# Can we inspect & maintain vehicles ONLY when necessary? Can we do that without stopping traffic?



The Commercial Vehicle Safety Alliance (CVSA) <u>https://www.cvsa.org/news/future-video/</u> Carnegie Mellon University





**Carnegie Mellon University** 



### **Towards Data-Driven and Continuous Safety Inspection of Commercial Trucks and Trailers**

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# Introduction

Based on research provided by the National Highway Transportation Safety Administration (NHTSA), around 20 percent of all traffic accidents are caused in some way by poor maintenance or lack thereof.



#### **Vehicle Inspection and Maintenance Plan**

#### Cost

 Financial expenses incurred by inspection and maintenance

#### Loss of Up-Time

• Vehicle operation time losses due to outages

#### Trade-off:

- More frequent inspection and maintenance would increase the cost and mobility reduction
- Less inspection would improve mobility but decrease the vehicles' operational safety



### Introduction

### The objective of motor carriers operating commercial fleets:

Make inspection and maintenance plans so that vehicles can operate safely with fewer costs, less idling time, and improved mobility

**Research questions:** what components are important that need more frequent inspection and maintenance?

- <u>Task 1</u>: What are the failure-prone components of specific types of vehicles?
- <u>Task 2</u>: What are the critical vehicles and risk-prone components for a given commercial fleet? Could we have priority queues?
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### Methodology - What are the failure-prone components of specific types of vehicles?

"Natural Language Processing" of vehicle inspection reports for identifying "clusters" of vehicles having similar failure trends and their critical vehicle components.



# Methodology



- Select violation records from 2021 and generate a violation text record for each vehicle during this year.
  - The purpose is to see what's the major problem for each vehicle during the year 2021.
- Filter violation by category id from 15 30.
- Filter vehicles by gross combination vehicle weight heavier than 19500 lbs



### Methodology

#### Input descriptions

∍d	msg_lemmatized	msg_stemmed	no_stopwords	msg_tokenied	lower_msg	clean_msg	length	Supp_Desc	INSP_UNIT_VEHICLE_ID_NUMBER
h, k, n]	[fire, extinguish, warn, devic, work, horn]	[fire, extinguish, warn, devic, work, horn]	[fire, extinguisher, warning, devices, working	[no, fire, extinguisher, no, warning, devices,	no fire extinguisher no warning devices no wor	No Fire Extinguisher No warning devices No wor	55	No Fire Extinguisher No warning devices No wor	0V200000X192801NE
g, e]	[axl, passeng, side]	[axl, passeng, side]	[axle, passenger, side]	[axle, passenger, side]	axle passenger side	Axle passenger side	21	Axle 4 passenger side	101CCKLA04G004376
p]	[left, tail, lamp]	[left, tail, lamp]	[left, tail, lamp]	[left, tail, lamp]	left tail lamp	left tail lamp	14	left tail lamp	101CCKLA5RG003246
e, g, ;]	[driver, side, measur, passeng, side, measur, ]	[driver, side, measur, passeng, side, measur, ]	[driver, side, measured, passenger, side, meas	[driver, side, measured, passenger, side, meas	driver side measured passenger side measured	Driver side measured Passenger side measured	59	Driver side measured 22.1%. Passenger side me	101CCVLBXYG003865
kl, ər, 	[, singl, axl, camper, trailer, strap, around,	[, singl, axl, camper, trailer, strap, around,	[, single, axle, camper, trailer, straps, arou	[, single, axle, camper, on, trailer, straps,	single axle camper on trailer straps around t	single axle camper on trailer straps around t	81	3 single axle camper on trailer straps around	101FR5327MG005241
n	Mello								

# Processed descriptions for topic analysis

### Methodology

#### Top 8 topics:

Торіс					Top 10 words	s and weights					Related violation
1	0.051*"inop"	0.045*" <b>lamp</b> "	0.034*"inope r"	0.031*"rear"	0.030*" <b>turn</b> "	0.029*" <b>signal</b> "	0.026*"front"	0.026*"right"	0.026*"left"	0.025*" <b>light</b> "	Light problem
2	0.034*" <b>air</b> "	0.024*" <b>leak</b> "	0.024*"axl"	0.021*" <b>brake</b> "	0.019*"hose"	0.016*"x"	0.015*" "	0.014*"cham ber"	0.014*"r"	0.013*"v"	Brake Air Leak problem
3	0.051*" <b>tire</b> "	0.050*"axl"	0.036*"psi"	0.035*"right"	0.031*"left"	0.027*"side"	0.026*"insid"	0.021*"outsi d"	0.021*"inop"	0.021*" <b>flat</b> "	Tire problem
4	0.027*" <b>displ</b> ay"	0.026*"numb er"	0.025*"name "	0.024*"usdot "	0.023*"dot"	0.022*"carrie r"	0.022*"lb"	0.017*"vehicl "	0.016*"comp ani"	0.015*"truck "	USDOT number display problem
5	0.021*"none "	0.020*" <b>traile</b> <b>r</b> "	0.019*"secur "	0.019*"chain "	0.018*" <b>break</b> away"	0.016*"cabl"	0.015*"unit"	0.015*" <b>attac</b> <b>h</b> "	0.013*"strap"	0.012*"conn ect"	Trailer Attachment problem
6	0.016*" <b>oil</b> "	0.015*"miss"	0.014*" <b>leak</b> "	0.014*"rear"	0.014*" <b>engin</b> "	0.012*"right"	0.012*"side"	0.011*"left"	0.010*"inop"	0.009*"cover "	Engine oil leak problem
7	0.049*" <b>expir</b> "	0.035*""	0.034*" <b>regist</b> r"	0.019*"curre nt"	0.016*" <b>plate</b> "	0.016*"inspe ct"	0.014*"proof "	0.014*" <b>insur</b> "	0.013*"card"	0.013*"displa y"	Insurance proof problem
8	0.027*" <b>wind</b> ow"	0.024*" <b>wind</b> shield"	0.023*"tint"	0.021*"fluid"	0.018*"wash er"	0.017*"meas ur"	0.016*"crack "	0.016*"driver "	0.014*"side"	0.013*"adjus t"	Windshield problem
•PT	4									Niell Univ	on ⁄ersity



### **Results - Failure-Prone Components**

NSP_UNIT_MA											
KE	1	2	3	4	5	6	7	8	Maximum	Second_Maxim	um Third_Maximum
BIGT	478	228	347	2501	534	1762	639	1229	4	6	8
RHT	7167	36879	6324	13643	5964	5888	14311	13980	2	7	8
GDAN	441	1528	446	722	235	289	656	880	2	8	4
GMC	458	391	264	1789	360	846	851	519	4	7	6
HINO	1146	1690	1111	3932	1281	1407	2198	1325	4	7	2
NTL	3272	19160	2812	9052	2852	3626	7650	6111	2	4	7
<w .<="" td=""><td>2685</td><td>14197</td><td>2373</td><td>4468</td><td>2604</td><td>3227</td><td>6829</td><td>5053</td><td>2</td><td>7</td><td>8</td></w>	2685	14197	2373	4468	2604	3227	6829	5053	2	7	8
МАСК	1096	3571	1064	2402	1386	2063	3227	2634	2	7	8
OTHR	481	799	456	2332	701	1322	1091	1032	4	6	7
PTRB	2251	9277	2359	3742	2407	2862	4414	4276	2	7	8
RAM	533	284	418	1806	509	1451	616	1077	4	6	8
FRLR	817	899	806	4310	794	2535	1133	1707	4	6	8
JNK	457	462	369	2058	380	1179	593	828	4	6	8
JTIL	705	2450	691	1263	490	511	1046	1442	2	8	4
VOLV	1152	6793	1218	1878	867	881	2136	2751	2	8	7
<b>\</b>	Diffor	ont vohiol						•	Trailer A	ttachment	
$\backslash$	Diller	ent venicie			1	Light prob	lem	5	nro	hlem	
$\backslash$	make	es have dif	ferent			Brake Air I	_eak		Engine		
Vobiolo "failure modes"					2	probler	n	6	nro	blem	
Make / Drand					3	Tire probl	lem		Insurar	ce proof	arnorio
Make/Brand					USDOT nur	mher	7	nro	blem	Jainegie	
					1	display pro		,			Viellon
				· · · · · · · · · · · · · · · · · · ·	т	uispiay più		8	Windshie	ld problem   📮	

# Methodology - What are the critical vehicles and risk-prone components for a given commercial fleet?

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Simulate the deterioration trends of a fleet and prioritize vehicles/components



## Methodology – Markovian Deterioration Prediction

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Brake Pad Thickness/Tire Tread Depth Deterioration Model – Percentages of Transitions from One State to Another in the Historical Inspection Reports



# Methodology – Markovian Deterioration Prediction

#### Transition probability example



For each vehicle in a fleet, given current inspected component state and the potential operating mileage, the prediction model can calculate the probability of state in the future. The next state is predicted by sampling according to the probability.

### **Deterioration Modeling and Prediction Results**

**Brake's Markovian Deterioration Prediction Model for Heavy Trucks and Trailers** 

Transition probability examples -Training dataset: 49,604





## **Deterioration Modeling and Prediction Results**

#### Brake's Markovian Deterioration Prediction for Heavy Trucks and Trailers

Testing results -Testing dataset: 1,000

- Test on the state prediction after operating a certain mileage
  - Accuracy: 48.3%
  - Soft accuracy: 63.6%
- Test on the state prediction after operating one year
  - Accuracy: 49.4%
  - Soft accuracy: 63.1%



#### Brake states' distribution in a heavy-duty fleet with 1,000 vehicles after one year

State(32/in)	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Current Inspection	0.0%	0.0%	0.1%	0.1%	1.1%	1.8%	4.4%	5.7%	10.6%	4.6%	13.9%	4.3%	16.7%	4.0%	12.4%	9.4%	8.7%	2.2%
Next Inspection -after one year (ground truth)	0.0%	0.0%	0.4%	0.3%	2.5%	3.2%	6.9%	8.9%	13.9%	4.7%	16.6%	3.5%	14.1%	3.3%	9.3%	6.2%	5.5%	0.7%
Next Inspection -after one year	0.0%	0.0%	0.3%	0.2%	2.1%	3.6%	7.0%	7.3%	13.0%	5.5%	17.2%	3.9%	13.3%	4.0%	10.4%	5.6%	5.9%	0.7%

### **Component's Ranking**

#### Rank according to the probability that the component transition to state 2 (2/32in)

Ranking of 1,000 brakes – after given certain mileages

Ranking	1	2	3	4	5	6	7	
Component ID	200	470	608	729	709	532	275	
Probability	100.00%	100.00%	8.33%	1.41%	1.08%	1.06%	1.05%	0

#### Ranking of 1,000 brakes –after one year

Ranking	1	2	3	4	5	
Component ID	200	470	626	783	188	
Probability	100.00%	100.00%	5.71%	1.12%	1.00%	0



### **Prioritizing Vehicles based on their Predicted Brake States**

#### Rank according to the probability that the component transition to state 2 (/32in)

Ranking of brake states – after given certain mileages (10,000 miles in this case)

	1	2	3	4	5	6	7
Vehicle ID	200	470	608	729	709	532	275
Probability	100.00%	100.00%	8.33%	1.41%	1.08%	1.06%	1.05%

#### Ranking of brake states - after one year





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### **Results -test on simulated tire states**

Simulated tire distribution



Training dataset (heavy trucks and trailers): 49,604 Test dataset (heavy trucks and trailers): 1,000

Prediction Models	Prediction states after	a certain mileage	Prediction states after one year						
	Accuracy	Soft accuracy	Accuracy	Soft accuracy					
Deterioration rate model	21.2%	44.3%	4.7%	13.1%					
Markov deterioration model	44.7%	60.8%	5.9%	15.1%					

Model based on heavy trucks and trailer

### **Results -test on simulated tire states**

#### A heavy-duty fleet with 1,000 operating brake components

State (/32in)	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Current Inspection	0.0%	0.0%	0.0%	0.0%	0.9%	1.2%	2.6%	3.2%	5.0%	5.0%	9.5%	5.3%	12.2%	8.2%	8.6%	7.5%	6.2%	4.8%	5.7%	4.3%	4.2%	2.7%	1.7%	0.2%	0.6%	0.1%	0.2%	0.0%	0.1%	0.0%	0.0%
Next Inspection -after one year (Markovian)	0.0%	0.0%	0.3%	0.6%	1.6%	1.4%	2.9%	2.4%	5.4%	5.6%	6.2%	4.9%	8.9%	6.6%	7.7%	6.7%	5.7%	6.8%	5.8%	4.8%	4.2%	3.4%	2.5%	1.6%	1.9%	0.7%	0.5%	0.4%	0.3%	0.2%	0.0%
State (/32in)	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Current Inspection	0.0%	0.0%	0.0%	0.0%	0.8%	1.2%	2.6%	3.2%	5.1%	5.0%	9.5%	5.3%	12.2%	8.2%	8.6%	7.5%	6.2%	4.8%	5.7%	4.3%	4.2%	2.7%	1.7%	0.2%	0.6%	0.1%	0.2%	0.0%	0.1%	0.0%	0.0%
Next Inspection -after one vear(DR)	40 70		2.00(	2.000	1.69(	2.40	2.20	4.00/	2.000	2 70(	4 70(	4 70/	5.00		4.00/		E 40(	4.204	2.400	2.40(	2.00/	2.00(	4 50(	4.400	0.000	4 204	0.000	0.000	0.000	0.000	0.004

The prediction using the Markovian deterioration model is closer to the ground truth.

The prediction using the DR model is more pessimistic than using the Markovian deterioration model.

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### Conclusion

- The topic analysis based on violation descriptions can identify failure-prone components of specific brand/make/type of vehicles.
  - Such identified failure-prone components are those that need more attention from fleet managers in their life cycle considering the vehicle type.
- The component risk ranking method can predict the probabilities that components transition to risky (violation) states (under 2/32 inches) in the future and rank the risky components in terms of their predicted states as inspection/maintenance priority queues.
  - Such ranking can help fleet managers decide what vehicle components need inspection and maintenance most in the following days considering vehicles' current states.
- The Markovian deterioration prediction model is validated to have a higher prediction accuracy compared with the prediction model using the linear-milage deterioration rates.



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