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Using deep learning and time-series forecasting to reduce transit delays

Mark Ryan mryan@ca.ibm.com
Alina Zhang alina.li.zhang@gmail.com

Introduction

- Use a publicly available dataset on streetcar delays to create a model to predict and prevent delays
- Apply time series forecasting to understand the seasonal nature of delays and deep learning to predict delays
- Example of:
  - Applying deep learning to a tabular dataset
  - Transforming ill-formed address information into map visualizations
  - Combining multiple data types (continuous, categorical and text) in a single deep learning model that incorporates embeddings

The problem: streetcar delays

- Toronto has the biggest network streetcar network in North America
- Advantages: greener / lower labour cost than buses; cheaper than subways
- Major disadvantage: delays trigger gridlock
- Prevent gridlock by predicting and preventing delays

The solution: DL + TSF

- Apply standard analysis techniques and time series forecasting to analyze the data
- Apply data transformations to prepare it for training
- Generate Keras DL model based on categories of columns in the data (categorical, continuous, and text)
- Iteratively train and assess model to improve accuracy
- Create pipeline to encapsulate data preparation steps + model training

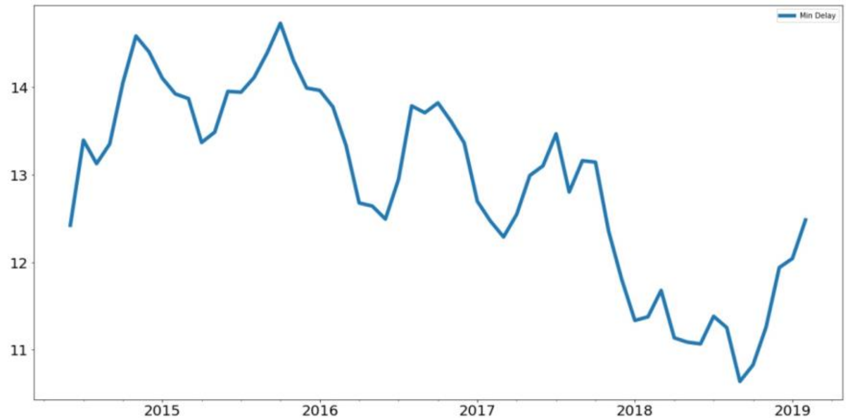
The dataset: overview

- ~70 k records with details of all streetcar delays since January 2014
- No error checking on data entry = messy data:
  - Invalid routes, vehicles, and direction of travel
  - Locations are free-form, inconsistent descriptions
- *Interesting, real-world dataset that demands serious effort to prepare for machine learning*

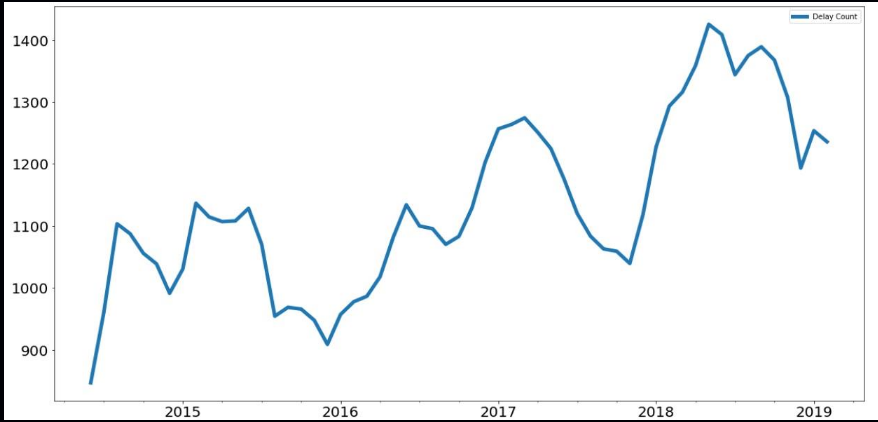
1	Report Date	Route	Time	Day	Location	Incident	Min Delay	Min Gap	Direction	Vehicle
2	2014-12-01	510	1:28:00 AM	Monday	Spadina and Oxford	Emergency Services	77	87	B/W	4124
3	2014-12-01	306	3:59:00 AM	Monday	Gerrard and Kingsmount Park Rd.	Investigation	41	71	W/B	4044
4	2014-12-01	512	5:02:00 AM	Monday	Exhibition Loop	Late Leaving Garage	8	16	W/B	4171
5	2014-12-01	504	5:36:00 AM	Monday	Queen and Roncesvalles	Late Leaving Garage	6	12	E/B	4233
6	2014-12-01	506	5:52:00 AM	Monday	Coxwell and Gerrard	Mechanical	4	8	E/B	4077

The dataset: variations by year

Delay duration averages

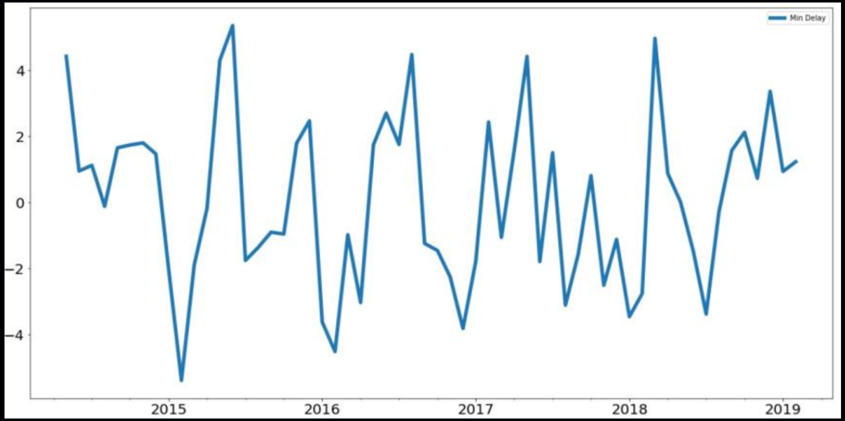


Delay count averages

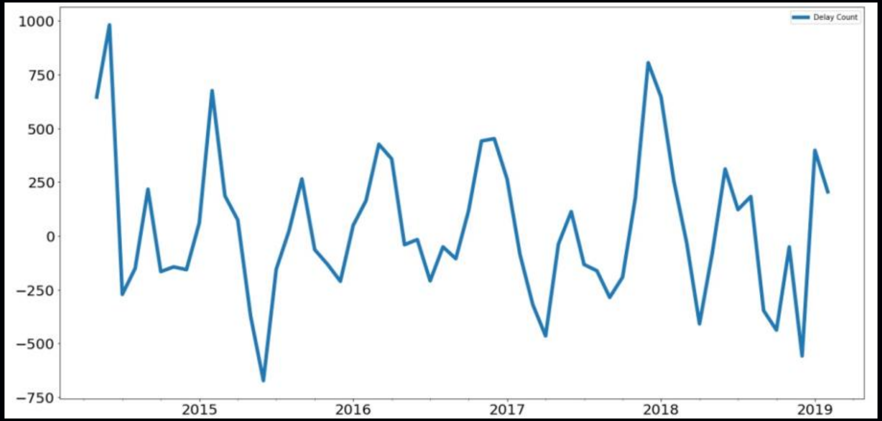


The dataset: variations by season

Delay duration seasonability



Delay count seasonability



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The dataset: messy addresses

Location
Dundas West stnt to Broadview stn
Fleet St. and Strachan Ave.
Queen St. West and Roncesvalles Ave.
Lake Shore Blvd. and Superior St.
Roncy to Neville Park

1

Clean *custom code*

Location
dundas west stationt to broadview station
fleet st. and strachan
queen st. west and roncesvalles
lake shore blvd. and superior st.
roncesvalles to neville park

2

Geocode *Google Geocode API*

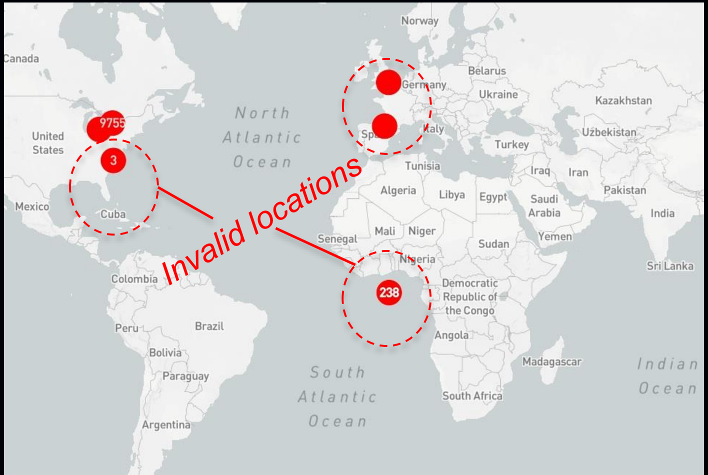
latitude	longitude
0.000000	0.000000
43.636298	-79.409635
43.645335	-79.413184
43.614962	-79.488658
0.000000	0.000000

How to get from messy input addresses to latitude / longitude?

1. Clean up location values:
   - Common casing
   - Consistent order of street names
   - Consistent terms (“”stn” -> “station” ; “Roncy” -> “Roncesvalles”)
2. Apply Google Geocode API:
   - Batch call on cleaned up location values
   - Parse returned JSON and save latitude and longitude values as new features

The dataset: visualize locations

Pixiedust: rough identification of invalid locations



Folium: zero in on hotspots

The dataset: transformations

Report Date	Route	Time	Day	Location	Incident	Min Delay	Min Gap	Direction
2016-01-01 00:00:00	511	02:14:00	Friday	fleet st. and strachan	Mechanical	10.0	20.0	e
2016-01-01 00:00:00	301	02:22:00	Friday	queen st. west and roncesvalles	Mechanical	9.0	18.0	w
2016-01-01 00:00:00	301	03:28:00	Friday	lake shore blvd. and superior st.	Mechanical	20.0	40.0	e
2016-01-01 00:00:00	505	15:42:00	Friday	broadview station loop	Investigation	4.0	10.0	w
2016-01-01 00:00:00	504	15:54:00	Friday	broadview and queen	Mechanical	6.0	12.0	e

Report Date	Route	Time	Day	Location	Incident	Min Delay	Min Gap	Direction	...	longitude	x	y	z
2017-09-04 00:00:00	13	18:52:00	1	old weston road and st.clair	[1]	27.0	54.0	5	...	-79.463024	0.925917	1.065716	0.942998
2016-07-01 00:00:00	4	21:18:00	0	connaught and queen	[1]	8.0	16.0	5	...	-79.322360	1.085382	0.939566	0.968273
2016-03-24 00:00:00	7	06:48:00	4	boustead and roncesvalles	[1]	6.0	12.0	4	...	-79.451723	0.933501	1.049577	1.002038
2015-08-10 00:00:00	13	13:56:00	1	roncesvalles yard	[5, 6, 7]	4.0	8.0	2	...	-79.449050	0.934383	1.044788	1.023267
2017-10-04 00:00:00	5	10:42:00	6	queen and river	[1]	10.0	20.0	5	...	-79.356530	1.045211	0.968827	0.990846

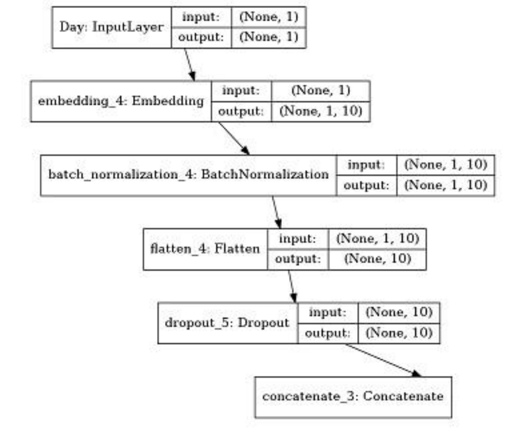
- Replace categorical values with numeric IDs
- Tokenize text values
- Replace latitude and longitude values with x, y, z normalizations

The model: layers by category

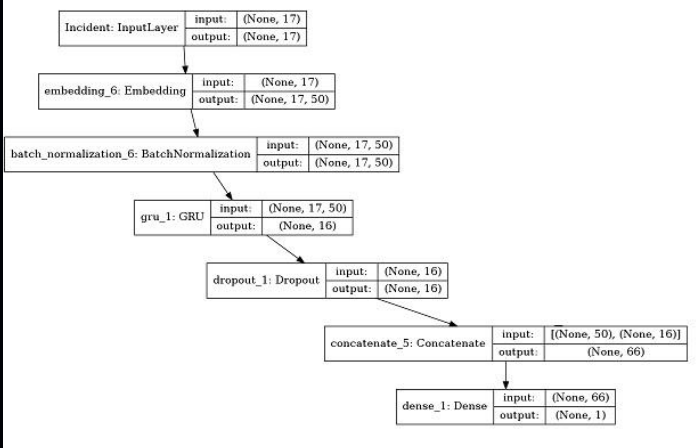
- Categorize columns in the dataset:
  - Continuous: length of delay
  - Categorical: route, vehicle, direction, time of day, day of week
  - Text: description of incident
  - Spatial: location
- Automatically build a simple Keras model:
  - Build model by iterating through columns by type
  - layers for each column type have distinct characteristics (e.g. GNU for text, embeddings for text and categorical columns)
  - As long as columns are categorized correctly, the model automatically adapts to new schemas / additional columns

The model: layers by category

Categorical



Text



The model: accuracy

- Experiment structure 1: predict whether a delay of less than a threshold occurs given all features:
  - High-water mark accuracy: 71%
- Experiment structure 2: predict whether a delay occurs given all features:
  - Generate augmented dataset with entries for all hour / route / direction combinations
  - Predict whether a delay will occur for a given set of conditions
  - High-water mark accuracy: xx%

Lessons learned

- Deep learning can be applied to medium-sized structured datasets
- Plan for the pipeline from the start
- Don’t assume which features are categorical – evaluate first
- Build the model to make it easy to add and drop features
- Save time by using pickle to save intermediate dataframes

Next steps

- Complete pipeline to simplify scoring
- Simple web deployment to allow scoring of single data points
- Deployment to allow scoring of batch data points
- Assess model on latest delay data from 2019

Code and data

Repo with code and associated material: https://github.com/ryanmark1867/ai_conference_june_2019

Original data source: https://www.toronto.ca/city-government/data-research-maps/open-data/open-data-catalogue/#e8f359f0-2f47-3058-bf64-6ec488de52da