ASONAM 2018 Presentation

Multi-task Learning for Transit Service Disruption Detection

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Transit Service Disruption

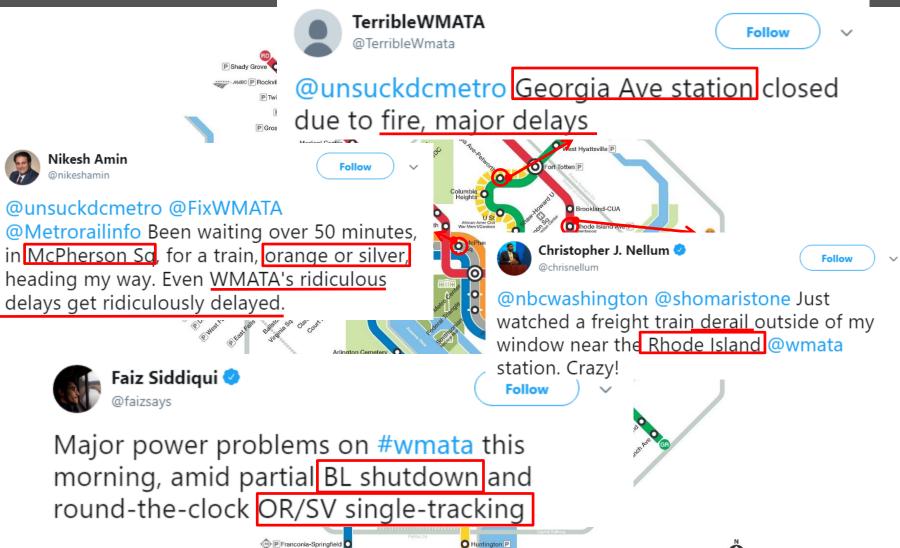
Patroller inspection

- Limited service areas are covered
- Lack of incident detection sensitivity
- Incidents reported after inspection

Twitter

- Higher coverage rate of service areas and incident reasons (e.g., fire, door, and track problem)
- More quickly response to metro service disruption incident
- People tweets about metro service only when they want to complain

Transit Service Disruption



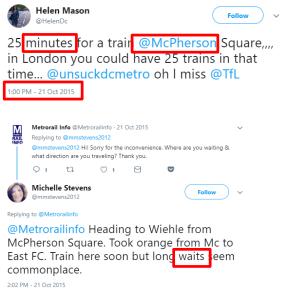
Metro is accessible.

Transit Service Disruption



October 21, 2015 1:34 p.m.
Train at McPherson Square was delayed 26 minutes due to a brake problem.

(Orange, Silver and Blue)



Problem Formulation

Input

- X_t^c is the feature vector for metro line c during time window t.
- Learn a function: $F_c(X_t^c) \to Y_t^c$,

Output

- $Y_t^c \in \{0,1\}^{1 \times T}$ determine if a disruption event happens at time window t

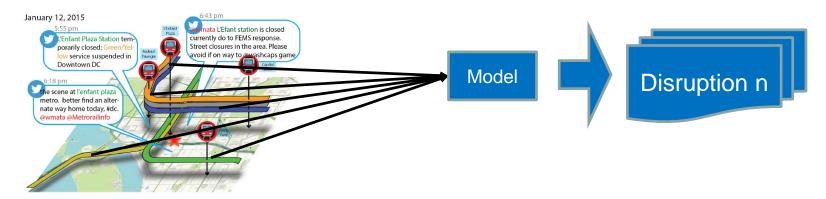
Features

Selected sentiment keywords from StaticTwitterSent dictionary

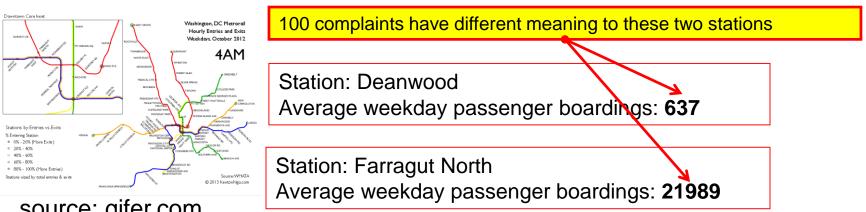
Transit Service Disruption Detection

One model for all metro lines

Pro: sufficient data to train



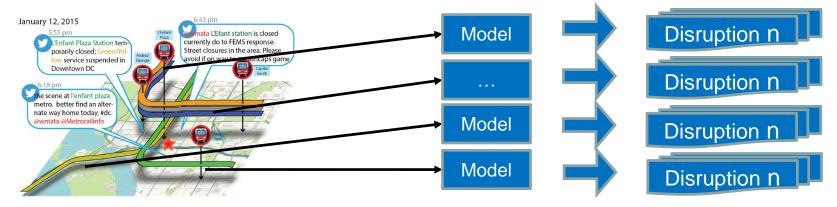
Con: ignore the metro line's exclusive characteristics (ridership, etc.)



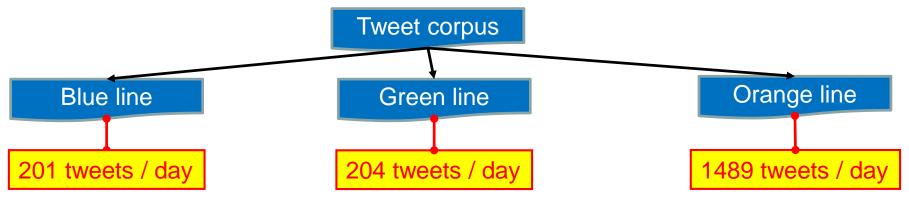
Transit Service Disruption Detection

One model for each metro line

Pro: consider the metro line's exclusive characteristics



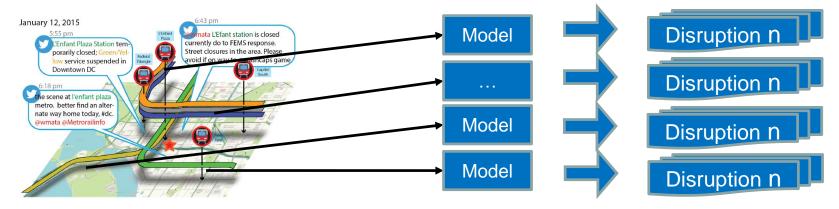
Con: performance is limited when the training data is not sufficient



Transit Service Disruption Detection

One model for each metro line

Pro: consider the metro line's exclusive characteristics



Con: relatedness between metro lines are ignored



Orange and silver lines share 83% of their stations

Different metro lines share similar "complaint vocabulary"

Challenges we address

One-to-one model

One-for-all model

Pro: consider the exclusive characteristics

Pro: Sufficient training data

Con: 1. Relatedness between metro lines

2. Insufficient data

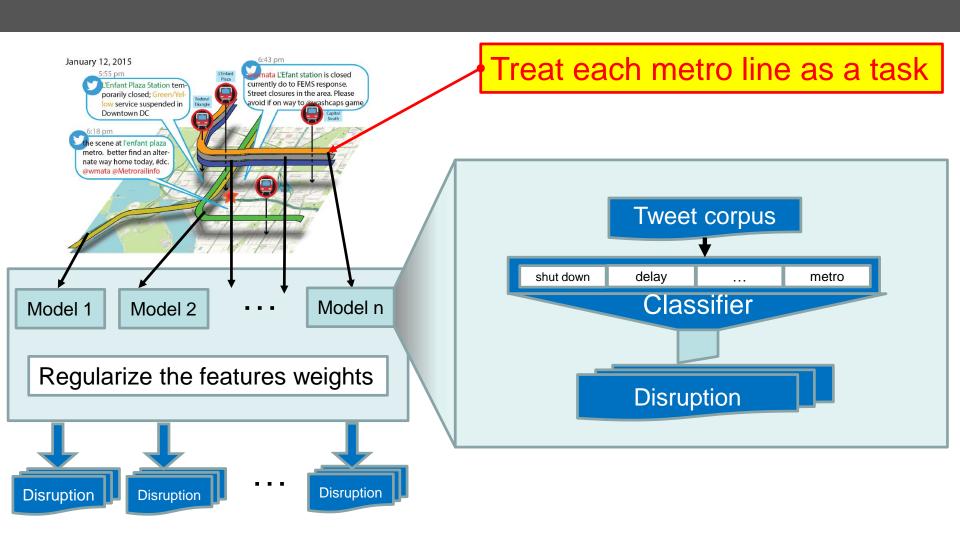
Con: Ignore the exclusive

characteristics

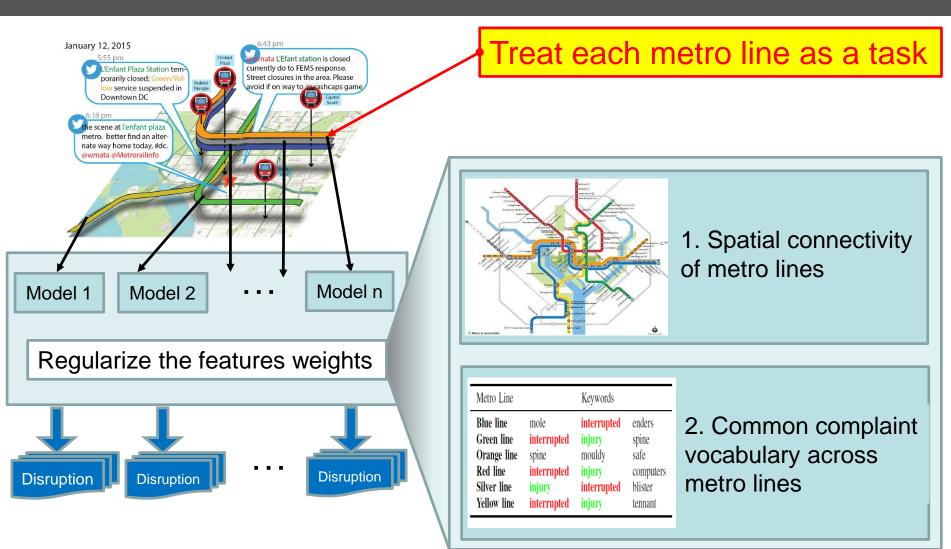
Combine

- Consider metro line's exclusive characteristics
- Consider the spatial connectivity of metro lines
- Consider the common "complaint vocabulary"
- Collect sufficient training data for each metro line

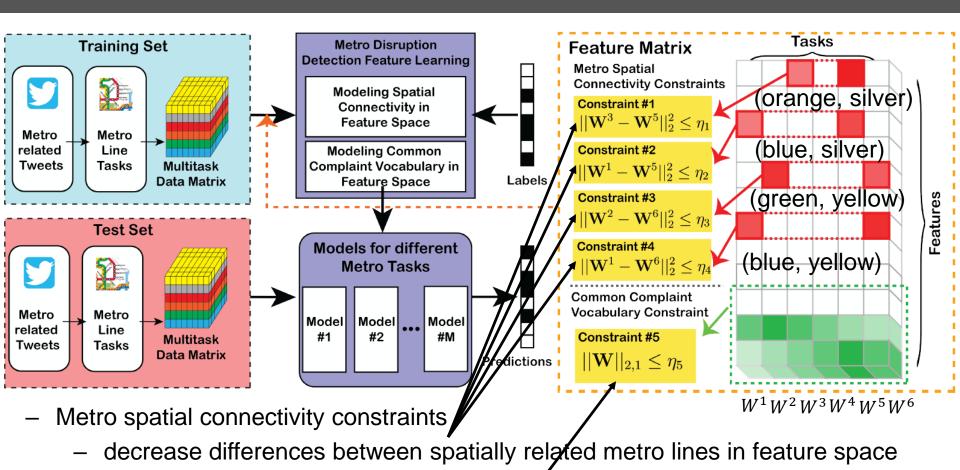
Model Formulation



Model Formulation



System Workflow



- Common complaint vocabulary constraint
 - identify a core set of words most commonly used for metro service

Proposed Model: MDDM

- Use logistic loss function
- Combine all application-specific constraints

$$\underset{\mathbf{W}}{\operatorname{argmin}} \sum_{c=1}^{|\Phi|} \sum_{t=1}^{m_c} \log \left(1 + \exp\{-\mathbf{Y}_t^c(\mathbf{X}_t^c \mathbf{W}^c)\} \right)$$
s.t.
$$\|\mathbf{W}^3 - \mathbf{W}^5\|_2^2 \le \eta_1, \|\mathbf{W}^1 - \mathbf{W}^5\|_2^2 \le \eta_2$$

$$\|\mathbf{W}^6 - \mathbf{W}^2\|_2^2 \le \eta_3, \|\mathbf{W}^1 - \mathbf{W}^6\|_2^2 \le \eta_4$$

$$\|\mathbf{W}\|_{2,1} \le \eta_5,$$

$$\eta_1 \ge 0, \eta_2 \ge 0, \eta_3 \ge 0, \eta_4 \ge 0, \eta_5 \ge 0.$$

Algorithm

multi-convex, nonsmooth problem with inequality constraints

Solution: decouple to two sub-problems (primal and dual variables)

Update primal variables

$$\mathbf{W}^{+} \leftarrow \underset{\mathbf{W}}{\operatorname{argmin}} \ \mathcal{Q} = \sum_{c=1}^{|\Phi|} \sum_{t=1}^{m_{c}} \log \left(1 + \exp\{-\mathbf{Y}_{t}^{c}(\mathbf{X}_{t}^{c}\mathbf{W}^{c})\}\right)$$

$$+ \lambda_{1} \|\mathbf{W}^{3} - \mathbf{W}^{5}\|_{2}^{2} + \lambda_{2} \|\mathbf{W}^{1} - \mathbf{W}^{5}\|_{2}^{2}$$

$$+ \lambda_{3} \|\mathbf{W}^{6} - \mathbf{W}^{2}\|_{2}^{2} + \lambda_{4} \|\mathbf{W}^{1} - \mathbf{W}^{6}\|_{2}^{2}$$

$$+ \langle \mathbf{U}_{1}, \mathbf{W} - \mathbf{U}_{w} \rangle + \frac{\rho}{2} \|\mathbf{W} - \mathbf{U}_{w}\|_{2}^{2}.$$

Update dual variables

$$\mathbf{U}_w^+ \leftarrow \operatorname{prox}_{f_1,1/\rho}(\mathbf{U}_1 + \mathbf{W}),$$

Experiments: Dataset

- Training set: Twitter data from January, 2015 to December, 2015
- Testing set: Twitter data from January, 2016 to June, 2016
- Ground truth: WMATA Daily Service Report from January 2015 to June 2016

time	location	problem	delay (min)	full text
November 16, 2016 5:13 a.m.	Capitol South	a signal problem.	8	5:13 a.m. A Franconia-Springfield-bound Blue Line train at Capitol South was delayed 8 minutes due to a signal problem.
November 16, 2016 6:04 a.m.		did not operate	8	6:04 a.m. A Largo Town Center-bound Blue Line train at King St-Old Town did not operate, resulting in an 8-minute gap in service.
November 16, 2016 6:46 a.m.		an equipment	6	6:46 a.m. A Greenbelt-bound Green Line train at Columbia Heights was offloaded due to an equipment problem. Passengers experienced a 6-minute delay.

Experiments: Features

- Sentiment features for Twitter (StaticTwitterSent)
 - Remove non-English words
 - Remove hastags and usernames
 - Remove single letter words, and numbers
 - Remove stopwords defined by NLTK
 - Remove words with frequency less than 10
 - Remove words which never appear in the metro-related tweets

TOP 3 MOST FREQUENT WORDS FOR EACH METRO LINE.

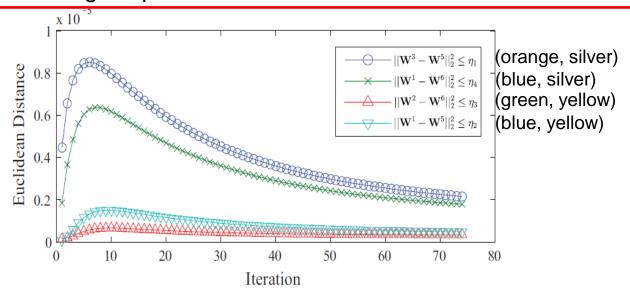
Metro Line		Keywords	
Blue line Green line Orange line Red line Silver line Yellow line	mole interrupted spine interrupted injury interrupted	interrupted injury mouldy injury interrupted injury	enders spine safe computers blister tennant

Event Prediction Performance

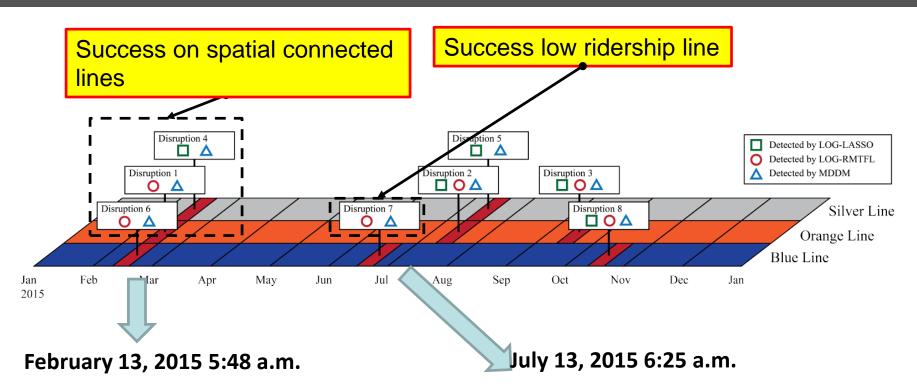
MDDM outperforms other models on 5 metro lines on F-measure.

Method	Blue	Green	Orange	Red	Silver	Yellow
LOGR	0.37	0.48	0.56	0.63	0.49	0.40
LOG-LASSO	0.42	0.50	0.56	0.67	0.49	0.43
LOG-RMTFL	0.35	0.52	0.59	0.68	0.49	0.39
MDDM	0.44	0.55	0.63	0.69	0.52	0.40

MDDM encourages spatial related metro lines to be similar.



Case Study



A train at **McPherson Square** was offloaded due to a brake problem. Passengers experienced a 12-minute delay.

A train at **Pentagon City** was offloaded due to a brake problem. Passengers experienced an 8-minute delay.

Summary

- Formulate a multi-task learning framework for metro disruption detection using online social media
- Model semantic similarity among metro lines in feature space
 - Spatial connectivity
 - Common complaint vocabulary
- Develop an efficient algorithm to solve the proposed model
 - Update primal variables
 - Update dual variables
- Conduct extensive experiments to validate the effectiveness and efficiency of the proposed model

Future Work

- Multi-resolution transit service disruption detection
 - Metro line level
 - Metro station level
- Multi-view transit service disruption detection
 - New York metro system
 - Washington, D.C. metro system
- Spatial-temporal transit service disruption detection
 - Spatial connectivity across metro lines
 - Temporal relatedness between events
 - Rush hours and non-rush hours

Thank You

The code and slides are available at https://github.com/TaoranJ/wmata_service_diruption_detection Welcome any related questions and suggestions.