

Mining Toronto Fire Services Incident Data

CKME 136: Data Analytics Capstone
by Geoffrey Clark
2018



Research Question

- What additional information, if any, can be provided to first responders at the time of incident call?



Dataset

- Open Source: Toronto Open Data Catalogue
- XML
- 720,340 Observations, 100 Features
- 2011 - 2016

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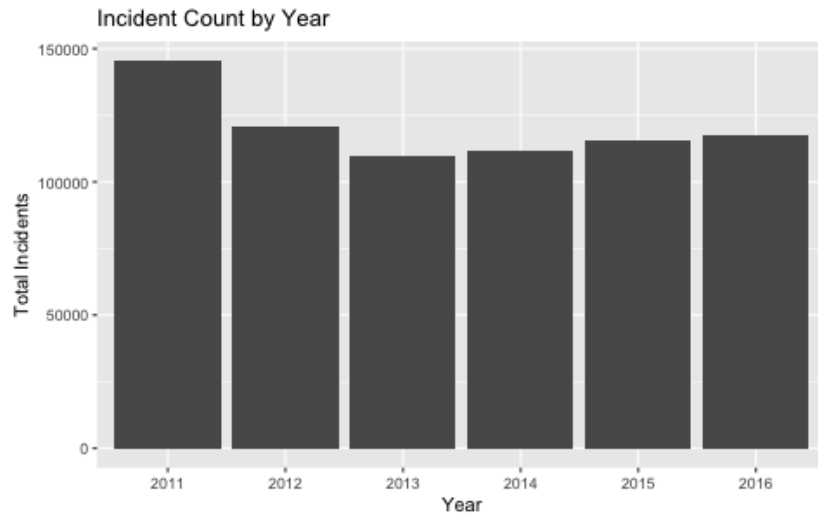


Features

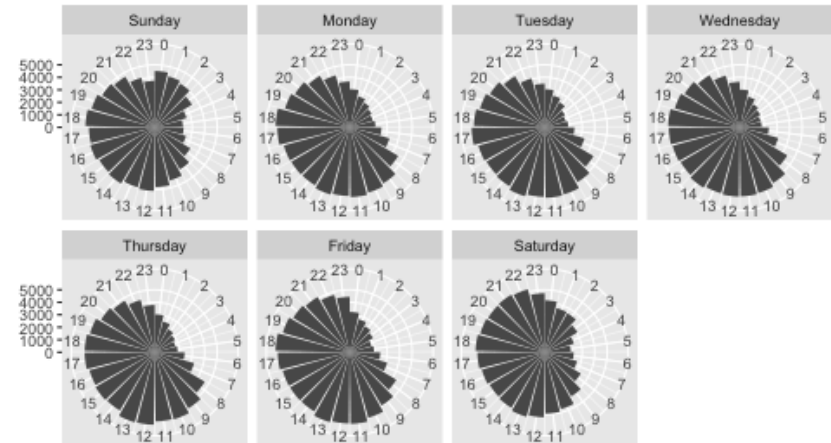
- Temporal: Date & Time of Incident call, dispatch, arrival (on-scene) & control
- Types of Incidents: Fire, Alarm, Vehicle, Rescue, Medical, ...
- Location: Property Type, FSA, Main & Cross Street
- Call Source: Agency, Ambulance, 911...



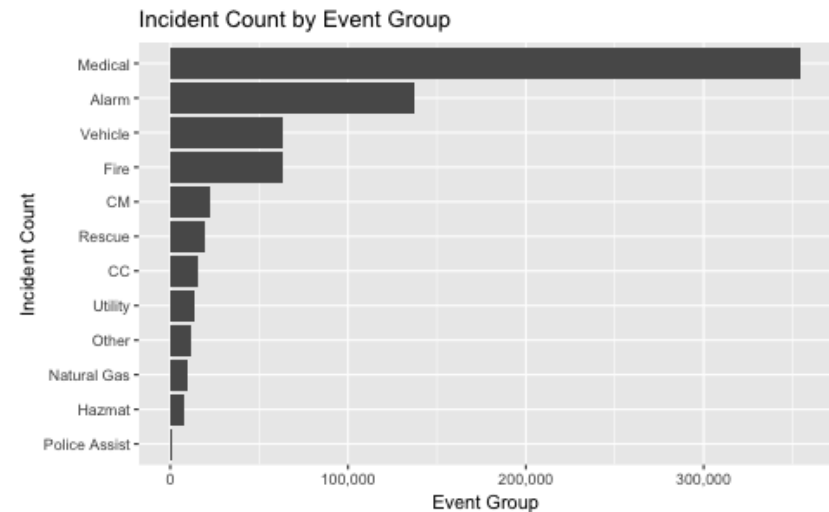
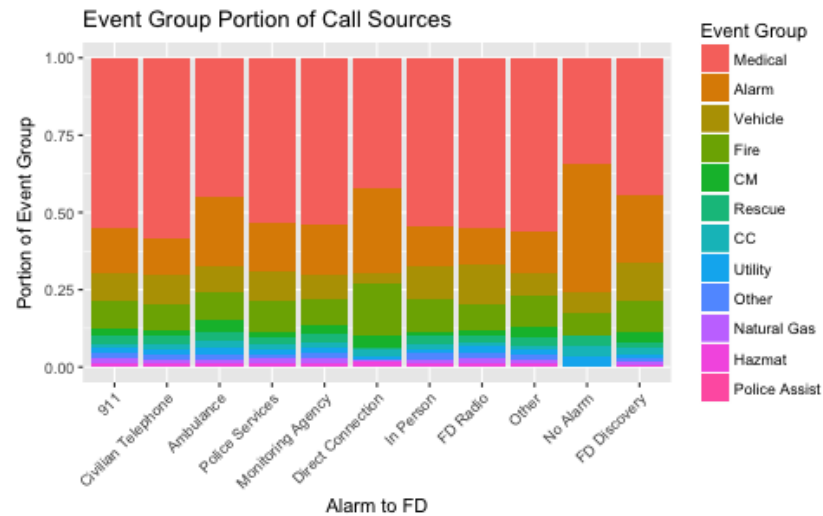
Some Patterns



Daily breakdown of event hours



Some Patterns



{Event group = Alarm} => {Response Group = False Fire Calls}

81% Confidence! 112,659 Incidents



Modeling

- Logistic Regression, Naive Bayes, Random Forest
- Train & Predict “Critical Incidents”
- Randomly selected training set (60%), test set (40%)
- “Before” and “After” features
- Accuracy, Precision, Recall & F_1 -Score



Supervised Learning

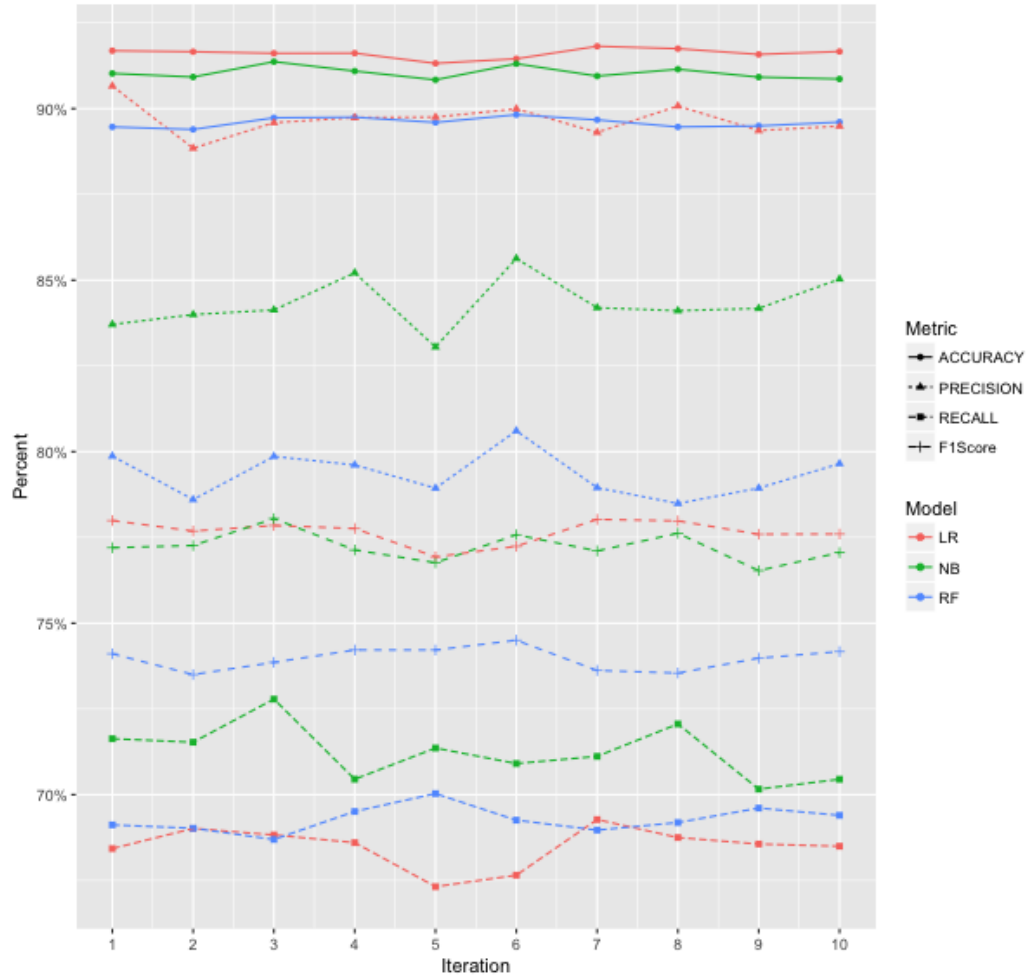
- Critical Incidents:
 - Class Label: Damage, Responding Units, OFM Investigations, Injuries, Fatalities, Rescues
 - Predict: Event type, call source, estimated km, month, day, hour..
- Only Fire Incidents Used

	Non-Critical	Critical
Whole Dataset	690,588 (96%)	29,782 (4%)
Fire Incidents	49,722 (79%)	13,512 (21%)



Modeling Results

Accuracy, Precision, Recall
& F1-Score for 3 Models



	Predicted	
	Non-Critical	Critical
Actual	Non-Critical	Critical
	19423	1175
Non-Critical	19423	1175
Critical	383	3717

Accuracy	91.6
False-Negative Rate	31.5
Precision	90.6
Recall	68.4
F ₁ -Score	77.9



Conclusion

- What additional information, if any, can be provided to first responders at the time of incident call?
- Logistic Regression: Accuracy, Precision
- Naive Bayes: Recall
- Generalizability
 - Entire Dataset
- Limitations
 - Time, Domain knowledge, Computation Power, Dataset



Questions & Thanks

