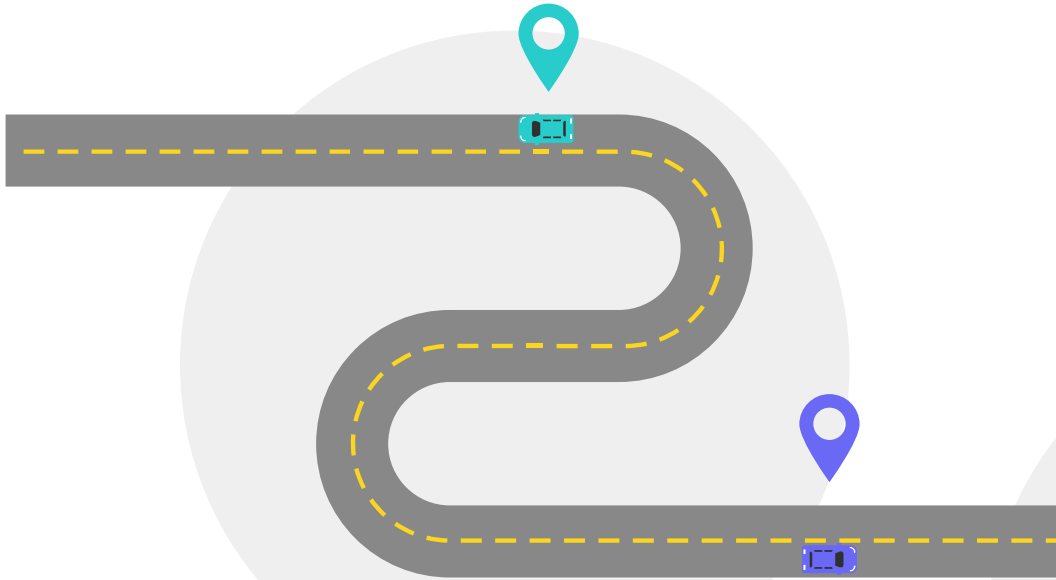
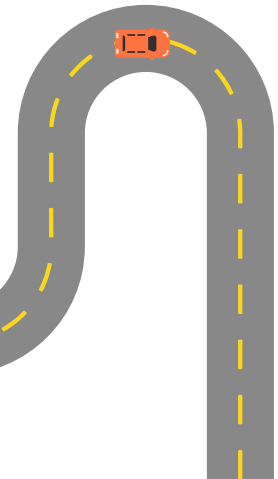
Optimize Road Traffic through Central Composite Design

William Scott-Curtis, Huy Nguyen

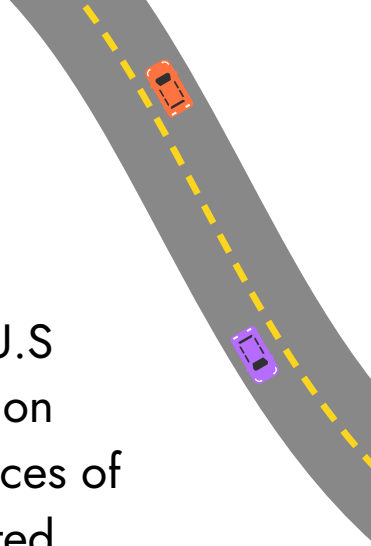


01

Introduction



Traffic Congestion

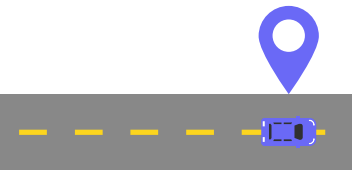


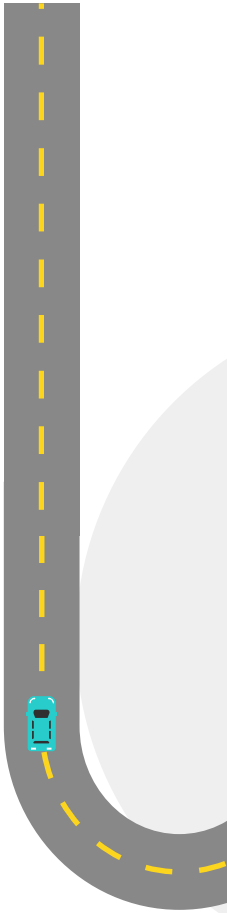
- Los Angeles is notorious for traffic congestion.
- The I-5, I-10, and I-405 are among the busiest highways in the U.S
- From "A Historical Perspective on Los Angeles' Traffic Congestion Fight" by UCLA's Luskin Center emphasized that the consequences of congestion (air and noise pollution, transportation taxes) impacted mostly marginalized communities.
- Through our project, we hope to use simple, existing means to propose feasible solutions for traffic congestion.

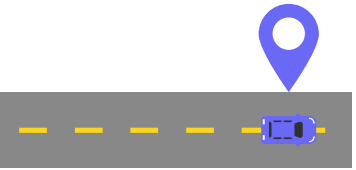
02

Experimental Design

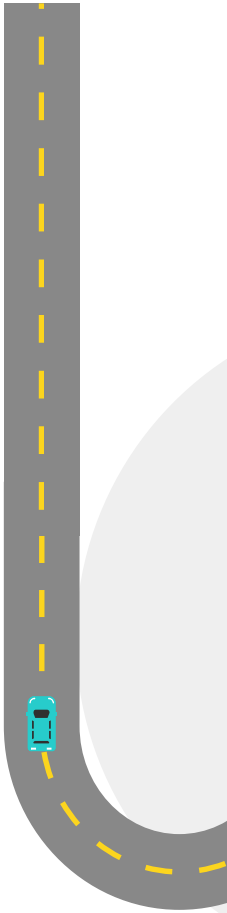
- This simulation was created by Dr. Martin Treiber from Dresden University of Technology
- Response Variable: Time until congestion (Speed under 40 kph)
- There are 7 factors:
  - Metering (A: On/Off)
  - Speed Sign Limit 1 (B: 80/60 kph)
  - Speed Sign Limit 2 (C: 80/60 kph)
  - Truck Percentage (D: 10/20 %)
  - Max Acceleration (E: 1.5/2.5 m/s^2)
  - Politeness (F: 0/0.5 m/s^2): How often vehicles swerve/change lanes.
  - Traffic inflow (G: 4500/5400 vehicles/hour)

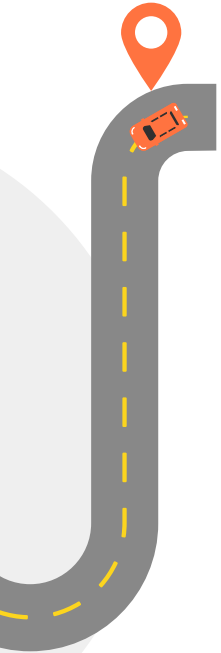


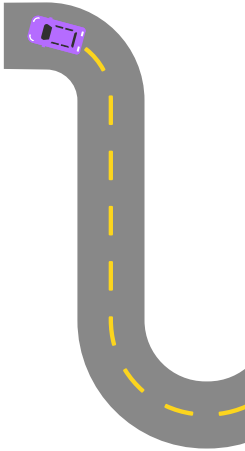


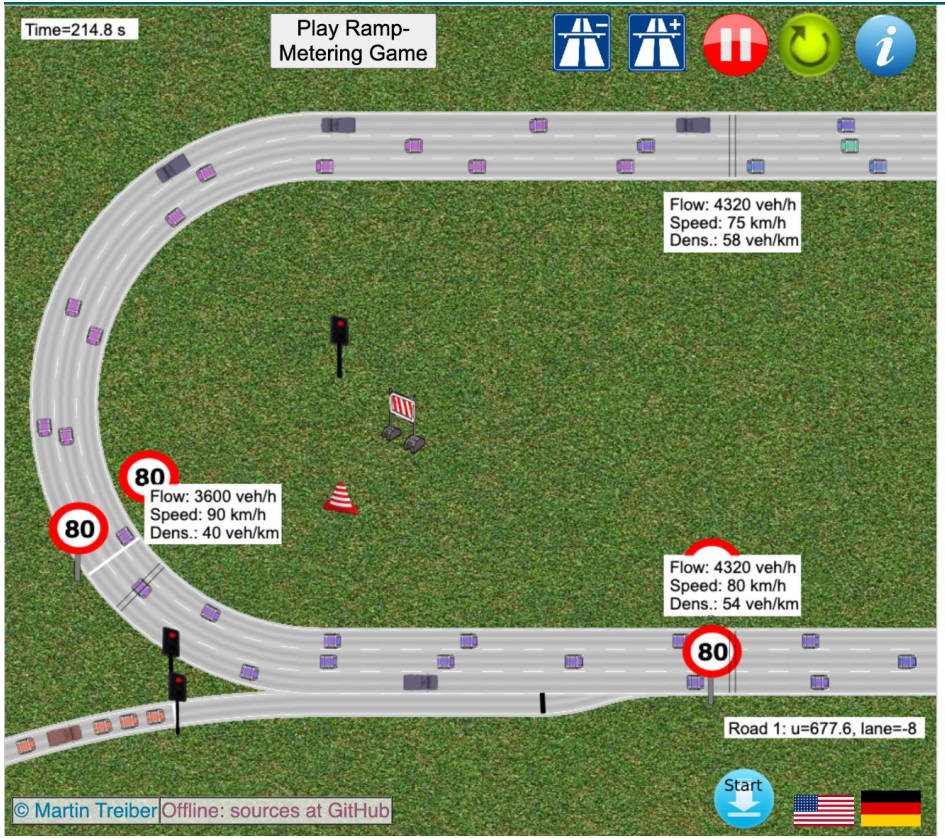


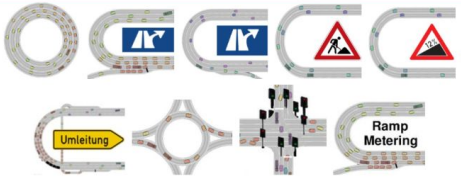
- There are many variables that we set to constants:
  - Onramp flow
  - Time lapse
  - Max speed: Speed of vehicles if it drives on an empty highway.
  - Time gap: Assume people leave the same time gap between cars before trailing.
  - Lane-changing threshold
  - Right-bias cars
  - Right-bias trucks
- Future experiments may include some of these variables.











Traffic Flow and General

Inflow	4800 veh/h
Onramp Flow	720 veh/h
Truck Perc	10 %
Timelapse	5 times

Car-Following Behavior

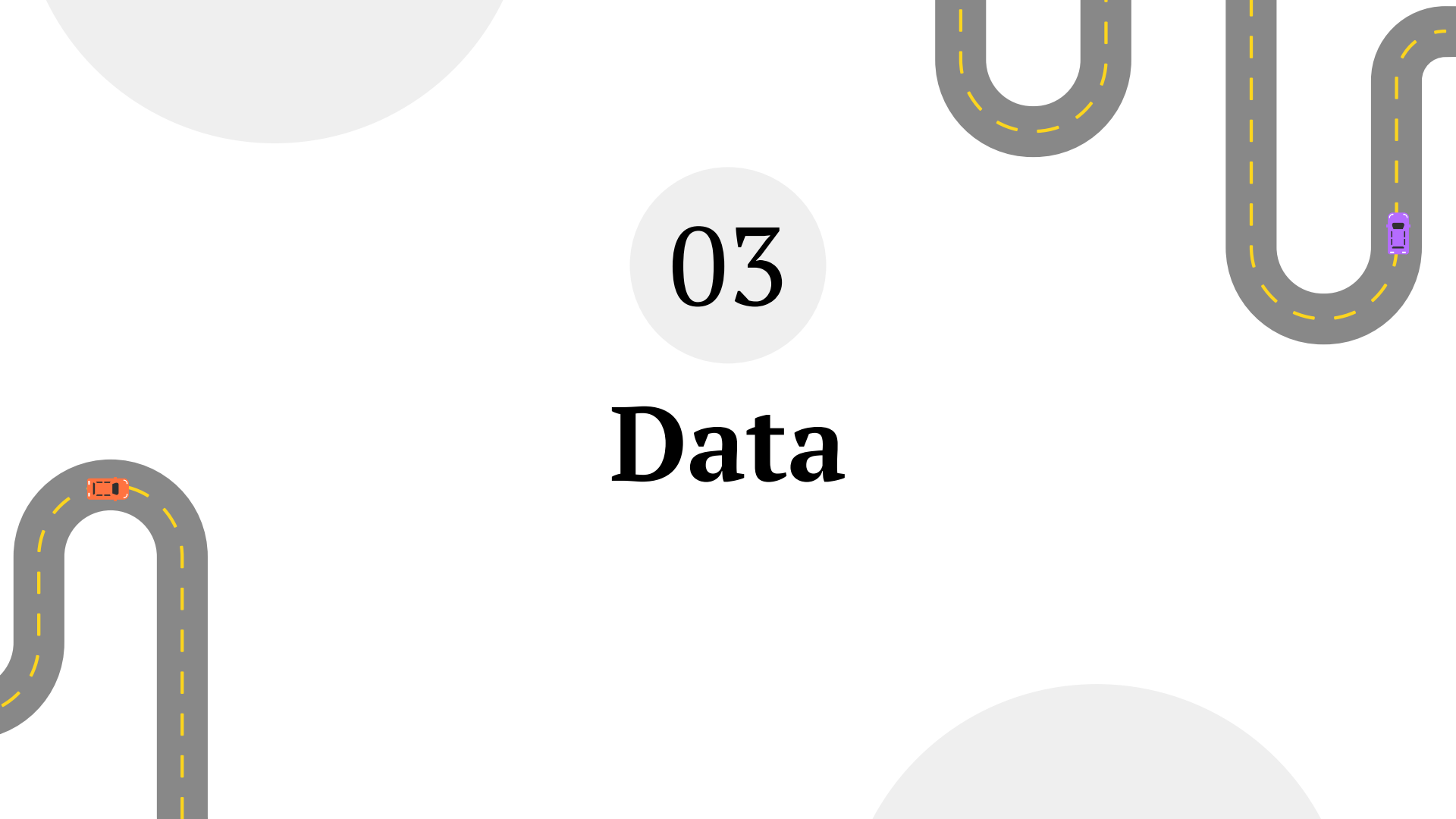
Max Speed v0	120 km/h
Time Gap T	1.4 s
Max Accel a	2 m/s^2

Lane-Changing Behavior

Politeness	0 m/s^2
LC Threshold	0.4 m/s^2
Right Bias Cars	0 m/s^2
Right Bias Trucks	0.1 m/s^2

Golf Course

- Click onto the road to disturb traffic flow
- Drag obstacles or construction vehicles to



03

Data

Data Randomization

- We ran 16 runs in our fractional factorial design, and 30 in our central composite design, with a randomized order.
- When we add Order into the model, we see that it is not significant (p = 0.21, 0.77). This means that Order is truly randomized.
- For each explanatory factor, we have two levels encoded as -1 and 1 in the fractional factorial design.

Data (Fractional Factorial)

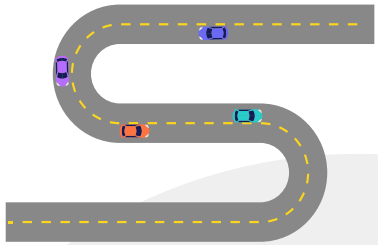
Order		G	A	B	C	D	E	F	Outcome
8	1	1	1	1	1	1	1	1	74.1
10	2	-1	1	1	1	-1	1	-1	147.2
3	3	-1	1	1	-1	1	-1	1	44.4
14	4	1	1	1	-1	-1	-1	-1	38.5
16	5	1	1	-1	1	1	-1	-1	26.3
6	6	-1	1	-1	1	-1	-1	1	44.7
5	7	-1	1	-1	-1	1	1	-1	38.6
12	8	1	1	-1	-1	-1	1	1	36.8
9	9	-1	-1	1	1	1	-1	-1	54
11	10	1	-1	1	1	-1	-1	1	54
1	11	1	-1	1	-1	1	1	-1	30.9
13	12	-1	-1	1	-1	-1	1	1	169.7
2	13	-1	-1	-1	1	1	1	1	59.9
7	14	1	-1	-1	1	-1	1	-1	34.2
4	15	1	-1	-1	-1	1	-1	1	34.2
15	16	-1	-1	-1	-1	-1	-1	-1	38.5

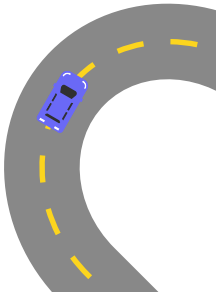
Data (Central Composite)

Order	Number	B	E	F	G	Outcome
15	1	1	1	1	1	246
19	2	1	1	1	-1	1800
14	3	1	1	-1	1	60.2
3	4	1	1	-1	-1	83.6
10	5	1	-1	1	1	23.6
18	6	1	-1	1	-1	94.7
22	7	1	-1	-1	1	15.9
11	8	1	-1	-1	-1	16.2
5	9	-1	1	1	1	10.8
20	10	-1	1	1	-1	14.1
28	11	-1	1	-1	1	8.6
24	12	-1	1	-1	-1	5.9
9	13	-1	-1	1	1	6
27	14	-1	-1	1	-1	7.1
8	15	-1	-1	-1	1	6.3
26	16	-1	-1	-1	-1	6
7	17	2	0	0	0	338.1
30	18	-1.5	0	0	0	5
25	19	0	1.4	0	0	385.8
17	20	0	-1.4	0	0	20.3
4	21	0	0	1.667	0	18.3
1	22	0	0	-1.667	0	4.1
23	23	0	0	0	1.5	8.3
21	24	0	0	0	-1.5	21.4
29	25	0	0	0	0	41.7
13	26	0	0	0	0	76.7
16	27	0	0	0	0	12.9
2	28	0	0	0	0	49.9
12	29	0	0	0	0	35.4
6	30	0	0	0	0	74.8

***(Nothing after

B	(40/60/80/100/120)
E	(1.2, 1.5, 2, 2.5, 2.7)
F	(-0.2, 0, 0.3, 0.6, 0.8)
G	(4200/4400/4800/5200/5400)
Timelapse	20
Onramp flow	1000
Max speed	120
Output	Time till speed drop at second check





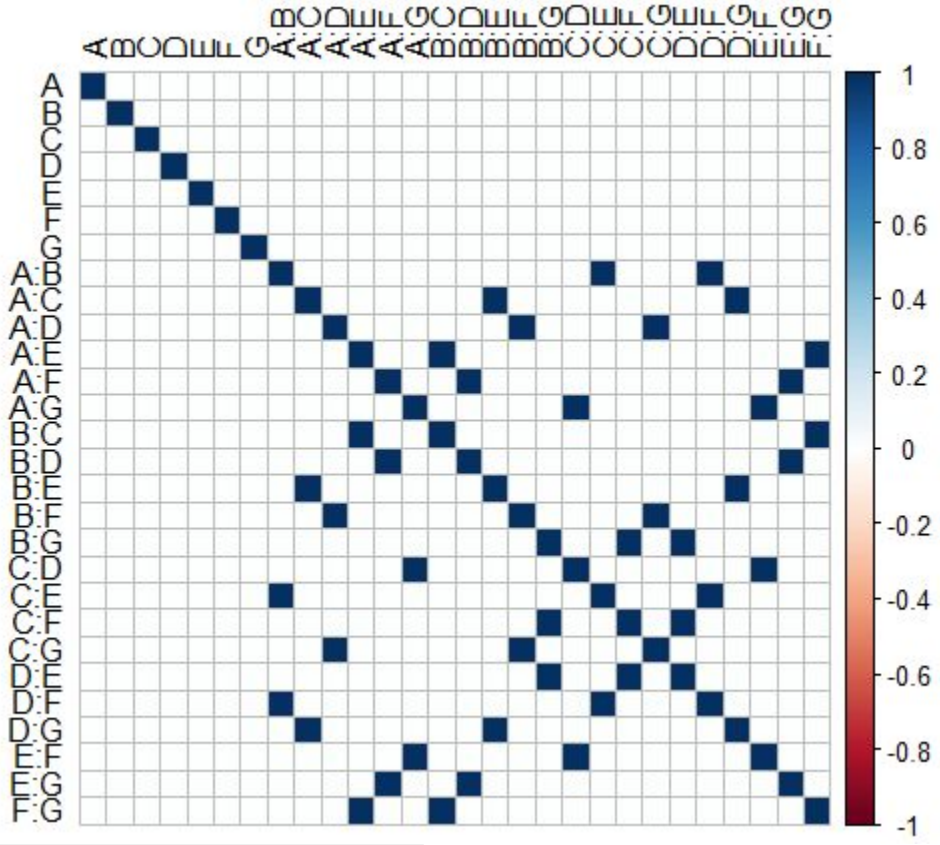
04

Design Analysis

Fractional Factorial Design

- This is a fractional factorial design- 2_{IV}^{7-3}
- We have 16 runs and 7 predictors
- E = ABC, F = ABD, G = ACD
- Since we are interested in all the variables, there will be no blocking factor
- The correlation plot shows that our main effects do not alias with any two-factor interaction effect.
- This design is mainly for feature selection. Our final design is the Central Composite Design

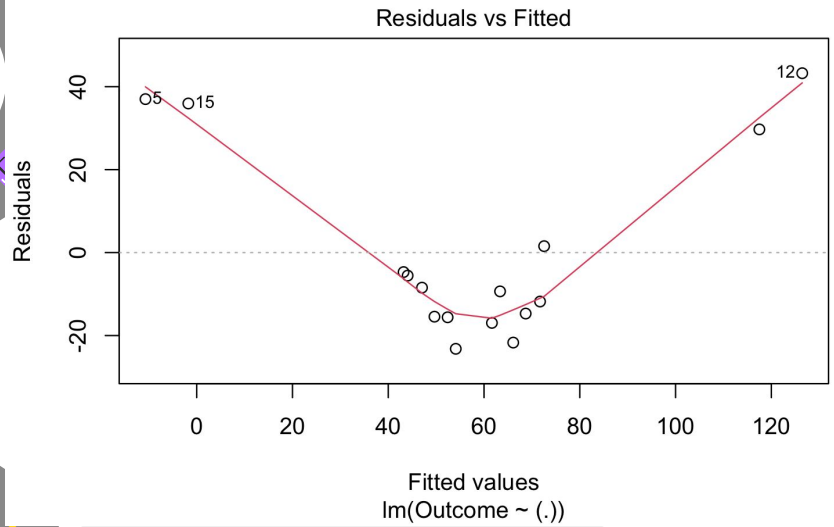
Correlation Plot

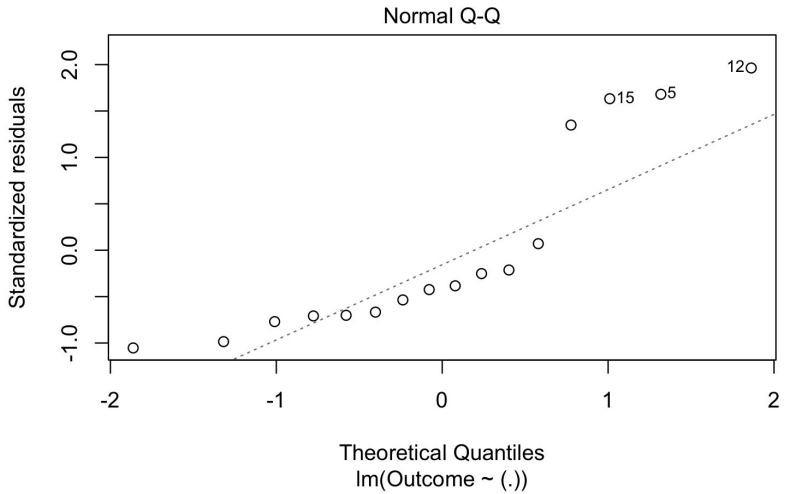


Linear Model

Predictor	Estimate	P-val
Intercept	57.875	7.39e-05 ***
A	-1.550	0.8472
B	18.725	0.0429 *
C	3.925	0.6278
D	-12.575	0.1450
E	16.050	0.0732 .
F	6.850	0.4047
G	-16.750	0.0637

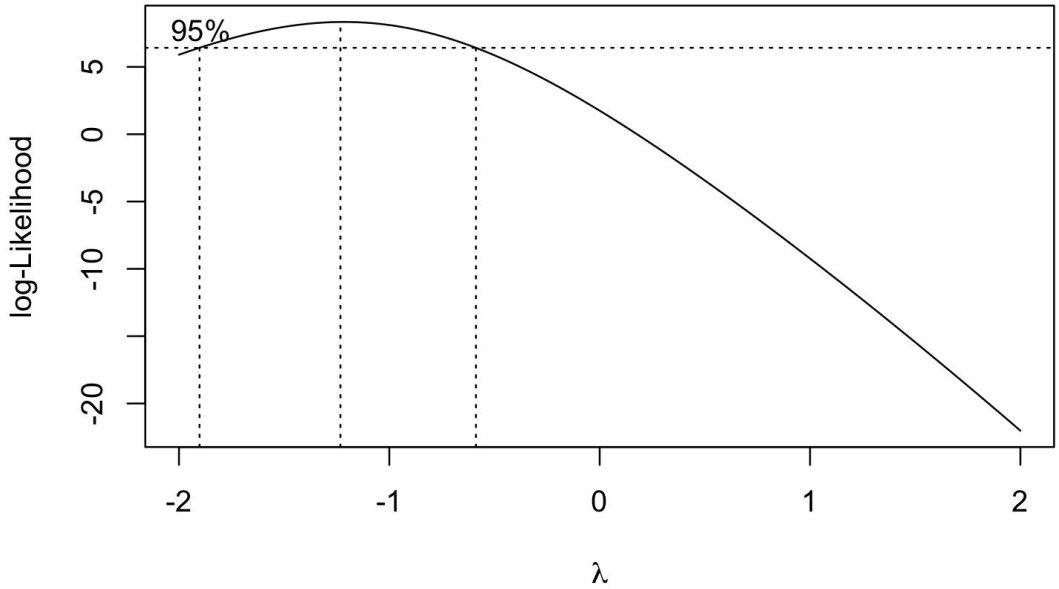
Residuals


Residuals vs Fitted
Residuals
Fitted values
lm(Outcome ~ (.))
5
15
12
-20
0
20
40
0
20
40
60
80
100
120


Normal Q-Q
Standardized residuals
Theoretical Quantiles
lm(Outcome ~ (.))
12
15
5
-1.0
0.0
1.0
2.0
-2
-1
0
1
2

Boxcox

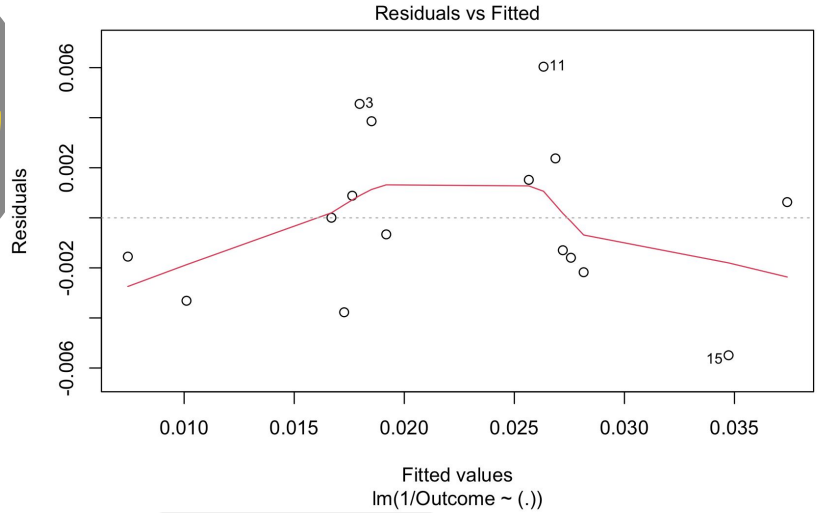
Interpretation: Rate

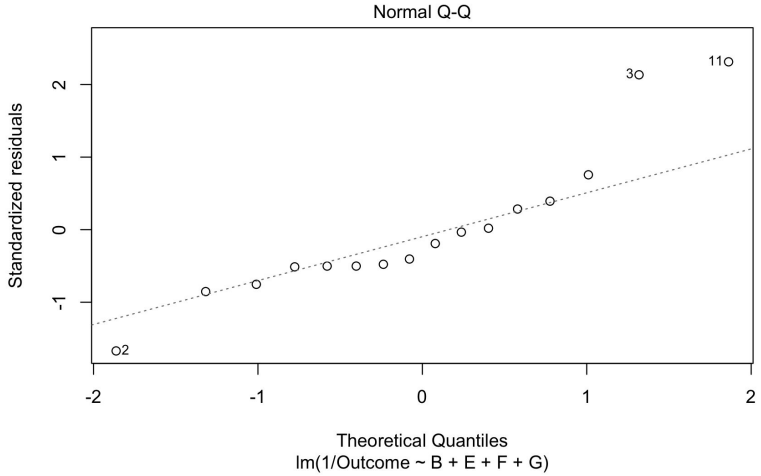


Inverse transform model

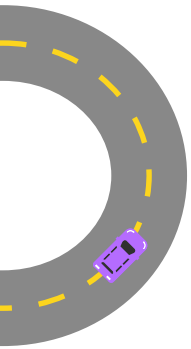
Predictor	Estimate	Pval
Intercept	0.02241	2.96e-08 ***
A (Metering)	0.00036	0.74413
B (Speed Limit 1)	-0.00441	0.00346 **
C (Speed Limit 2)	-0.00196	0.10582
D (Truck density)	-0.00218	0.07782 .
E (Acceleration)	-0.00272	0.03523 *
F (Politeness)	-0.00293	0.02616 *
G (Inflow)	0.004335	0.00381 **

Residual Plots



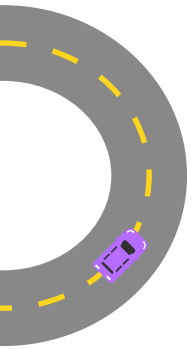


Central Composite Design



- Trying to estimate error variance, interaction effects, and quadratic effects
- 16 Cube Points, 8 Star Points, 6 Center Points, 30 total runs in random order
- Only 4 predictors, no aliasing
- α is about 1.5
- New Setup:
  - New output: Time until congestion near ramp
  - Higher timelapse: 20
  - Higher onramp flow: 1000 veh/hour
  - Truck rate: 10%
  - Max speed: 120 kph
- New levels
  - Speed limit 1: (50/60/80/100/120)
  - Acceleration: (1.2/1.5/2/2.5/2.8)
  - Politeness: (-0.2/0/0.3/0.6/0.8)
  - Onflow: (4200/4400/4800/5200/5400)

Design table



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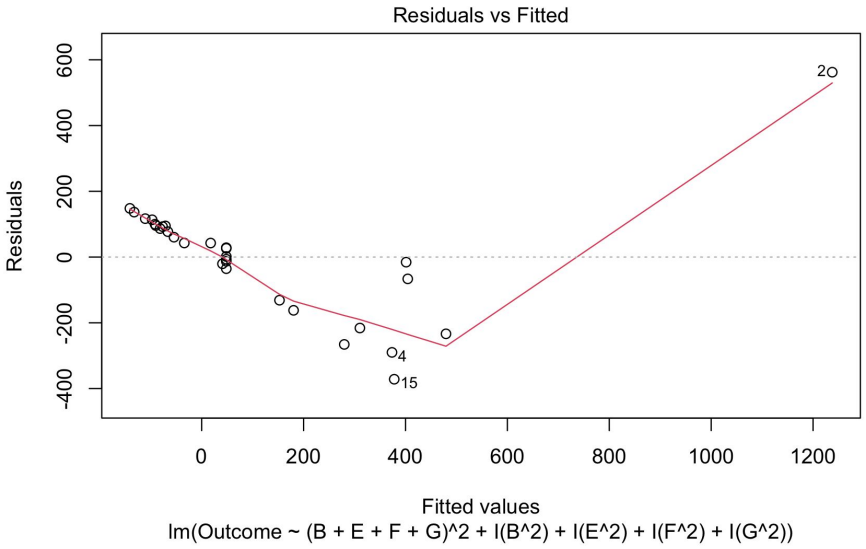
21	24	0	0	0	-1.5	21.4
29	25	0	0	0	0	41.7
13	26	0	0	0	0	76.7
16	27	0	0	0	0	12.9
2	28	0	0	0	0	49.9
12	29	0	0	0	0	35.4
6	30	0	0	0	0	74.8

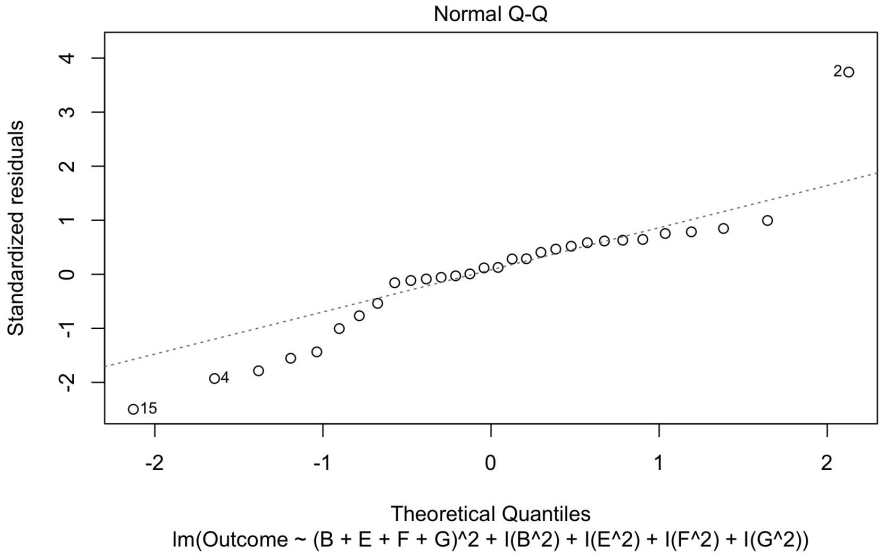
Linear Model

Predictor	Estimate	P-val
Intercept	48.249	0.6057
B	125.799	0.0305 *
E	128.770	0.0320 *
F	93.853	0.932 .
G	-81.456	0.1500
B^2	26.149	0.6411
E^2	88.156	0.2743
F^2	-8.768	0.8886
G^2	-7.881	0.9139

Predictor	Estimate	P-val
B:E	126.588	0.0548 .
B:F	123.575	0.0601 .
B:G	-102.963	0.1109
E:F	114.100	0.0800 .
E:G	-94.113	0.1423
F:G	-100.550	0.1188

Residuals



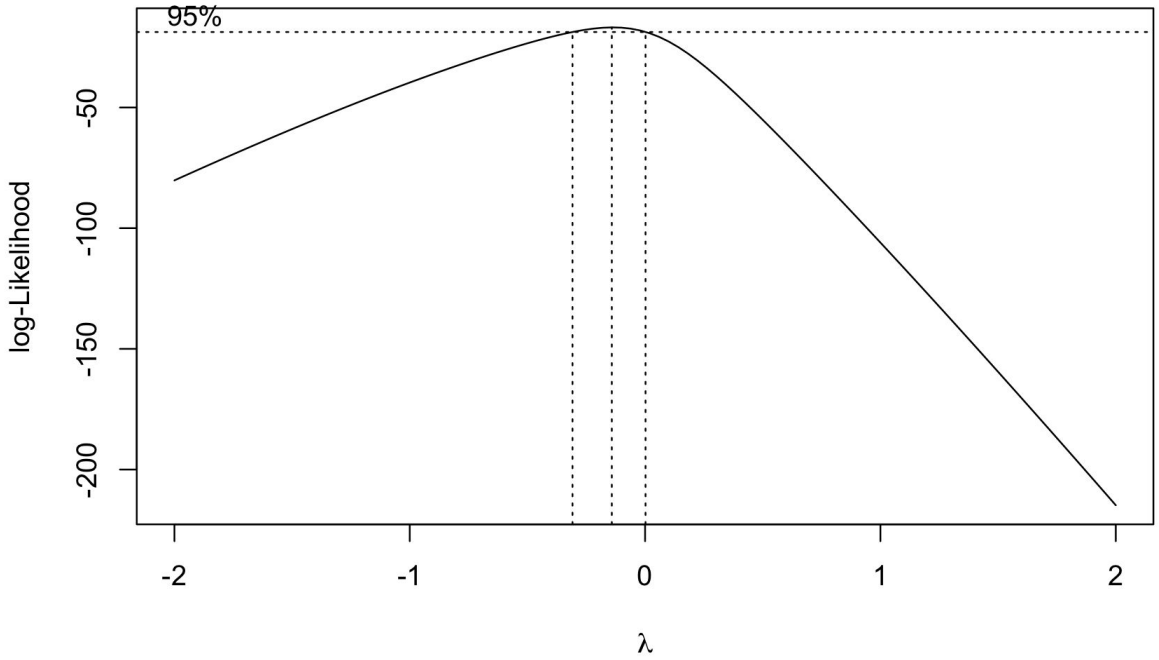


Point 2 is an extreme outlier (it took about 30 mins for traffic to occur*)

Boxcox

Use Log transform

Waiting time in Poisson process is distributed as an exponential RV. Our transformed model's parameters can be thought of as the negative log of the rate of the Poisson process.

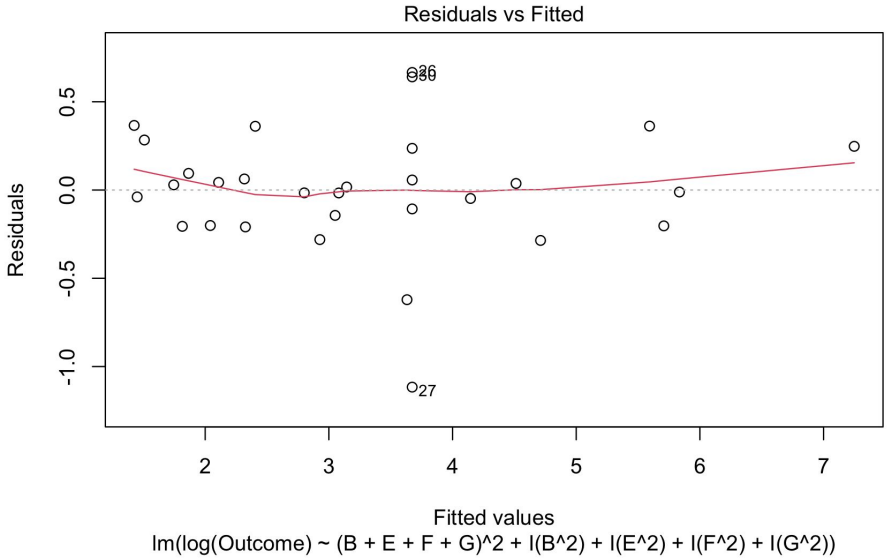


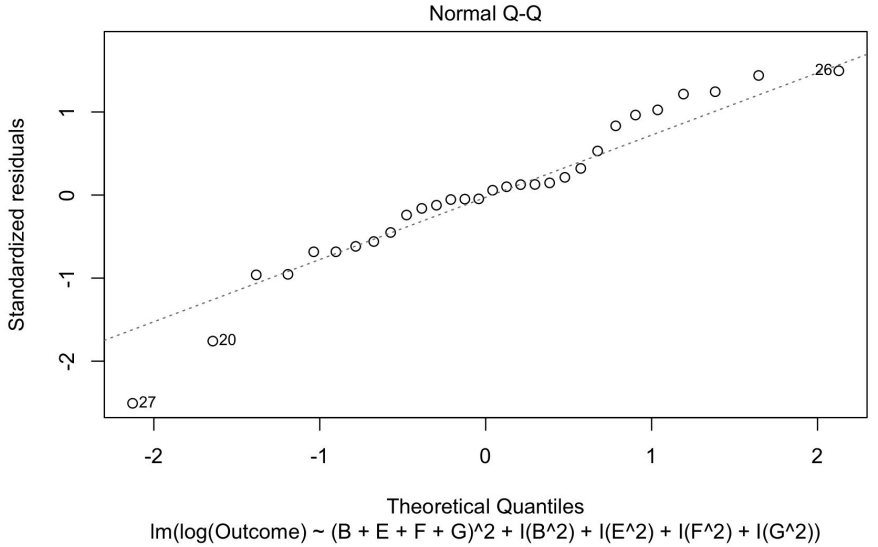
Log Model

Predictor	Estimate	P-val
Intercept	3.67376	2.54e-12 ***
B	1.17108	1.04e-08 ***
E	0.70041	9.97e-06 ***
F	0.48011	0.000322 ***
G	-0.25155	0.031655 *
B^2	-0.04533	0.682514
E^2	0.47895	0.007059 **
F^2	-0.51224	0.000757 ***
G^2	-0.43160	0.008184 **

Predictor	Estimate	P-val
B:E	0.41831	0.003351 **
B:F	0.33870	0.0129665 *
B:G	-0.23234	0.072285 .
E:F	0.20600	0.107063
E:G	-0.04254	0.728242
F:G	-0.24332	0.061062 .

Residuals

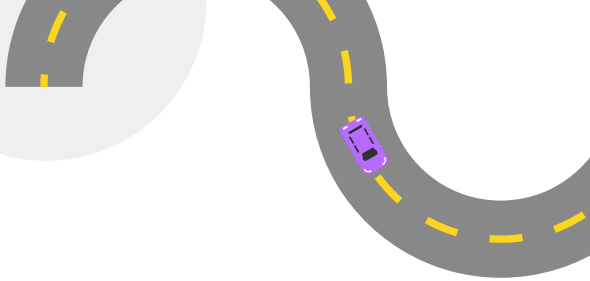

Residuals vs Fitted
Residuals
0.5
0.0
-0.5
-1.0
2
3
4
5
6
7
Fitted values
lm(log(Outcome) ~ (B + E + F + G)^2 + I(B^2) + I(E^2) + I(F^2) + I(G^2))


Normal Q-Q
Standardized residuals
1
0
-1
-2
-2
-1
0
1
2
Theoretical Quantiles
lm(log(Outcome) ~ (B + E + F + G)^2 + I(B^2) + I(E^2) + I(F^2) + I(G^2))

Final Model

- Adj. R^2: 0.8951
- Residual SE: 0.4838

Predictor	Estimate	P-val
Intercept	3.6449	2.42e-14 ***
B	1.1623	1.28e-09 ***
E	0.7004	4.45e-06 ***
F	0.4801	0.000219 ***
G	-0.2516	0.030135 *
E^2	0.4738	0.006544 **
F^2	-0.5117	0.000564 ***
G^2	-0.4339	0.006994 **
B:E	0.4183	0.002805 **
B:F	0.3387	0.011834 *
B:G	-0.2323	0.070746 .
F:G	-0.2433	0.059478 .



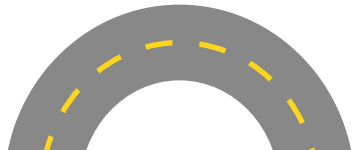
05

Results

Results

$$\begin{aligned}\log(\hat{y}) =& 3.645 + 1.1623x_B + 0.700x_E + 0.480x_F - 0.2516x_G \\ &+ 0.4738x_E^2 - 0.512x_F^2 - 0.4339x_G^2 \\ &+ 0.4183x_Bx_E + 0.3387x_Bx_F - 0.2323x_Bx_G - 0.2433x_Fx_G\end{aligned}$$

- Predictors
  - B: Speed Limit
  - E: Max Acceleration
  - F: Politeness
  - G: Inflow
- Maximize speed limit and acceleration, minimize inflow.
- Politeness should be high, but the negative quadratic term restricts the benefits
- Politeness peaks at around 1.4 (0.7 m/s^2)
  - There is a point where changing lanes can help alleviate congestion
- Interaction terms
  - Higher speed limits make higher accelerations more effective
  - Higher speed limits makes politeness more effective (synergy)
  - Higher speed limits makes lower inflow more effective
  - More politeness makes lower inflow more effective

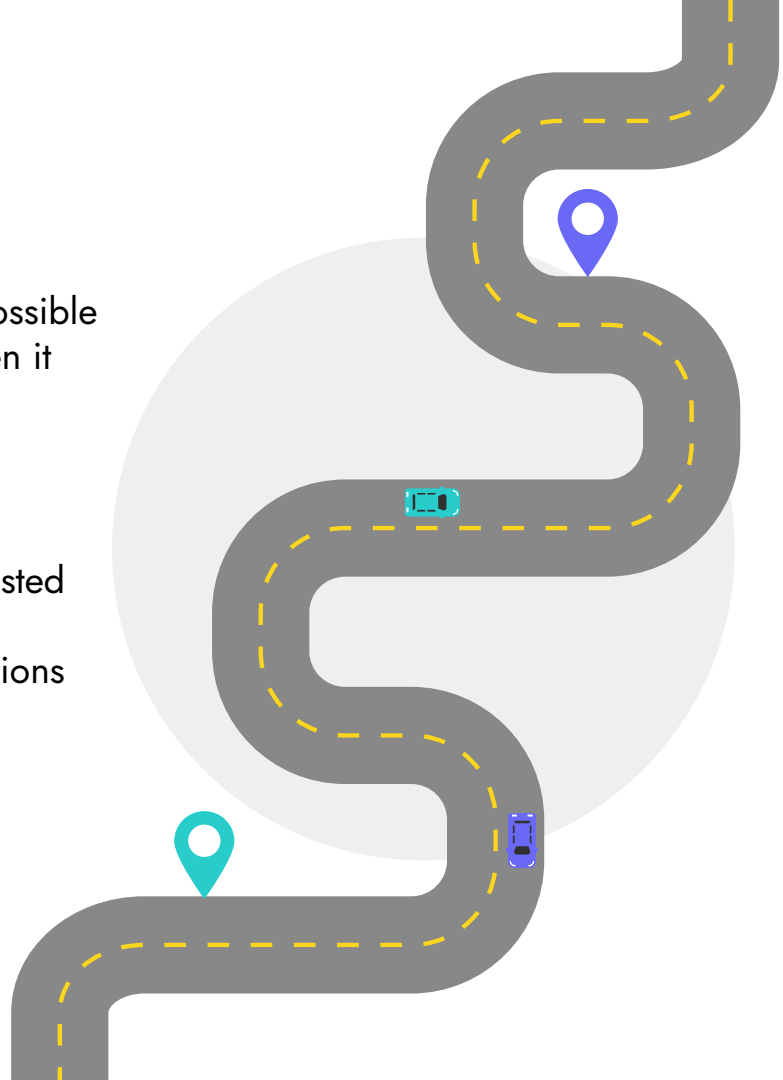


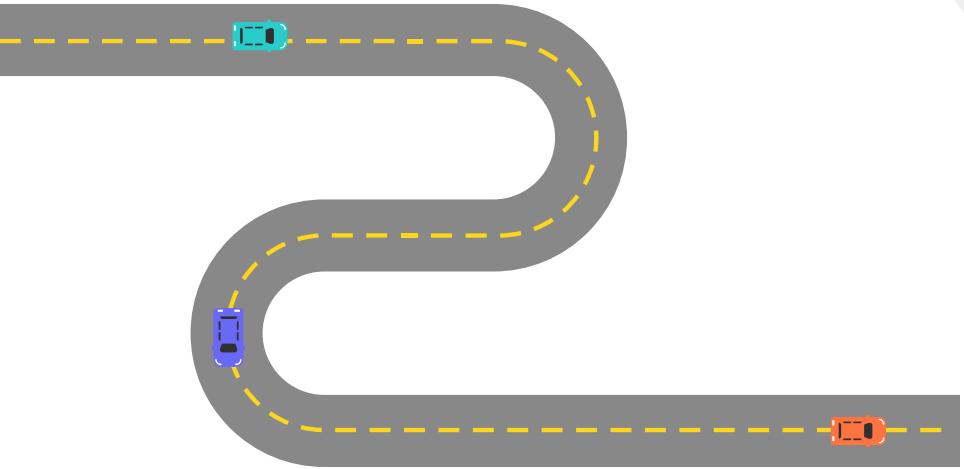
06

Conclusions

Conclusion

- Maximize speed limits (Autobahn)
- Educate drivers
  - Accelerate quickly out of congestion when possible
  - Be polite on the road, only change lanes when it helps everyone
- Decrease number of cars on the road
  - Prioritize public transit, advocate carpooling
- This analysis neglects safety considerations
  - The maximum speed limit and acceleration tested are very high (120 kph, 2.8m/s^2)
- This is a very idealized simulation. Real traffic situations are more chaotic, and traffic has more causes than onramp merging.





Thanks!

Any Questions?

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