Machine Learning Approach to Travel Modeling

A Reflection with Two Case Studies

Liming Wang Portland State University

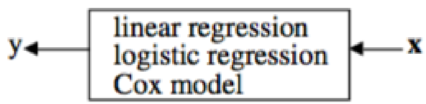
6/26/2018

About me

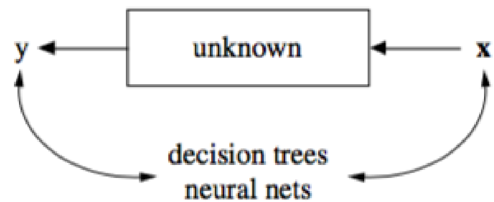
- Currently an assistant professor of Urban Studies and Planning at Portland State University
- Did dissertation research on urban simulation models
- Worked as a developer for UrbanSim for a number of years
- Research interests on land use - transportation interaction (LUTI) models
- Don't have formal computer science training/background

Statistical Modeling vs Machine Learning

Two cultures of developing models (Breiman, 2001):



Model validation. Yes–no using goodness-of-fit tests and residual examination.
Estimated culture population. 98% of all statisticians.



Model validation. Measured by predictive accuracy.
Estimated culture population. 2% of statisticians, many in other fields.

Statistical models ("the data modeling"): Assuming a data generation model and use data and hypothesis testing framework to recover parameters of the data generation process;

Machine learning ("algorithmic modeling"): With no assumption of data generation process, use computer algorithms for pattern recognition and data-driven predictions-making

The End of Theory: The Data Deluge Makes the Scientific Method Obsolete

'Petabytes allow us to say: "Correlation is enough." (…)
We can throw the numbers into the biggest computing clusters the world has ever seen and let statistical algorithms find patterns where science cannot.'

Chris Anderson, WIRED.com, 2008

http://archive.wired.com/science/discoveries/magazine/16-07/pb_theory

Challenges to Statistical Models

Or the case for machine learning:

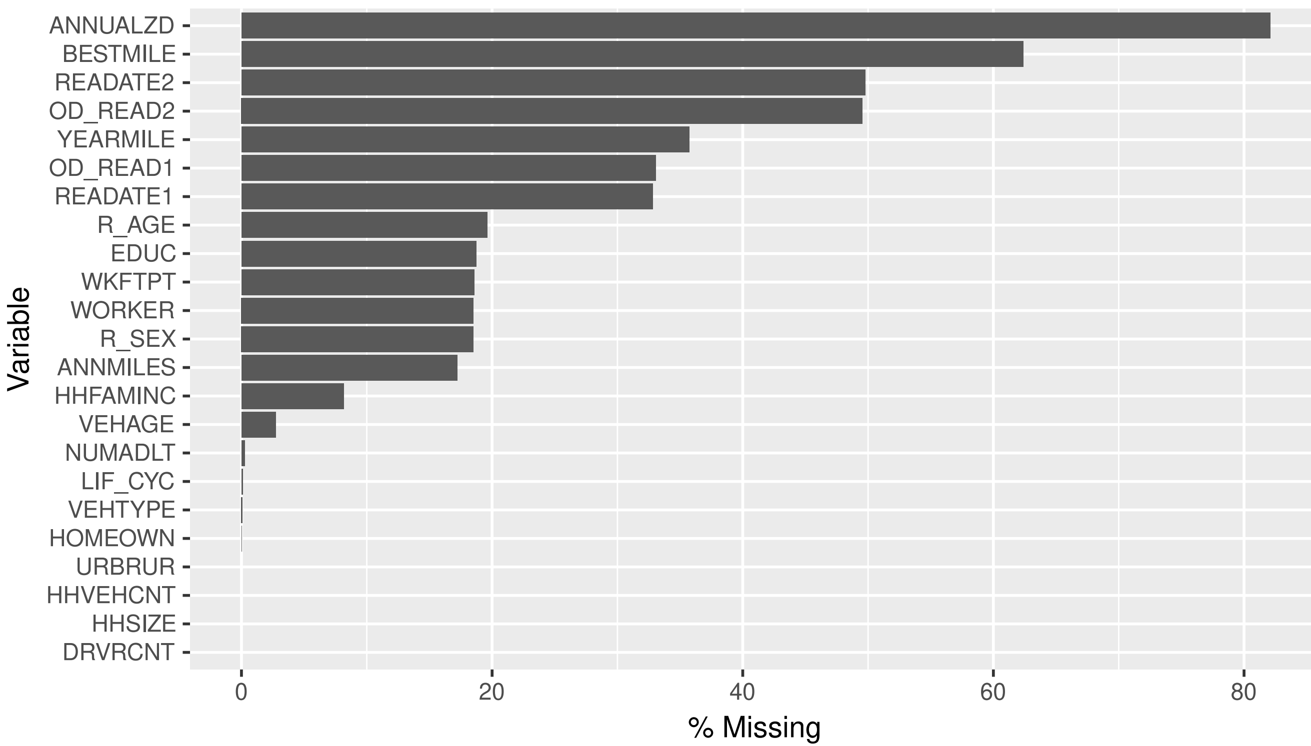
- Assumption/theory of the data generation process may be wrong
- Competing data generation models may give different pictures of the relation between the predictors and response variable;
- Changing landscape of data availability
  - Curse of dimensionality
  - Easy to detect significant correlations with large sample size
  - Increasingly models involving data of the population instead of a sample
  - Missing data issue

Two Case Studies

- Imputation of missing data in travel surveys
- Models travel outcomes (Annual Average Daily VMT)

Case I: Imputation of Missing Data

Annual Vehile Miles Travelled information in the 2001 National Household Travel Survey (NHTS)



Only 12% (17037 out of 139382) observations are complete.

Multiple Imputation by Chained Equations

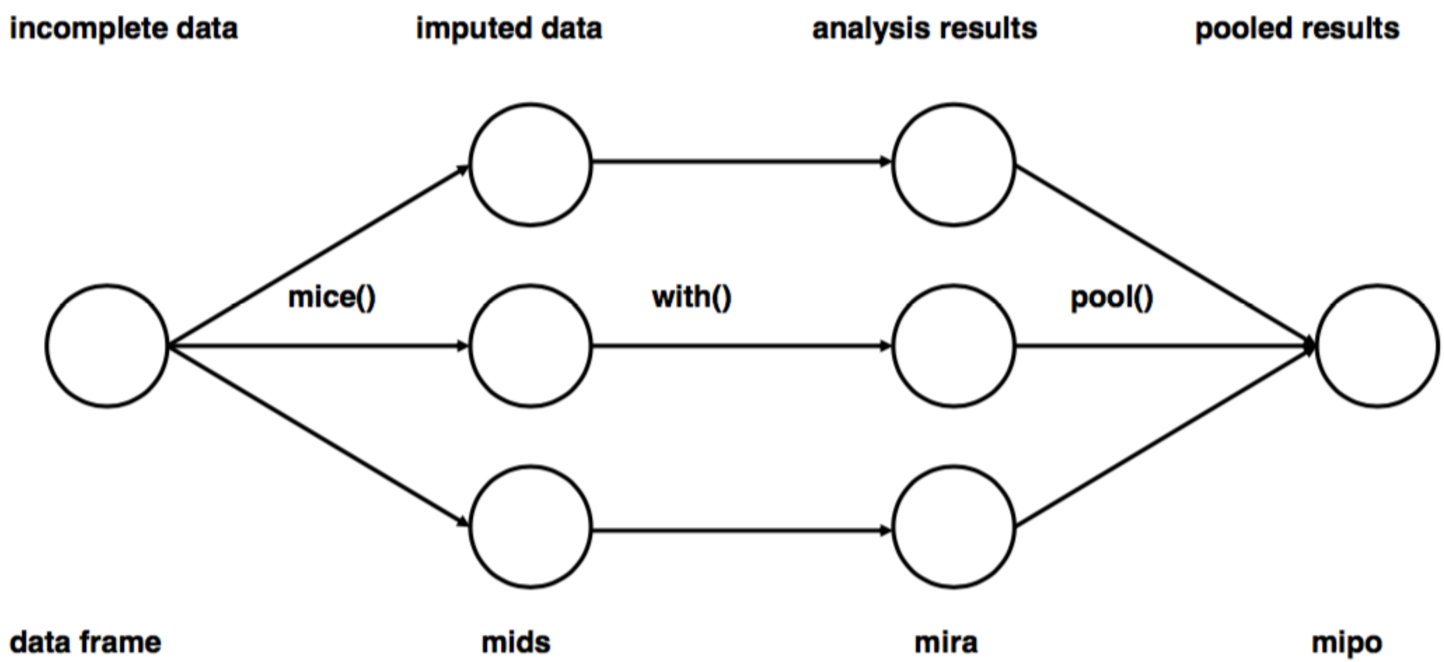


Figure 1: Main steps used in multiple imputation.

Source: van Buuren, Stef and Karin Groothuis-Oudshoorn, 2011. mice: Multivariate Imputation by Chained Equations in R, Journal of Statistical Software, Vol 45 (3).

Imputation Results (1)

Validation: randomly set 10% of values to missing, impute them and compare with actual values

Variable	**Normalized RMSE**
ANNMILES (Self reported annual VMT)	31.8240
ANNUALZD (VMT annualized from two Odmeter readings)	22.2640
HHFAMINC (Family income)	0.0475

Imputation Results (2): Comparing linear regression results (y=ANNUALZD) without and with multiple imputation

	No Imputation	**w/ Imputation**
(Intercept)	8904.27***	8722.34***
	(306.50)	(185.89)
Workers	2497.73***	1912.89***
	(173.60)	(120.73)
Urban	-1321.43***	-908.94***
	(159.87)	(126.99)
Income ($ 30k – 60k)	837.84***	769.23***
	(167.85)	(103.22)
Income ($ 60k+)	1713.78***	1515.67***
	(173.96)	(81.99)
Parents with young children	2003.62***	1356.74***
	(272.99)	(148.76)
Couples w/o children	771.46**	259.57
	(274.32)	(141.73)
Empty nesters	-1195.52***	-1400.96***
	(283.42)	(151.84)
# Drivers	544.21***	508.79***
	(96.55)	(57.33)
Pop. Density (bg)	-0.05*	-0.017
	(0.03)	(0.014)
Emp. Density (tract)	-0.33***	-0.124***
	(0.08)	(0.037)
R^2	0.08	
Adj. R^2	0.08	
Num. obs.	23647	

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Case II: Travel Behavior Modeling

Data Sources:

- 2009 NHTS for household's SES, travel outcome (VMT);
- EPA's Smart Location Database (for blockgroup level 5D built environment measures);
- Highway Performance Measure System for regionwide roadway information;
- National Transit Database for regionwide transit supply.

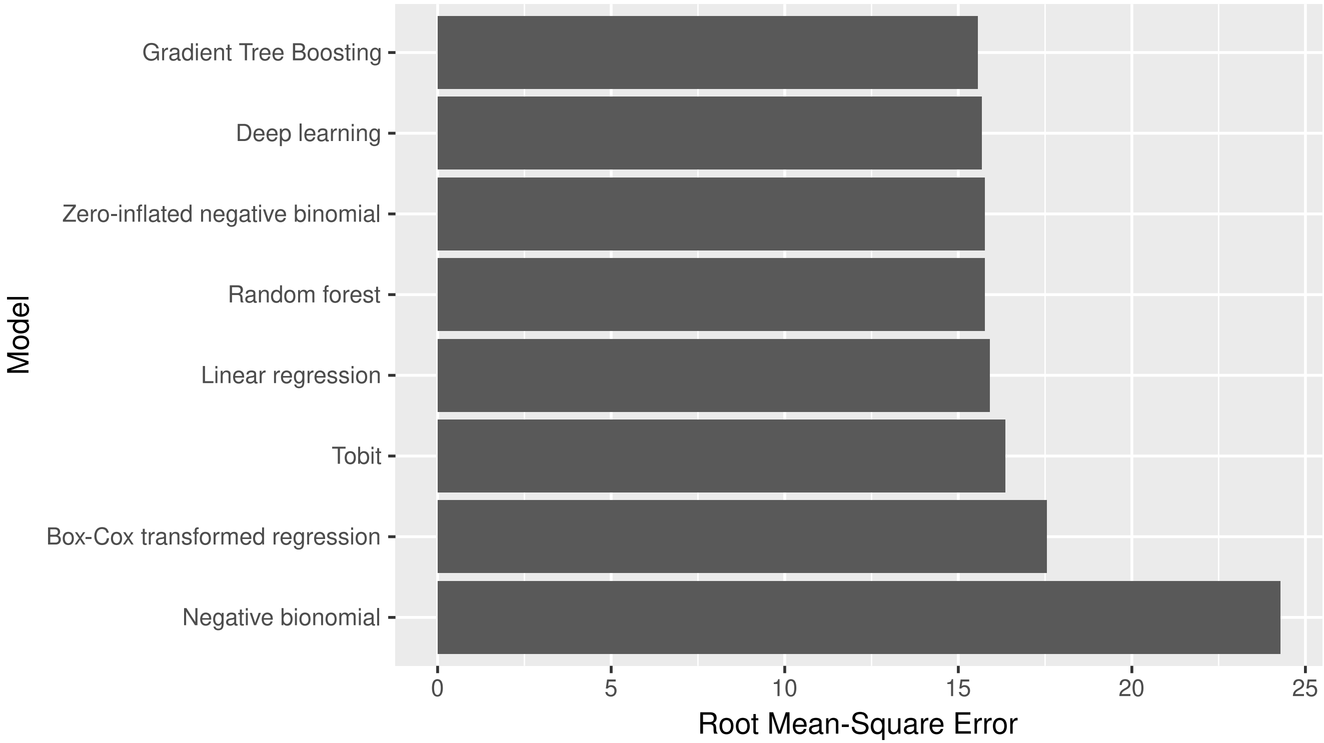
150,000 households with more than 200 independent variables (before considering non-linear transformation or interaction between variables)

VMT models

- Statistical Models
  - linear regression
  - non-linear regression (transformed dependent variable)
  - tobit model
  - zero-inflated negative binomial model
- Machine learning algorithms
  - Random Forest
  - Gradient Tree Boosting
  - Deep Nureal Network

Cross Validation Results

- Dependent variable is household VMT on the day of survey
- Data are randomly partitioned into 5 parts for a 5-fold cross-validation



Conclusion and Discussion

Conclusions:

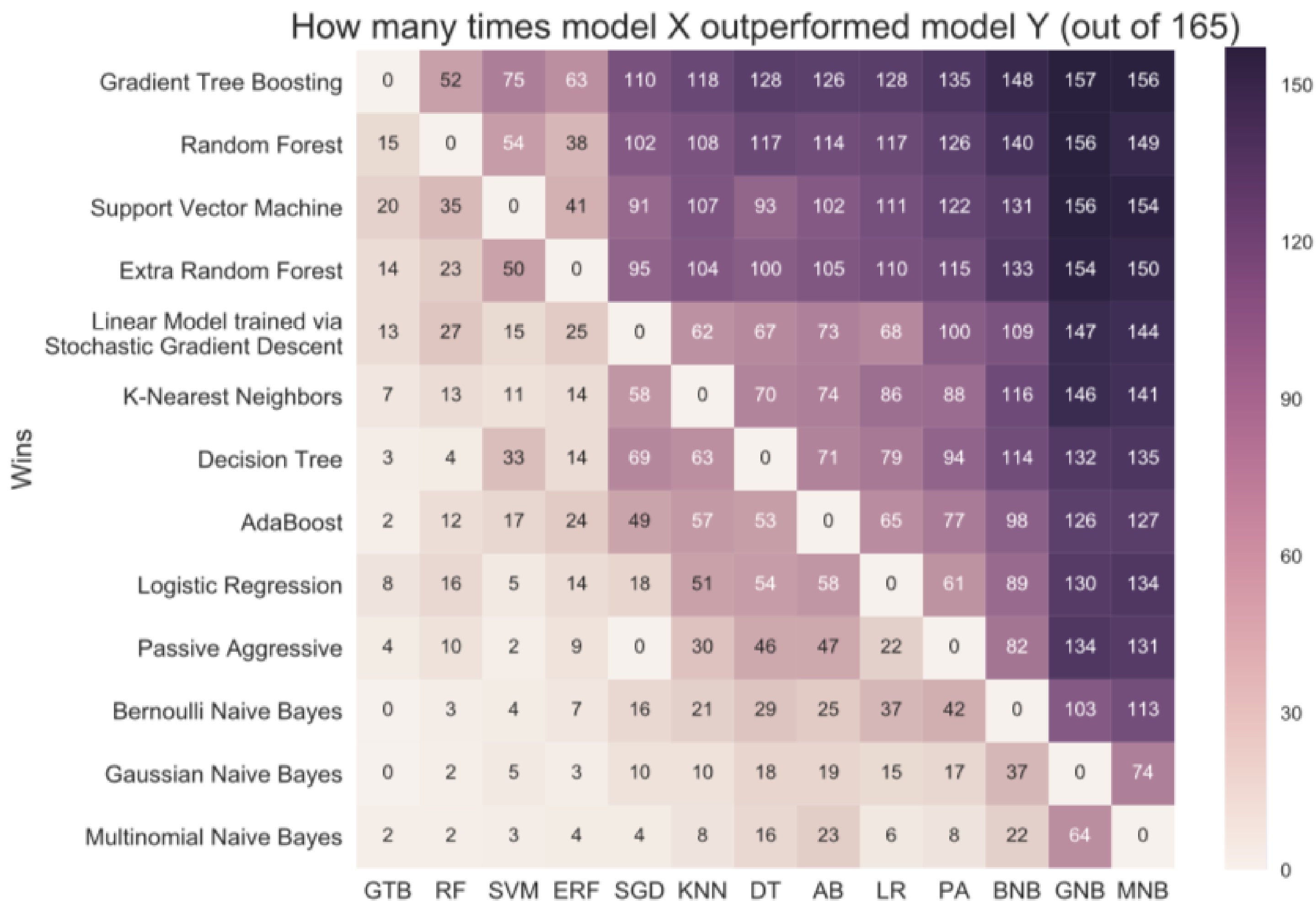
- Some tasks, such as multivariate data imputation, are hard or impossible to do with statistical models but possible with machine learning,
- Growing modeling complexity adds challenges to statistical models, machine learning has an advantage in complex models
- If you're developing models for prediction, there are few reasons not to look into machine learning algorithms

Challenges

- Combining machine learning skills with the domain knowledge of planning;
- Train planning students with machine learning skills
- Computation intensity & access to computer resources

Acknowledgements

- Oregon Department of Transportation (SPR 788)
- National Institute for Transportation and Communities (NITC-881)
- Portland Institute for Computational Science and its resources acquired using NSF Grant #DMS 1624776 and ARO Grant #W911NF-16-1-0307



Benchmarking Machine Learning Algorithms

Source: Randal S. Olson and William La Cava et al., 2018.