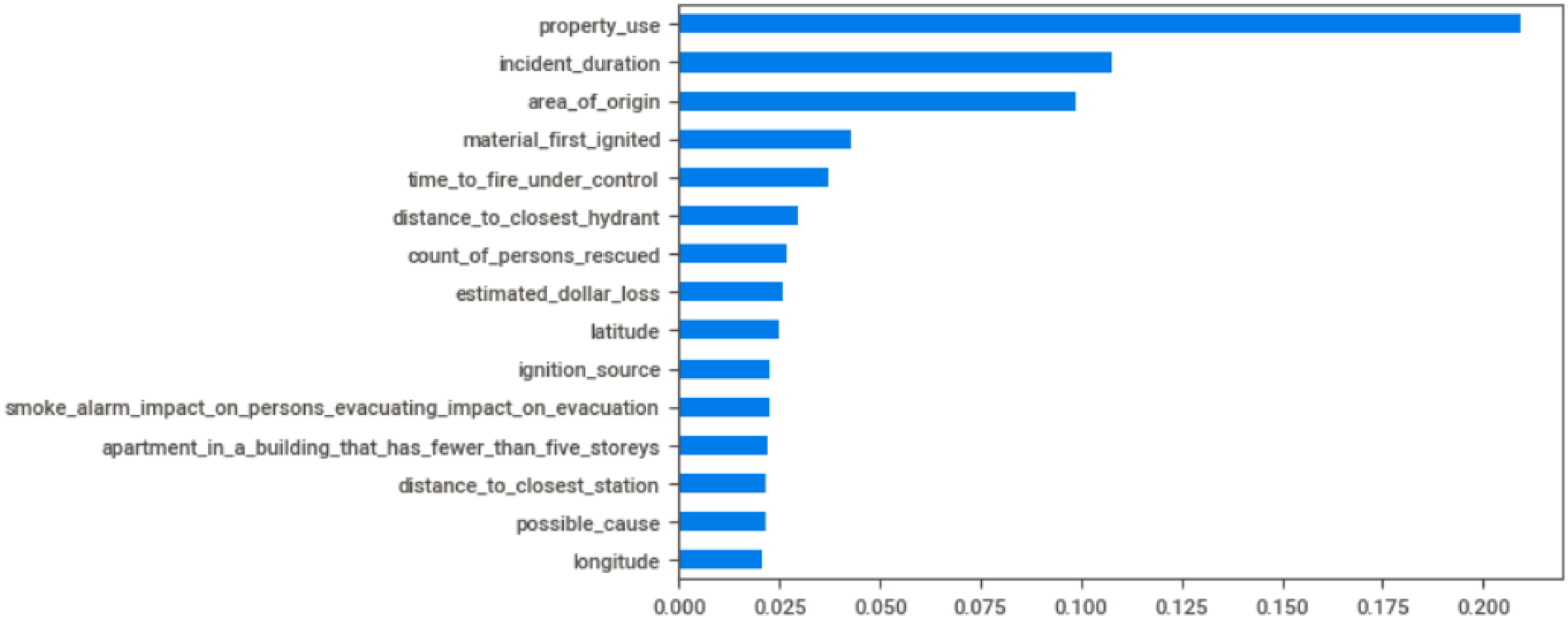
Duration of the incident

Year of the incident

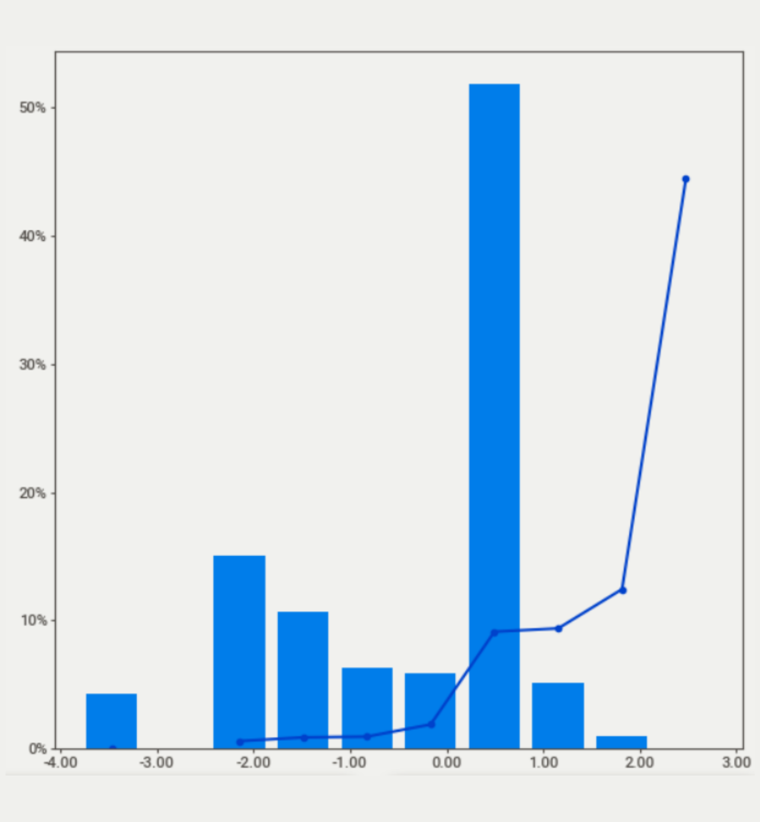
Distance to the nearest hydrant

Feature Importance Analysis

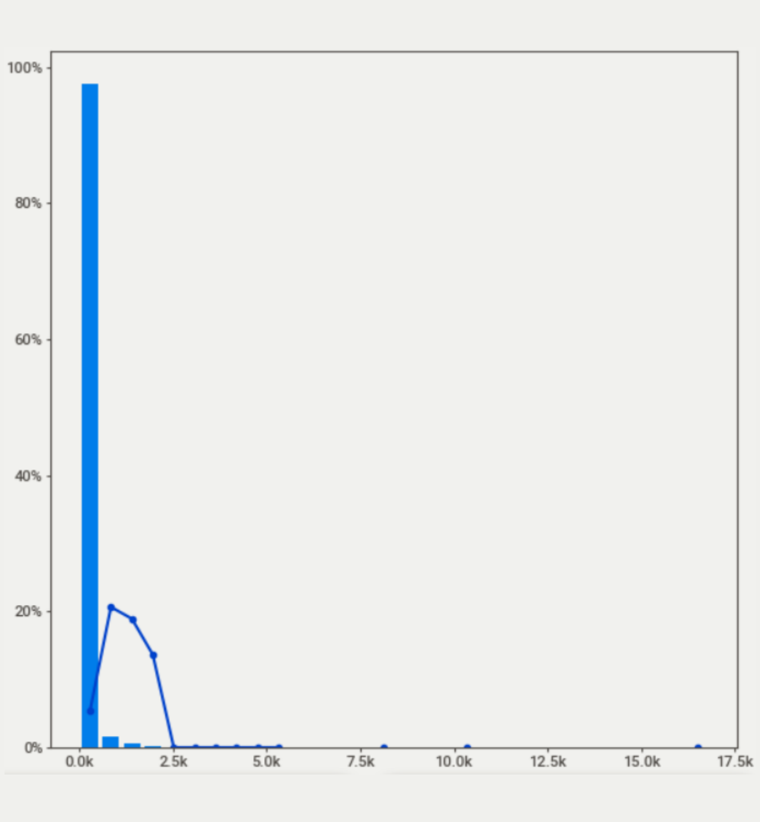
~30% of the top 15 features are features that came from **another data set** or was **created based on other features**.
About 45% of the new features created are among the top 15 most important features.



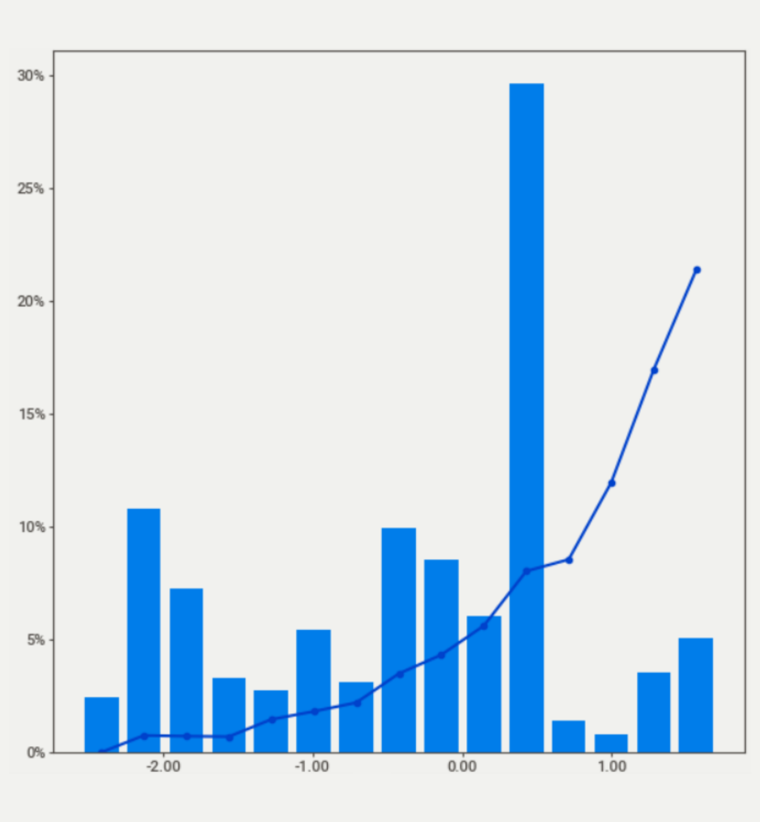
The **top 3 most** important features were responsible for **42%** of the model **variance**



Property Use (WoE)



Incident Duration

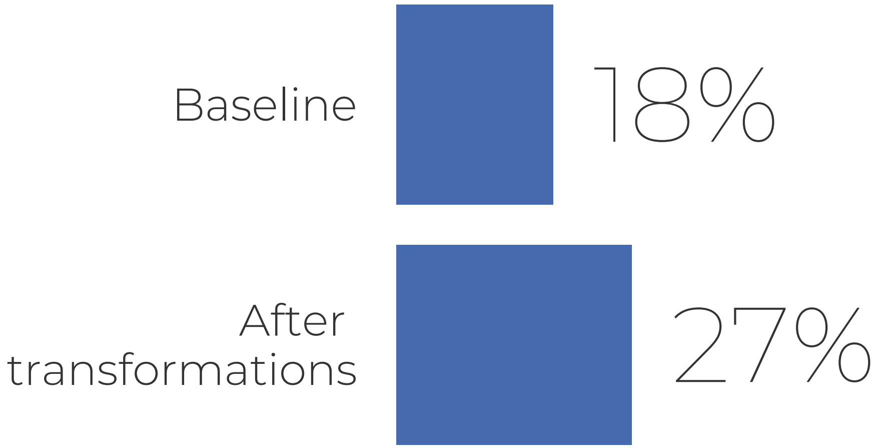


Area of Origin (WoE)

After apply feature engineering techniques, the fire incident model improved by 19 p.p

Model and Feature selection

- We used Decision Tree
- The model was evaluated using F1 score
- We kept features that contributed for 75% of the variance



There are many more opportunities to improve the Toronto Fire Incidents models

Next Steps

1. Analyze how insurance companies assess risk related to fire incidents

2. Research the most common causes of exposure

3. Gather data of new potential features discovered in steps 1 and 2

4. Create pipelines based on the feature engineering analysis

Thoughts? Questions?

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