

# Using machine learning to support autonomous vehicles making moral decisions

## STAT 451 Project

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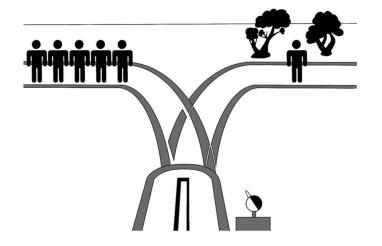
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## ☐ Research Questions

How autonomous vehicle deal with moral dilemmas?

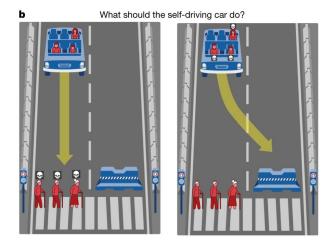




Objective: develop a model to help AV make decisions when facing moral dilemmas.

## ☐ Research Questions

➤ If you were an AV, what will you do? — an online experiments conducted by Edmond et al., 2018.

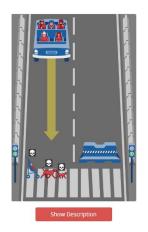


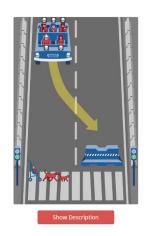
Q1: What model can help to make moral decisions from a human perspective?

Q2: What features (attributes of the characters and the situations) influence individuals' moral preferences to save or sacrifice specific groups in AV-related dilemmas?

## Datasets and methods

- ➤ Each row is a scenario, which is a combination of people with different characteristics.
- > total: 10505 rows/observations





(one scenario example)

 children	dog	cat	 old male	old female		
 1	1	1	 0	0	•••	

## Datasets and methods

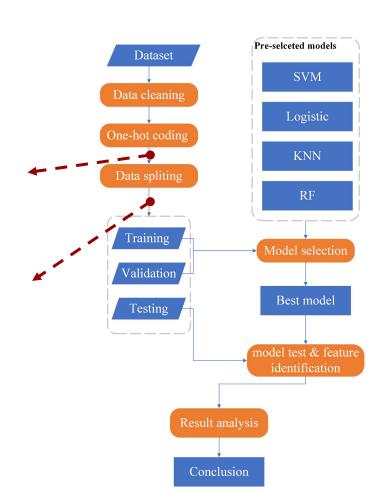
> Technique routes

#### One-hot encoding:

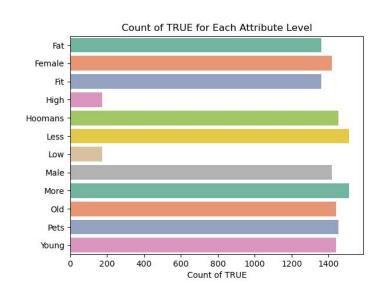
• 10505 × 112 (111 features + 1 target variable)

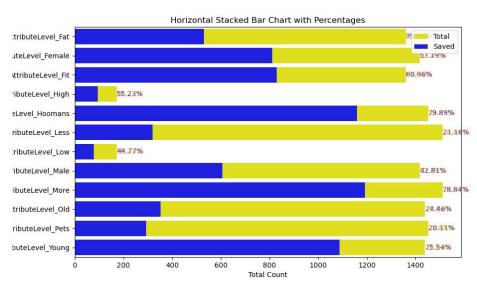
#### Data splitting:

- training data (7353, 112) 70%
- validation data (1576, 112) 15%
- testing data (1576, 112) 15%



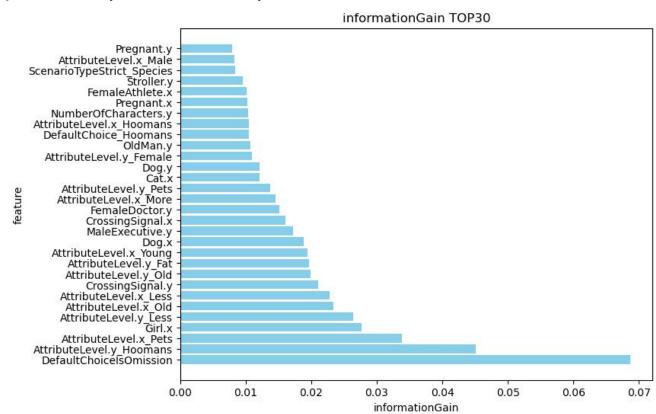
## Exploratory Data Analysis





## ☐ Results

Exploratory Data Analysis



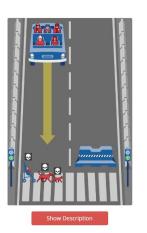
# Preprocessing

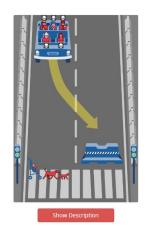
Two rows with the same ID



One row with feature labeled .x and .y

Remove the same or contrary features in .y





	children.x	dog.x	Intervention.x	 children.y	dog.y	Intervention.y	
•••	1	1	0	 0	1	1	

# Preprocessing

- 1. Choose the rows from the US
- 2. Combine rows and remove some .y features
- 3. Remove rows contain missing values
- 4. One-hot encoding
- 5. Data splitting:
  - training data (7353, 112) 70%
  - validation data (1576, 112) 15%
  - testing data (1576, 112) 15%

## ☐ Results

> Model performance

prediction

**SVM** 

**RF** 

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	positive	negative	
positive	464	252	
negative	182	678	

	positive	negative
positive	465	251
negative	207	653

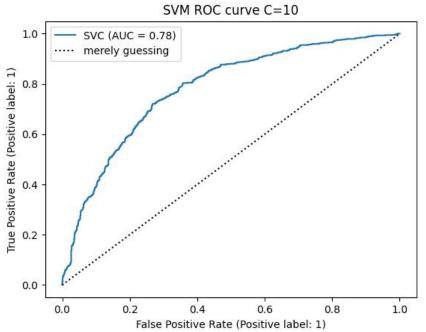
### **kNN**

	positive	negative	
positive	437	279	
negative	191	669	

## Logisti

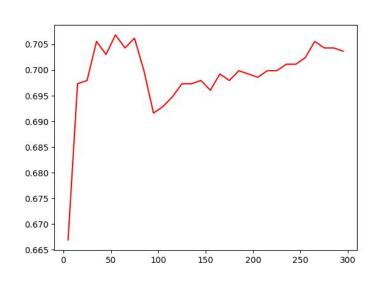
	~		
	positive	negative	
positive	469	247	
negative	187	673	

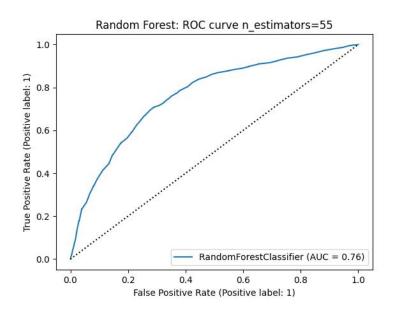
> SVM (C=10,kernel='rbf',probability=True)



On test data, accuracy:0.725, precision score: 0.729, recall score: 0.788

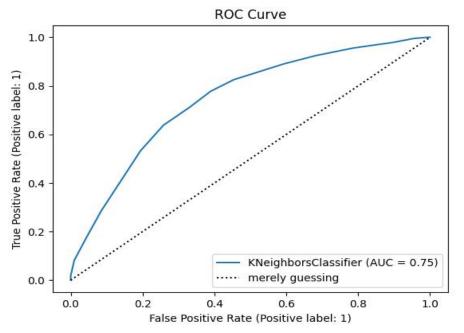
Random Forest (n\_estimators=55)





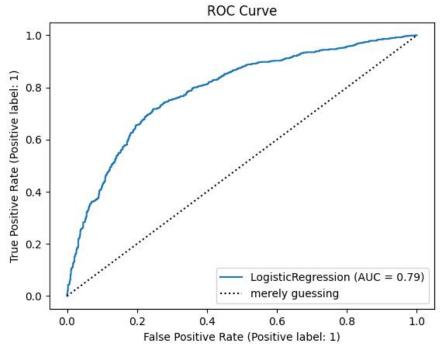
On test data, accuracy:0.709, precision score: 0.722, recall score: 0.759

kNN (metric='euclidean', n\_neighbors=17)



On test data, accuracy:0.702, precision score: 0.778, recall score: 0.706

Logistic Regression (C=2, max\_iter=500)



On test data, accuracy:0.725, precision score: 0.783, recall score: 0.732

## Conclusion

- Models
- > Features

ScenarioOrder: 0.0968961397961013 CrossingSignal.y: 0.039959649151486726

NumberOfCharacters.x: 0.03857100216475041 NumberOfCharacters.y: 0.03704163729547549

DefaultChoiceIsOmission.y: 0.03203180845558651 CrossingSignal.x: 0.03171784452507852

DefaultChoiceIsOmission.x: 0.02612886372150328

JefaultChoicelsUmission.x: 0.02612886372150328

Man. y: 0.0236415643118627 Woman. y: 0.022573508764777556 Man. x: 0.02109407822013728 Woman. x: 0.02068058292891325 LeftHand. x: 0.019733409611225015

LeftHand.y: 0.01948737424878349 Barrier.x: 0.01934453516860985 PedPed: 0.01864154637011021

DescriptionShown. x: 0.018388277915336426 DescriptionShown. y: 0.017563617457196944 Template.x\_Mobile: 0.016484783205943532 Template.v Mobile: 0.015245619133468178

Barrier. y: 0.014658707335310567

## ☐ Conclusion

- > Takeaway
- > What to improve

