Enriching Transportation Survey Datasets Using Big Data and Machine Learning

With an Application for Transferring Attitudinal Variables across Transport Surveys

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Georgia Institute of Technology
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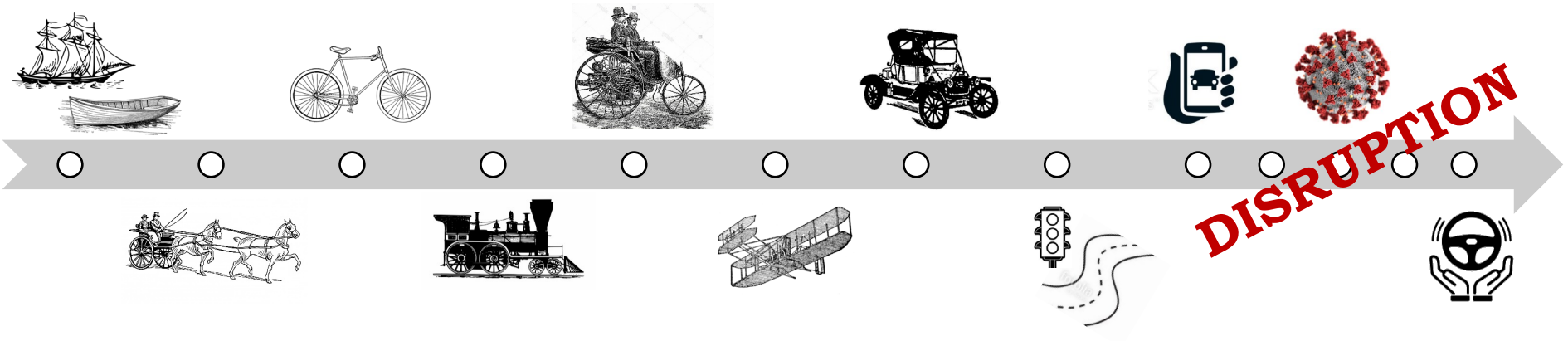
Unprecedented changes occurring rapidly…

across multiple dimensions



Technologies

- Uber, Lyft, car/bike-sharing, etc.
- Long-range electric vehicles
- Autonomous vehicles, drones
- Virtual reality “travel” experiences

Societal shifts

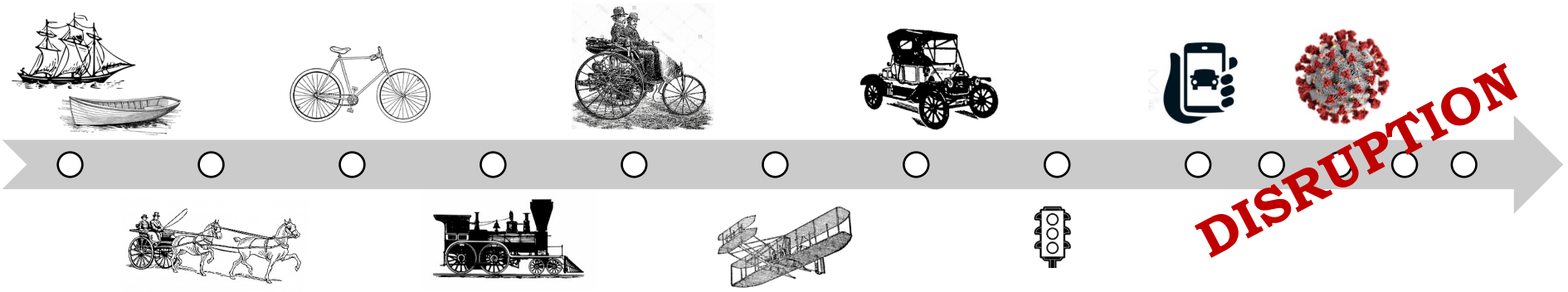
- Delayed or deferred marriage and childbearing
- Greater education
- Increasing ethnic diversity
- Shifting values

Policy instruments

- Denser, more diverse land uses
- Changing revenue base away from fuel taxes
- Yet-to-be-determined AV policies

Improving behavioral forecasting

Two approaches: functions or data



Behavioral decision-making

$$\begin{cases} Mobility\ Patterns_{today} = f_{today}(x_{today}) \\ Mobility\ Patterns_{future} = f_{today}(x'_{future}) \end{cases}$$

functions:

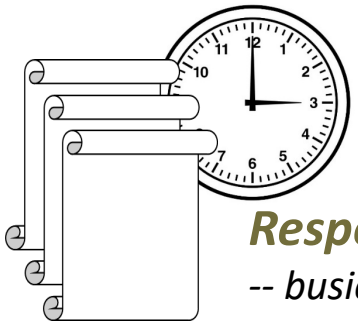
- *machine learning*
- *latent variable models*
- *advanced discrete choice models*

data:

- *passive data streams*
  - *big data: mobile phone location data, etc.*
- *active data streams*
  - *survey data*

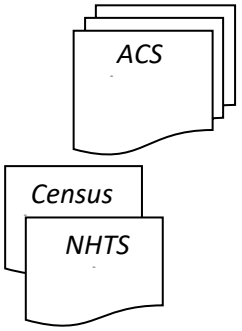
Obtaining good survey data is getting harder…

…and all evidence indicates this will continue

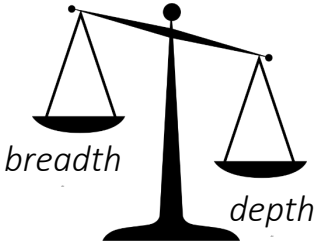


Respondents have gotten

-- busier
-- more "jaded"
-- more distracted

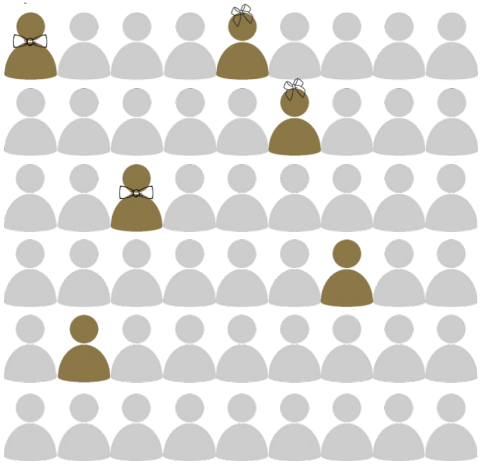


Finding a balance in content



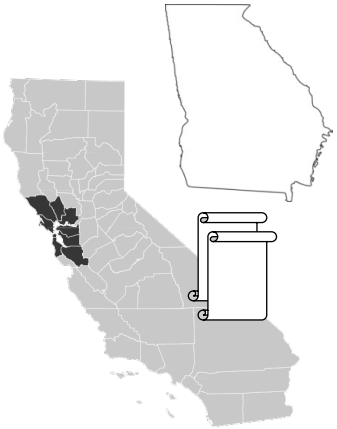
Longer surveys

→ lower response rates,
→ increased survey bias



Large-scale surveys like the National Household Travel Survey (NHTS)

-- socio-economic characteristics
-- observed travel behavior attributes
-- across a nationwide sample



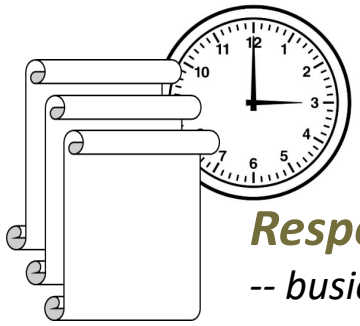
Smaller studies

-- broader set of variables
-- smaller samples
-- limited geographic areas

Large-scale household travel surveys

How can we get rich variables like attitudes into them?

Option 1: ask some attitudinal q's on the survey itself - easier said than done



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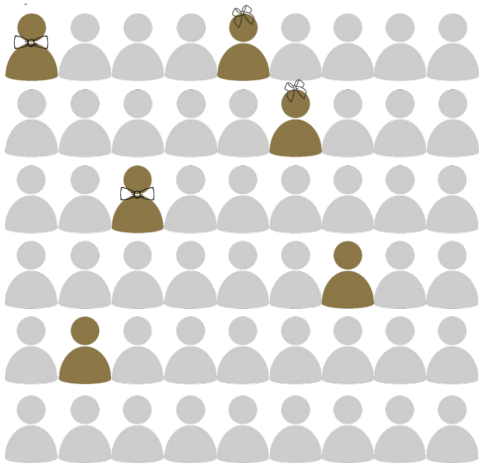
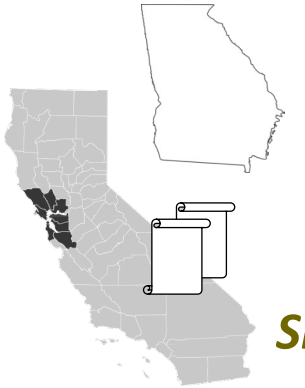
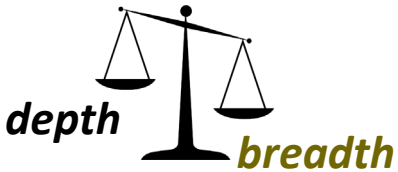


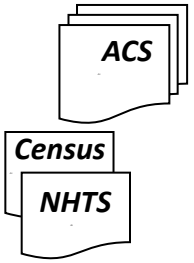
Large-scale household travel surveys

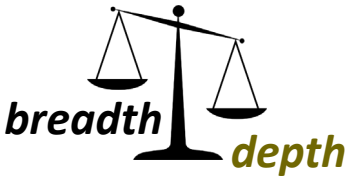
How can we get rich variables like attitudes into them?

Option 2: *"transfer" the info from other surveys*









Smaller studies

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-- smaller samples

-- limited geographic areas

National/regional surveys like NHTS

-- socio-economic characteristics

-- observed travel behavior attributes

-- sample drawn across a large area

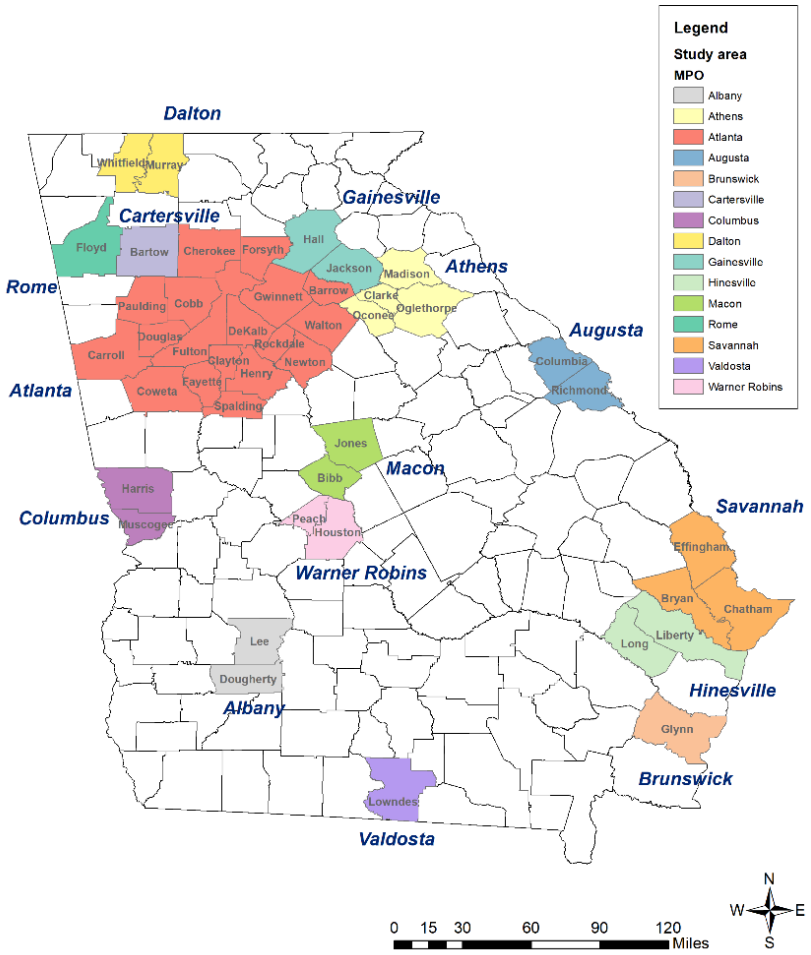
*Taking information from richer studies could be useful for lots of difficult-to-measure variable types (e.g. other **psychometric variables**)*

GDOT emerging technologies survey

The smaller, variable-rich survey – the "donor"

- **Purpose**:
  - To understand the impacts of emerging technologies and trends on travel behavior in Georgia (GA)
- **Details:**
  - Conducted Fall 2017
  - Invited sample: 15 MPO areas
  - ***Current*** N ~ 3300
- **Contents:**
  - ***A : Attitudes and personality***
  - *B : Technology usage*
  - *C : Key aspects of lifestyle*
  - *D : How you travel*
  - ***E : Evolving transportation services***
  - *F : Desires for future travel*
  - *G : Autonomous vehicles*
  - ***H : Sociodemographic traits***

Study area (15 MPOs, 45 counties)

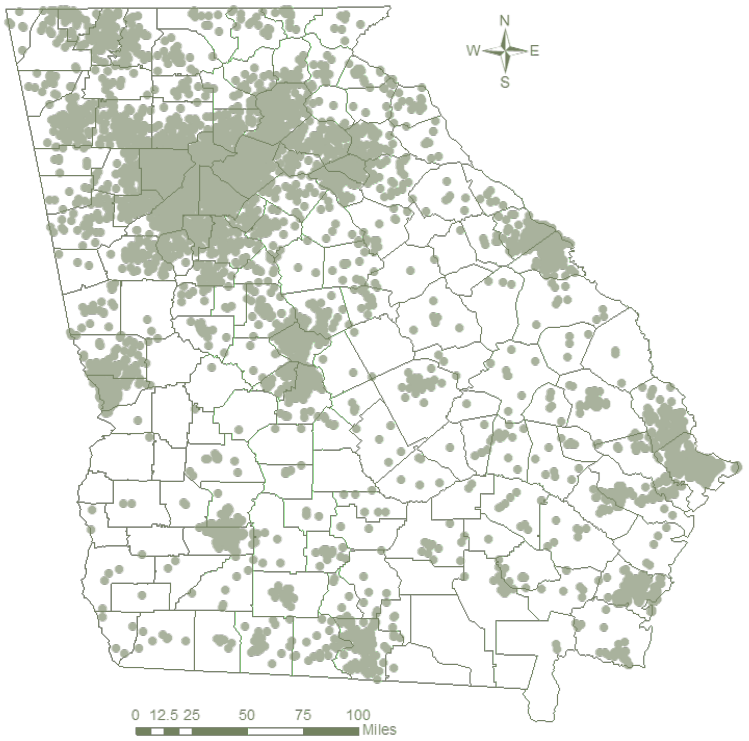


National Household Travel Survey (NHTS)

The national large-scale survey – the "recipient"

- **Purpose:**
  - To support travel demand modeling & long-range transportation planning across U.S.
- **Details:**
  - Repeated cross-sectional travel behavior survey
  - Georgia subsample used in this study
  - Wave: April 2016 to May 2017
  - ***Original*** N ~ 8632 (GA respondents)
- **Contents:**
  - ***Household data module***
  - *Long distance module*
  - *Vehicle data module*
  - ***Person level module***
  - *Person trips module*
  - ***Person health module***
  - *Person drive module*

Georgia subsample of 2016-17 NHTS respondents

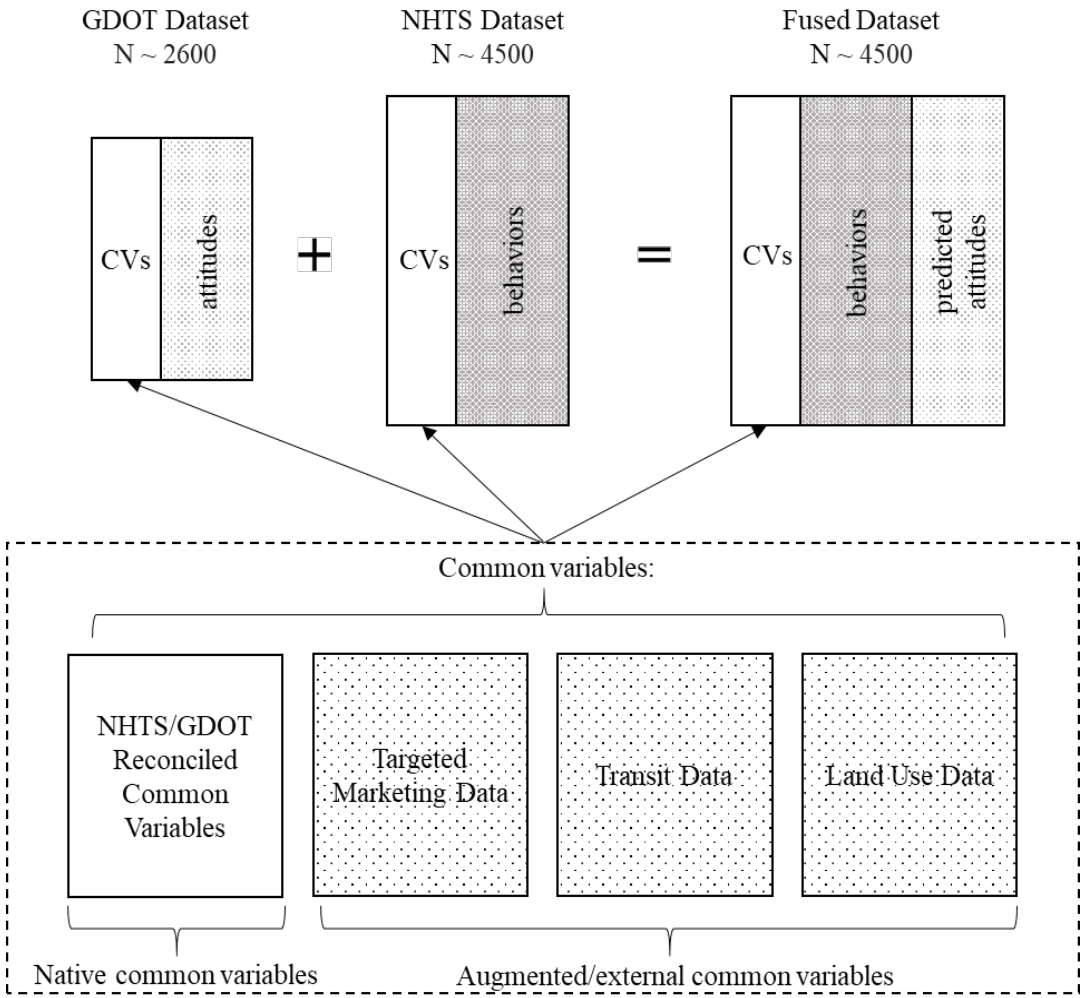


Expanding transportation survey datasets

Using common variables to transfer attitudes

$$Attitudes_{GDOT} = f_{GDOT}(CV_{GDOT}, augCV_{GDOT}) + \varepsilon_{GDOT}$$

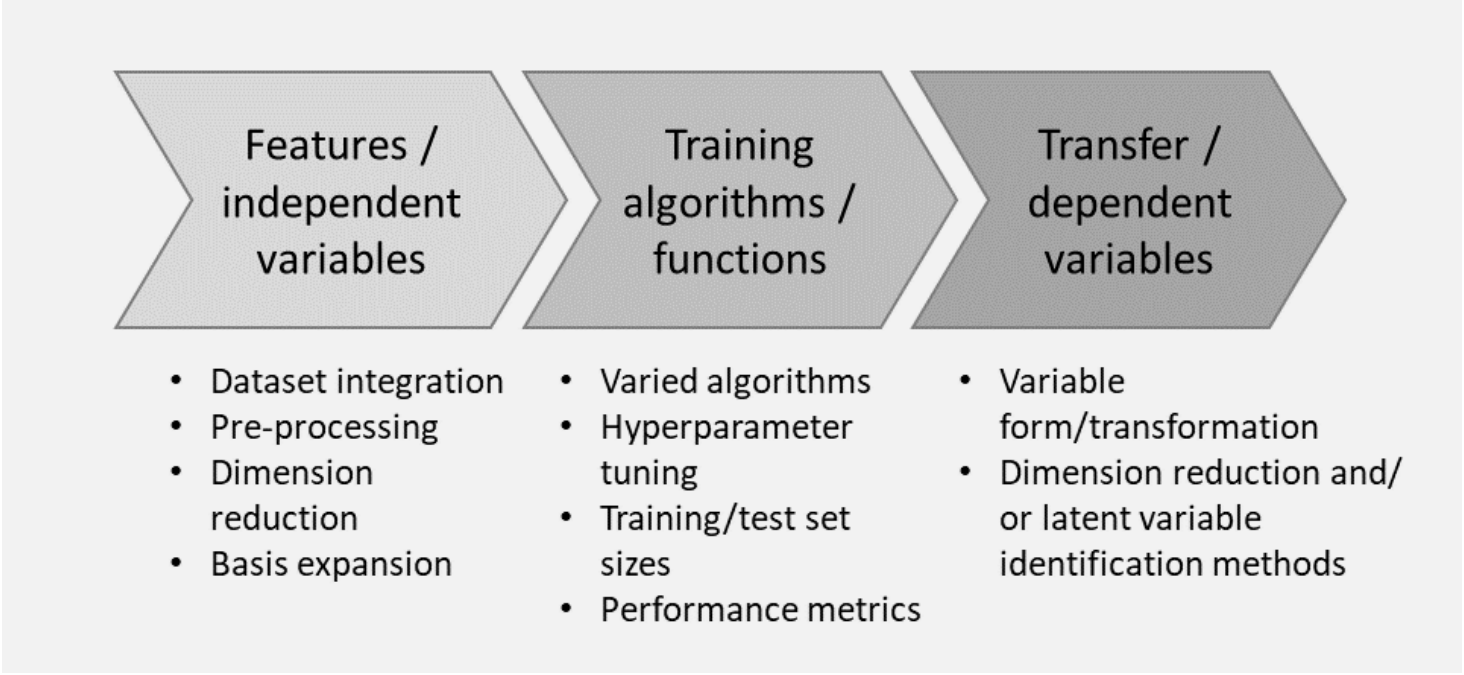
$$\widehat{Attitudes}_{Fused} = f_{GDOT}(CV_{NHTS}, augCV_{NHTS})$$



Expanding transportation survey datasets

Components of transfer process

- **Transfer variables**: variables of interest being transferred across datasets
- **Features**: inputs to the training algorithm that are used to model/predict the transfer variables
- **Training algorithms**: used to transfer the variables across datasets



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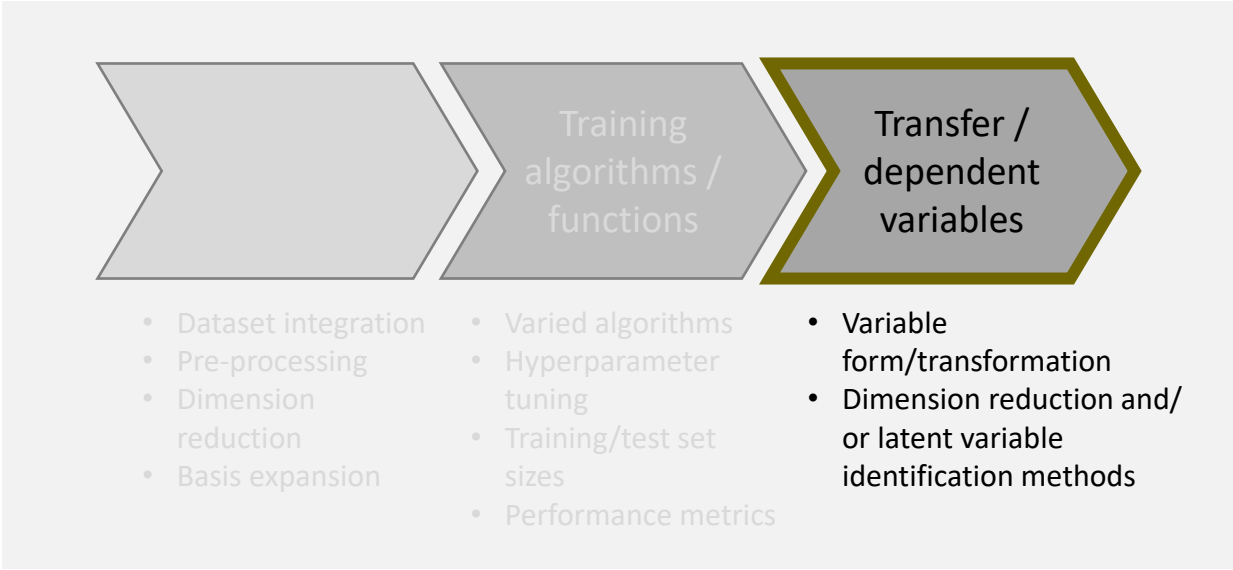

Transfer variables

Introducing the attitudinal variables for transfer

	Name	Example statement
Lifestyle	Tech Savvy	Learning how to use new technologies is often frustrating for me (-)
	Work-oriented	… having fun is more important to me than working hard (-)
	Pro-exercise	I am committed to exercising regularly
	Materialistic	I would/do enjoy having a lot of luxury things
	Family-oriented	Family/friends play a big role in how I schedule my time
Land use	Pro-suburban	I prefer to live in a spacious home, even if it's farther away ...
	Urbanite	I like … having stores, … mixed among the homes in my n'hood
Travel	Non Car Mode	I like the idea of walking [bicycling, PT] as a means of travel for me
	Commute Benefit	My commute is a useful transition between home and work
	Travel Liking	I generally enjoy the act of traveling itself
	Car-owning	I definitely want to own a car
Personality	Polychronic	I prefer to do one thing at a time (-)
	Wait Tolerant	Having to wait is an annoying waste of time (-)
	Environmental	Cost or convenience takes priority over environmental impacts … (-)
	Sociable	I consider myself to be a sociable person

Components of the transfer process

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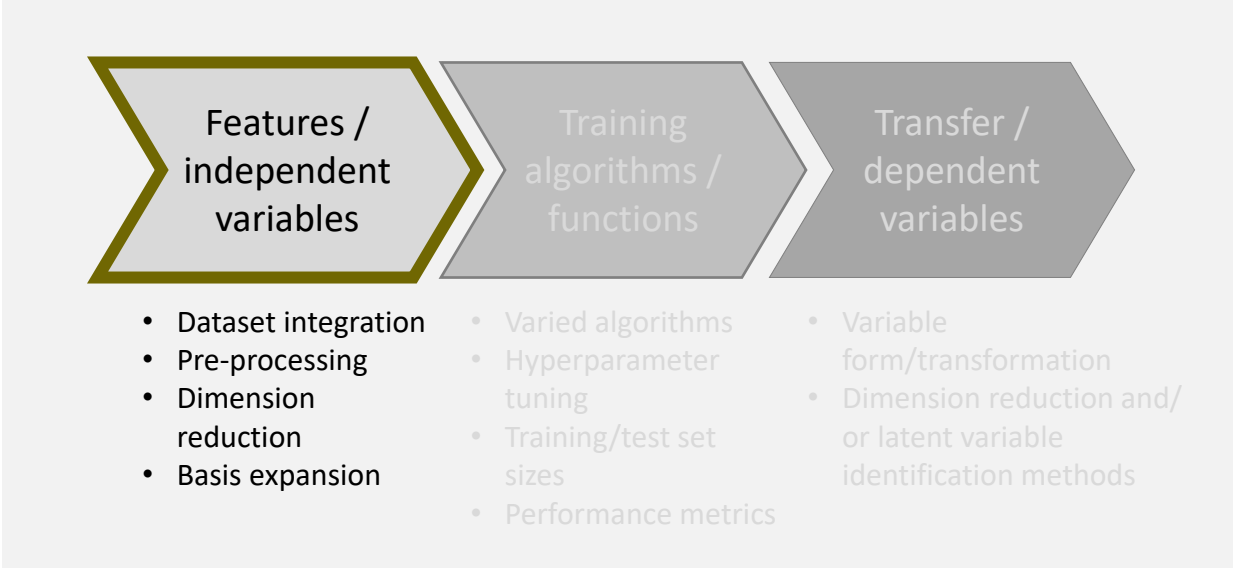


Features

Two types of features available for use

Survey Data Streams

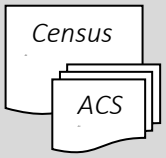
GDOT Emerging Technologies Survey
N ~ 3000

National Household Travel Survey Georgia Subsample
N ~ 8000

External Data Streams

Targeted Marketing Data
N ~ 6000

All Transit Data



Land Use Data

Native common variables – active data sources

- Exist initially in both datasets
- Tend to be SED variables
- Often must be adjusted and recoded across sources

Augmented common variables – passive/active data sources

- Obtained from external active or passive datasets
- Must be appended to both the donor and recipient datasets at either:
  - Household level
  - Individual level
  - Geographic level

Components of the transfer process

Algorithms

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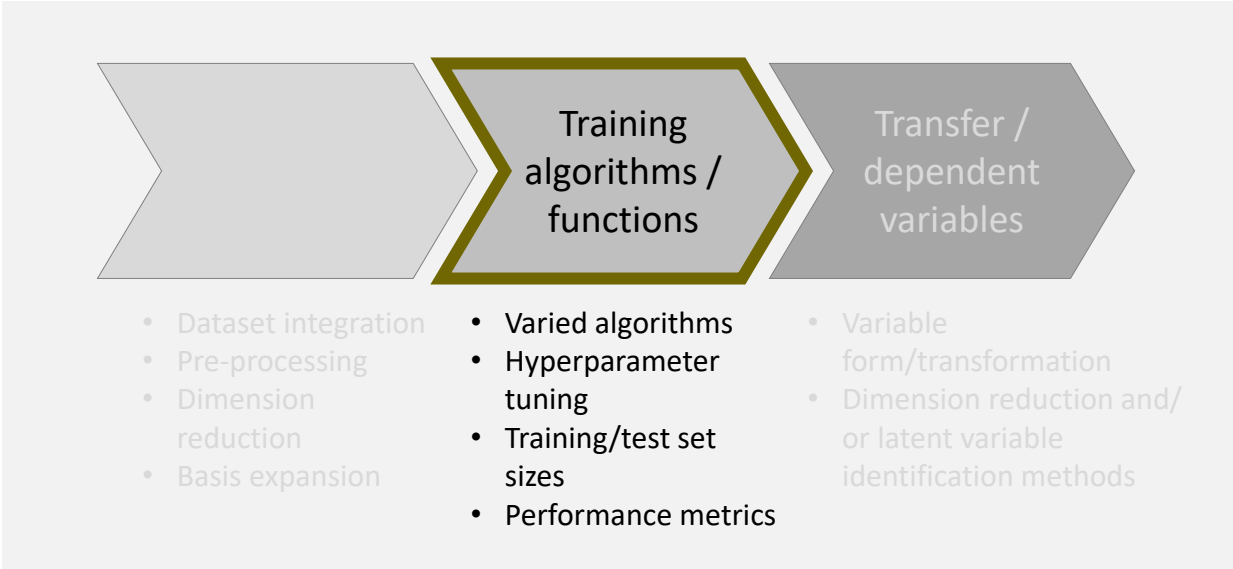


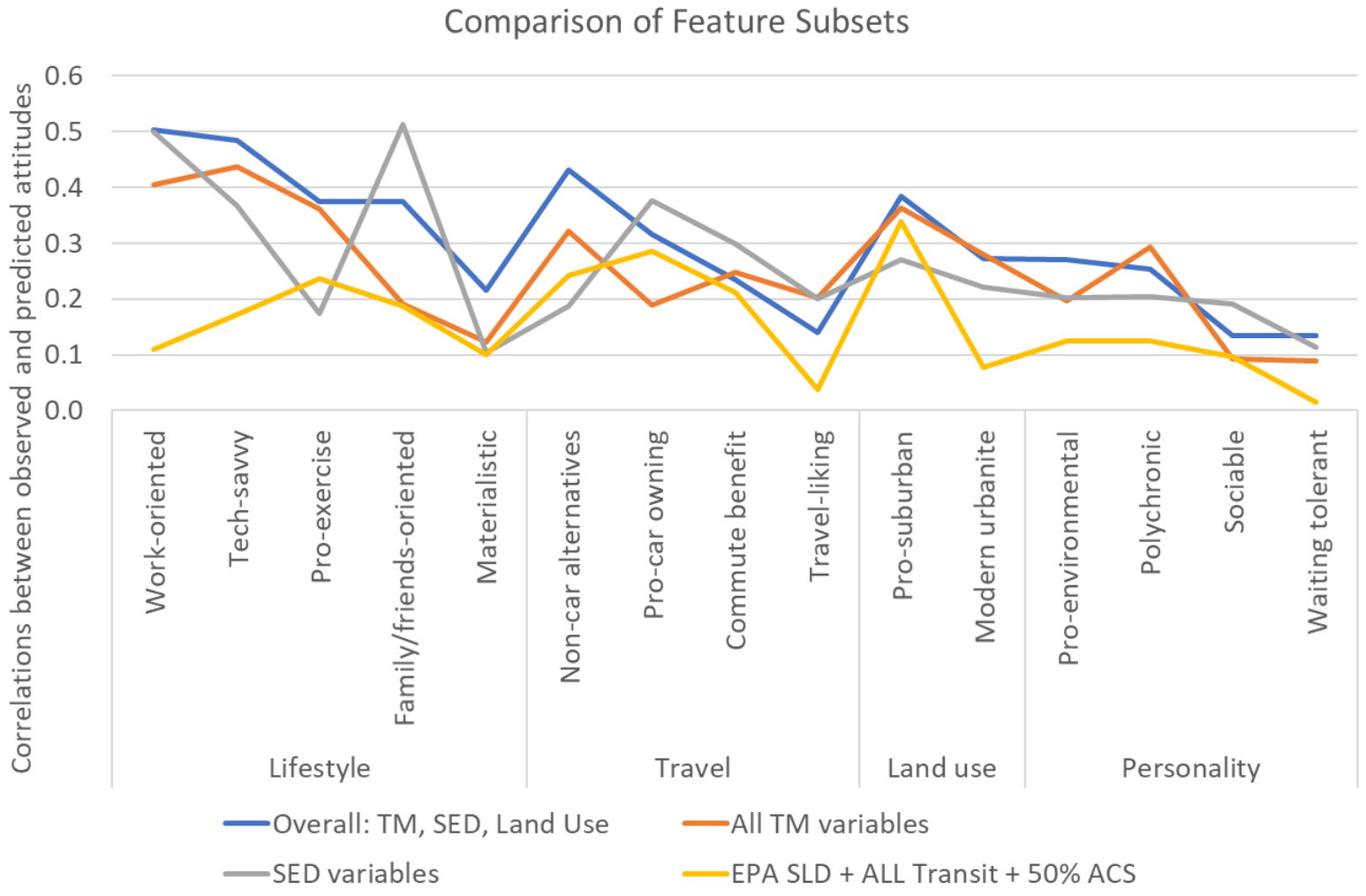
Algorithms

Possible variations within algorithm selection process

- **Algorithm selection**
  - Linear regression, random forest, support vector machine, **elastic net regression**, lasso regression, ridge regression, random forest, extreme gradient boosting
- **Algorithm tuning**
  - Training/test sample split: 80/20
  - Hyperparameter tuning using k-fold cross validation
  - Final metrics on test/hold-out sample
- **Algorithm performance**
  - Possible metrics: R-squared, **correlations (between observed and predicted),** mean squared error, misclassification error, etc.

How well are we transferring variables?

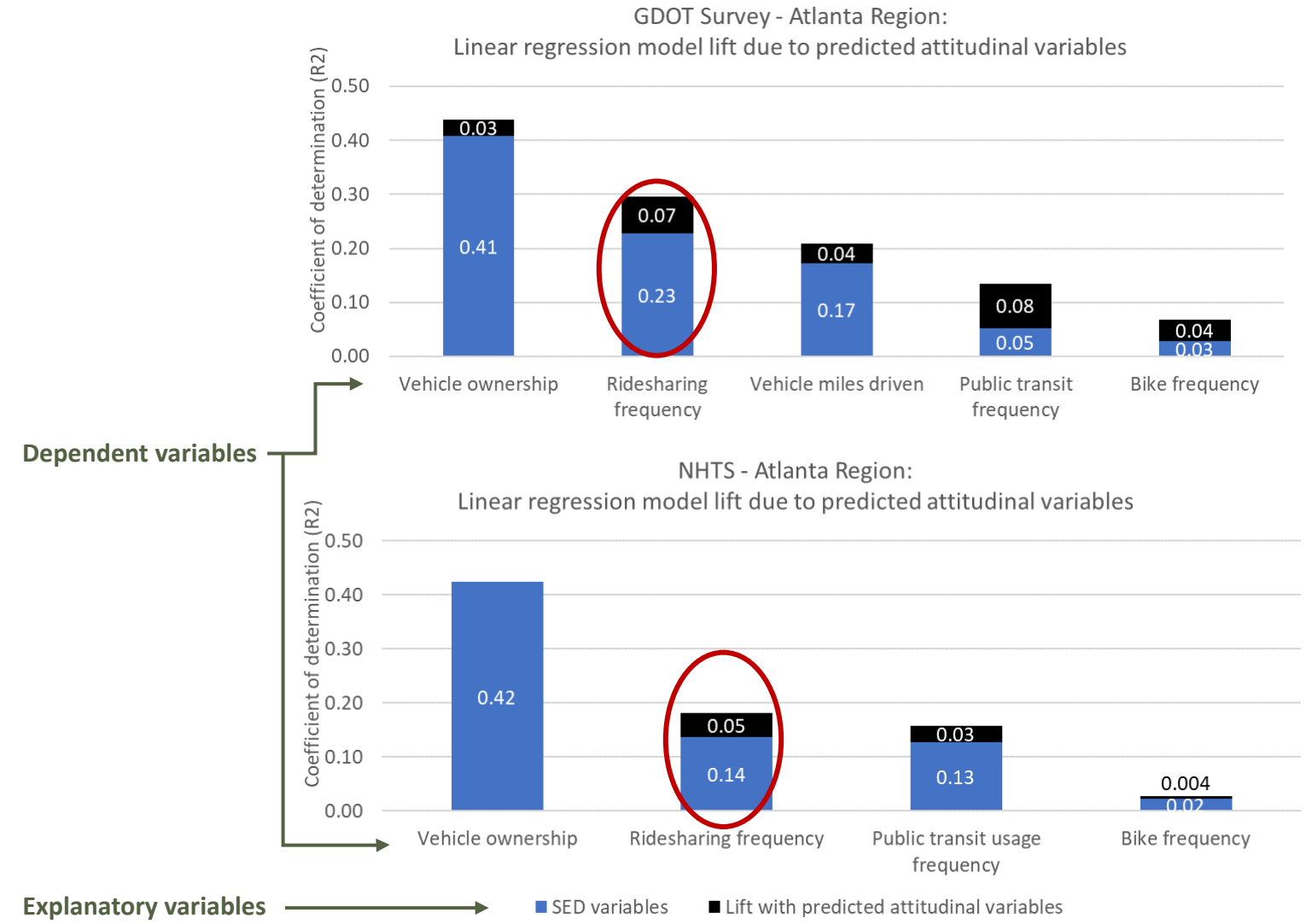
Internal validation



Are the transferred variables any good?

External validation:

How much are they helping in travel behavior models?



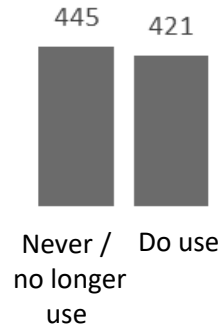
What will we be modeling for external validation?

Atlanta region: Ridehailing frequency

GDOT Survey

4. Please indicate *how often* you typically use each of the following transportation services.

	Never used / No longer use	*Less than once a month*	*1-3 times a month*	*1-2 times a week*	*3 or more times a week*
a. Carsharing	☐1	☐2	☐3	☐4	☐5
b. On-demand ride service	☐1	☐2	☐3	☐4	☐5
c. Shared on-demand ride service	☐1	☐2	☐3	☐4	☐5
d. Traditional taxi service	☐1	☐2	☐3	☐4	☐5

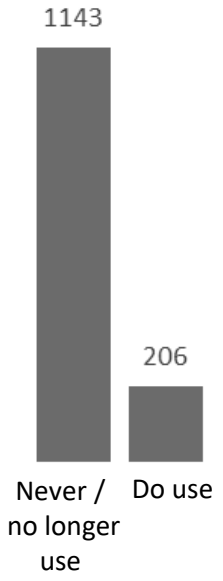


NHTS

RIDESHARE
Range: 0 - 99
ProgrammerNote: Asked if subject is at least 16 years of age

In the past 30 days, how many times [$HAVE_YOU] purchased a ride with a smartphone rideshare app (e.g. Uber, Lyft, Sidecar)?

WEB ATEXT	CATI ATEXT	AVALUE
ENTER NUMBER	ENTER NUMBER	
I don't know	DON'T KNOW	-8
I prefer not to answer	REFUSED	-7



How much are the transferred variables helping?

External validation: linear regression, R^2 values

GDOT Survey

explanatory variables

NHTS

explanatory variables

How much are the transferred variables helping?

Ext· validation: prediction accuracies for choice models

GDOT Survey

NHTS

LCCM: Latent Class Choice Model

Latent class choice model of ridehailing adoption

A preliminary look at some insights!

GDOT model w/ observed attitudes: three latent classes

- Travel liking class
- Family-oriented & car-owning
- Urbanite & tech-savvy

} *Emergent classes*

Choice model

Predictors	Travel-liking	Family-oriented	Urbanite
Education	--	(+) *	(+) **
Age	(-)***	(-) *	(-) **
Household income	(+) ***	--	--
Household size	--	(-) *	(-) **

Benefits:

- Improved predictive accuracy
- Nuanced interpretation
- Slight increase in model fit

Will the predicted attitudes yield similar benefits for GDOT and NHTS?

Study overview

The process in a nutshell…

1 DATA ACQUISITION

- Acquire **source** domain data
- Acquire **target** domain data
- Acquire **targeted marketing data (TMD)** for source and target domain

2 ESTABLISH COMMON VARIABLE SPACE

- Determine **common variables** original to source and target domains
- Determine **TMD augmented** common variables for source and target domains
- Determine **land use augmented** common variables for source and target domains

3 DATA PROCESSING

Prepare the following datasets for analysis:

- **Source** domain data
- **Target** domain data
- **TMD** data
- **Land-use** data

4 MACHINE LEARNING ALGORITHMS

- Determine ML algorithms for testing
- Train, optimize, and cross validate ML algorithms
- Evaluate ML algorithms relative to each other and benchmark measures

5 EXTERNAL VALIDATION

- Select dependent variable(s) that are possible candidates for external validation
- Evaluate model improvement due to imputed attitudinal variables

Study overview

Takeaways

- We can **impute attitudes** reasonably well!
  - …and we're getting better
- **Attitudes improve**:
  - Model fit
  - Model interpretability
  - Predictive accuracy (small increases)
- And **interpretations improve**:
  - Latent class choice models of travel behavior in demand forecasting models!
    - Policy implications of more nuanced segments

Study overview

Looking to the future

- In the **short-term**: let's use what we have!
  - Use trained algorithm to predict attitudes into Atlanta Household Travel Survey
  - How does it affect the final outcomes?
    - Is it moving the outcome in the same direction as the adjustment factors?
- In the **medium-term**: let's get better at predicting attitudes
  - Continued refinement of machine learning models
  - Additional common variables purchased and integrated into attitudinal prediction functions
- In the **long-term**: let's talk attitudinal variables!
  - Attitudinal marker statements that could be included on future household travel surveys
    - Can help us obtain improved predictions of attitudes
    - Can be used directly to improve our travel demand models
    - Will not be highly correlated with other explanatory variables

Thank you!

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