Learning from Route Plan Deviations from Last-Mile Delivery

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AGENDA

INTRODUCTION	What route plan deviation is and why it matters
DATA	Ask the driver through data
METHODOLOGY	Getting the tools ready
RESULTS	Here are the model
CONCLUSIONS	So what…
Q&A	Love to hear questions

INTRODUCTION

- 1 mile of reduction in average route distance results in **$50M** of annual cost savings for UPS in US only
- Urbanization and new costumers demands are making last-mile delivery optimization **increasingly complex and relevant** to retail companies
- Lacking tools and/or capabilities to include costumer specific or environmental constrains such us:
  - **Time windows (implicit or explicit)**
  - **Congestion patterns**
- Even for companies wiling to make **capital investment**, if the driver failed to follow the plan it forfeits the investment
- Drivers stated preference is studied but not **revealed preference**, so this project is actually asking the driver through data

Figure 1: Planned Route

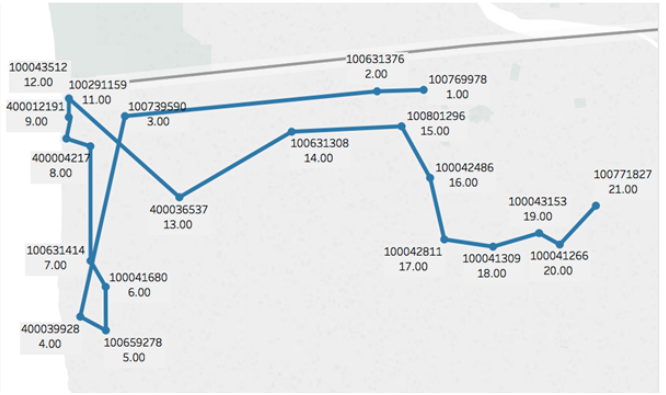
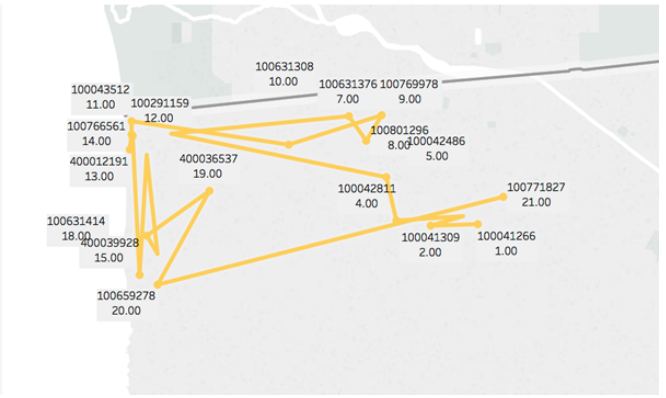


Figure 2: Actual Route



DATA

- Data Description:
  - Information about the **route instances**
  - Information about the **stops**

- Measuring deviation:
  - **Deviation**
  - **Sequence Deviation = Arcs not followed by driver / Total Arcs**
  - **Distance Deviation = Actual Distance / Planned Distance – 1**
  - **SLD Deviation = Actual Sequence SLD* / Planned Sequence SLD – 1**

    ** SLD: Straight Line Distance*

Figure 1: Planned Route

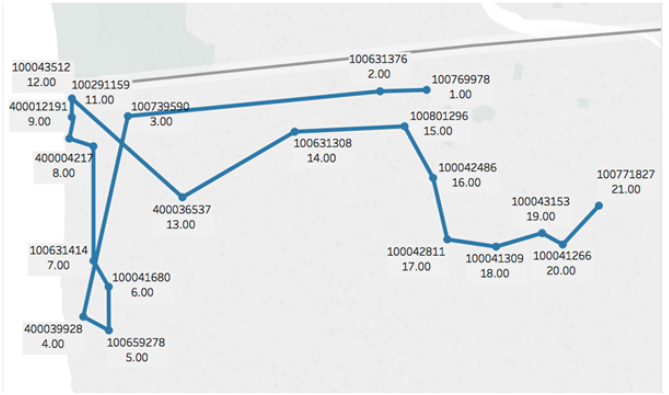
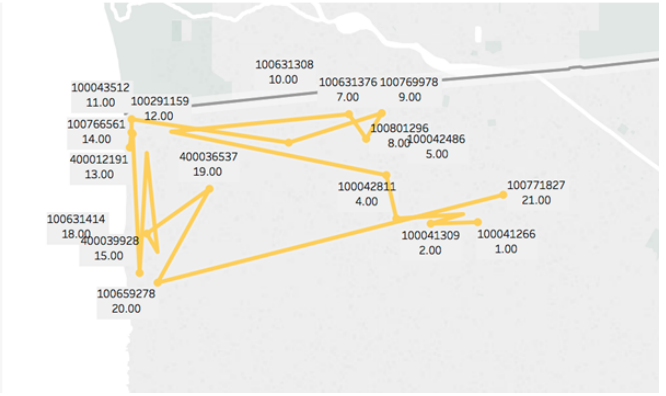
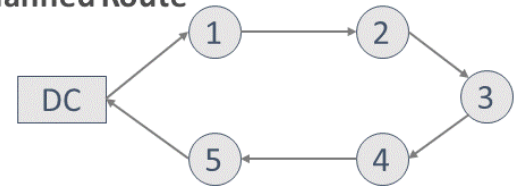


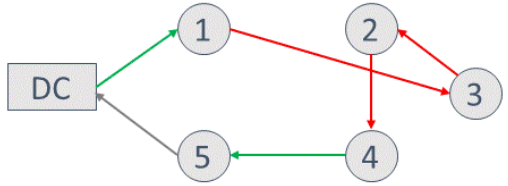
Figure 2: Actual Route



Planned Route



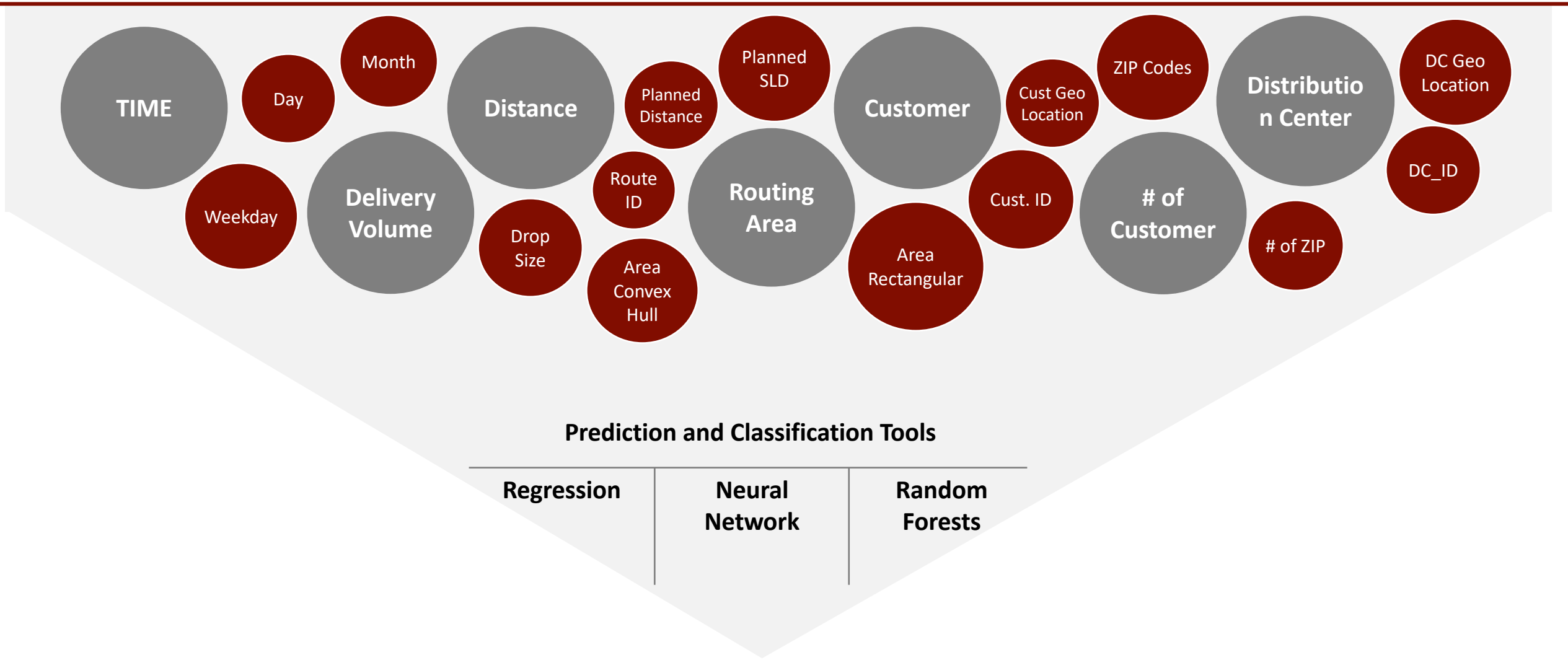
Actual Route



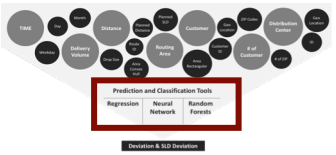
Example:

- **Deviation = 1**
- **Sequence Deviation = 3/5**
- **Distance Deviation = 15/11-1 = 36.4%**
- **SLD Deviation = 7/6 - 1 = 16.7%**

METHODOLOGY



METHODOLOGY



Prediction and Classification Tools – Performance Metrics

Regression

- Continuous Variable — **Adjusted R^2**
- Binary Variable — **Generalized R^2**

Neural Network & Random Forests

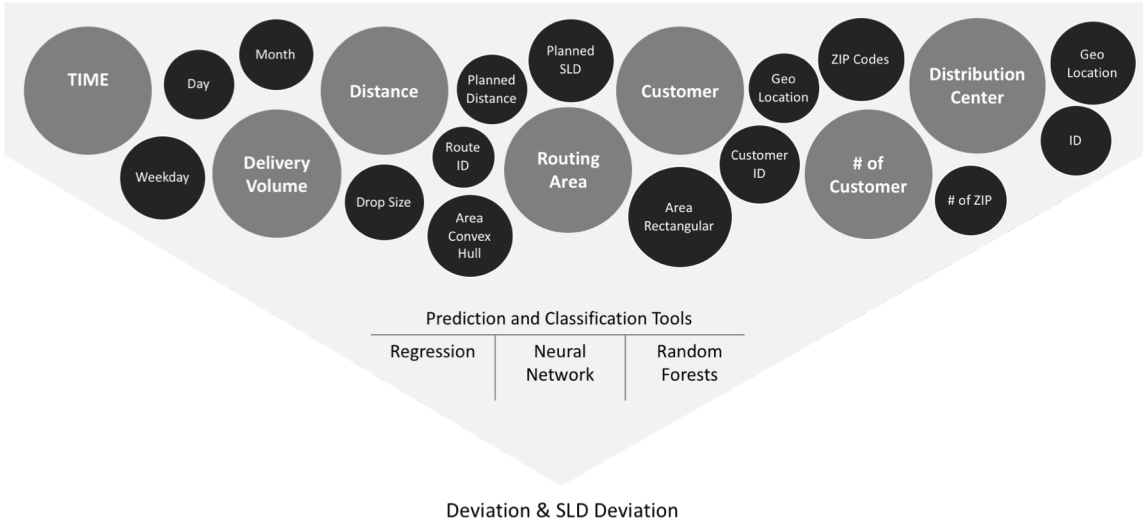
- Both Variables — **Generalized R^2**
- Binary Variable — **Confusion Matrix**
  - Specificity
  - Sensitivity
  - Accuracy
- Fixed 70% Validation Set and 30% Training Set

METHODOLOGY

	Mexico	US	All
Route Instances	7,644	47,881	55,525
Number of DCs	9	9	18
Stops per Route	17.9	12.8	13.5
Route Distance (km)	73.0	106.9	102.2
Deviation	**45.8%**	**79.8%**	**75.1%**
Sequence Deviation*	61.8%	54.7%	55.3%
SLD Deviation*	**12.1%**	**1.7%**	**2.6%**

* Only considering deviated routes

- > US valid data size is **6X** the Mexico data size
- > US deviated routes deviate more
- > US routes' deviation impact on SLD is lower
- > **Significant difference** in deviation between countries



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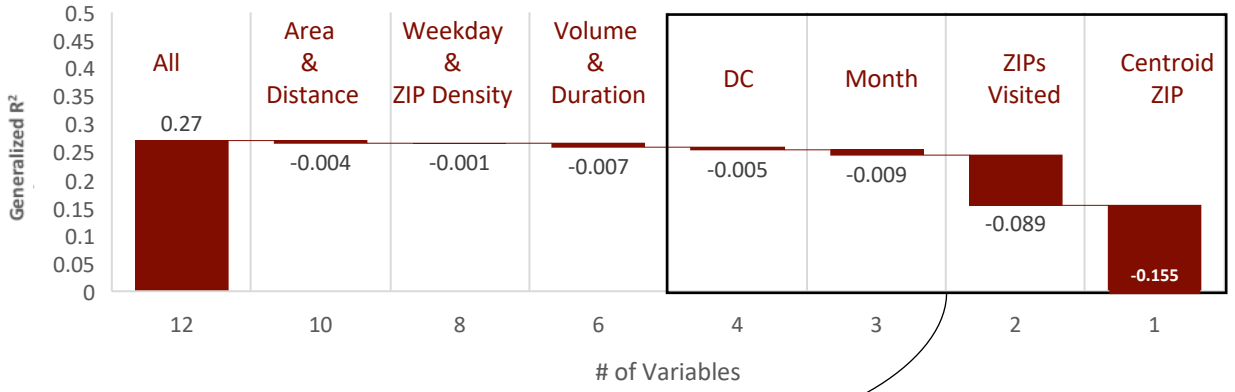
Results – *Deviation* by Regression Analysis

> Iterative Process of selecting significant variables

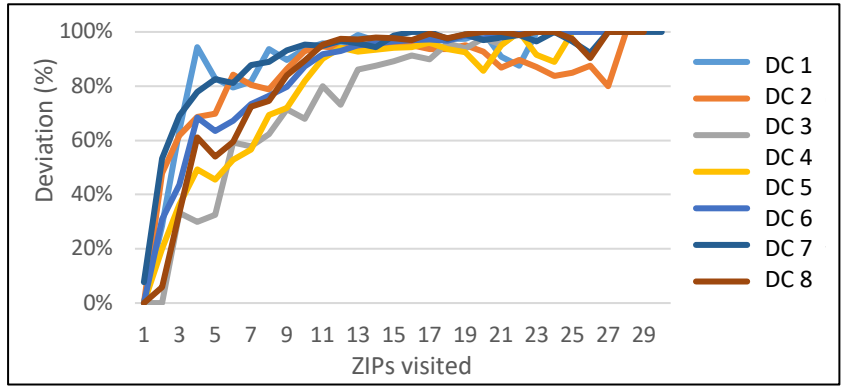
> Performance measured by Generalized R^2



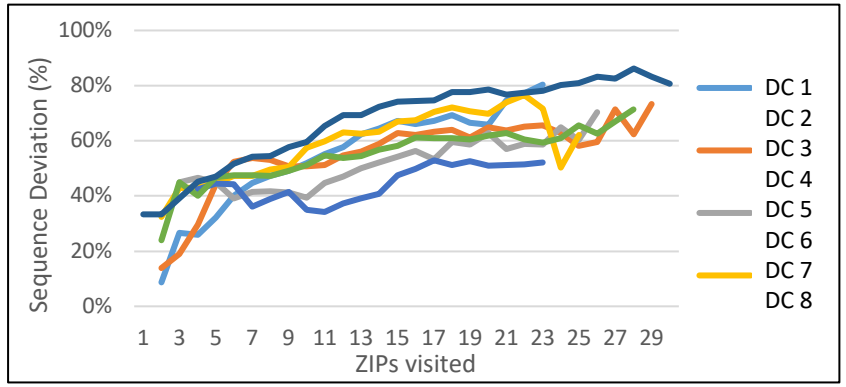
> Sensitivity Analysis

	Gen. R^2	Difference
ZIPs visited	0.167	0.091
Centroid ZIP	0.188	0.070
Month	0.244	0.014
DC_ID	0.253	0.005
All included	0.258	0.000

Deviation vs ZIPs visited, by DC

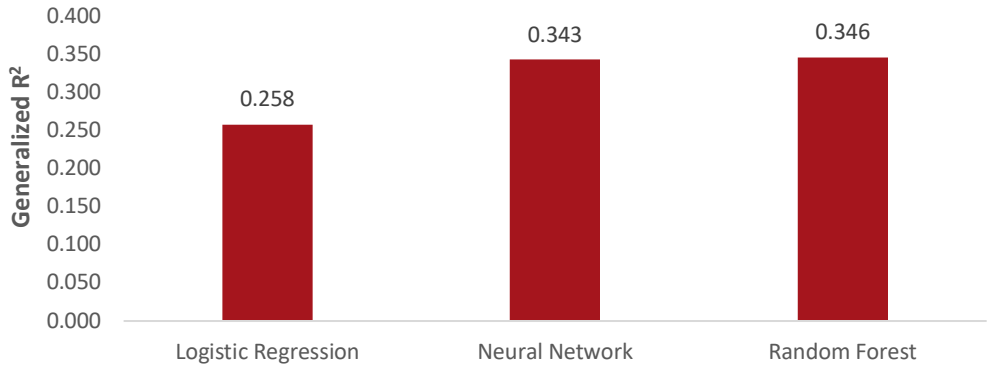


Sequence Deviation vs ZIPs visited, by DC

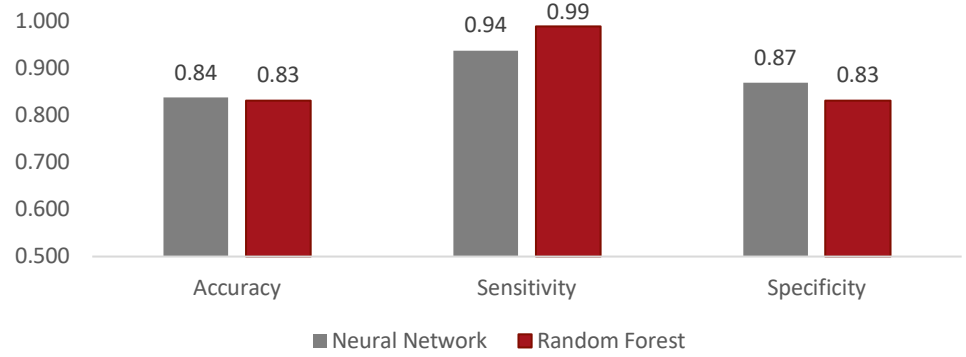


Results – *Deviation* by Classification Methods

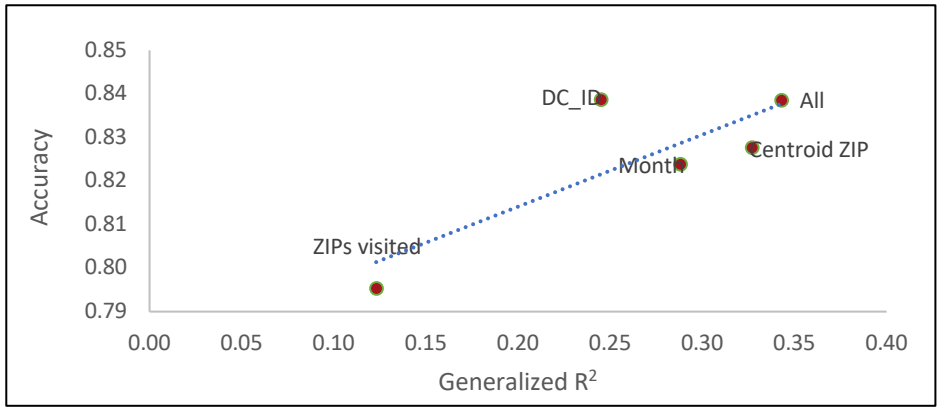
> **Significantly Higher Generalized R^2 than logistic Regression**



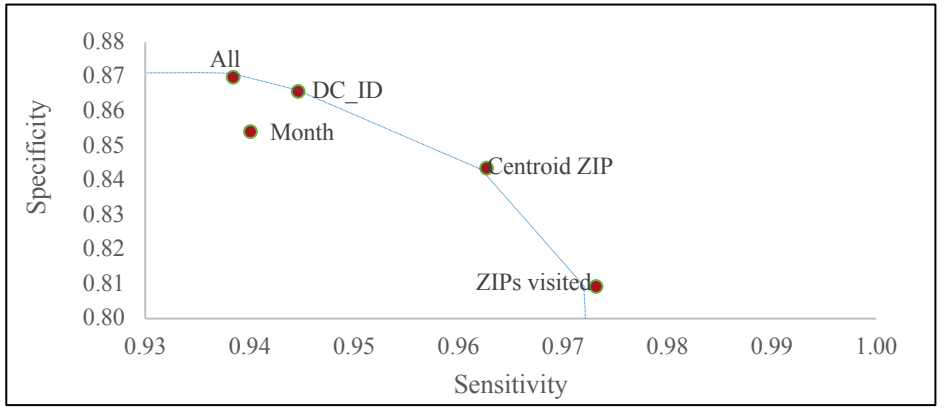
> **Random Forest has higher Sensitivity but lower Specificity**



Accuracy vs Generalized R2 for Neural Network (US)



Specificity vs Sensitivity for Neural Network (US)



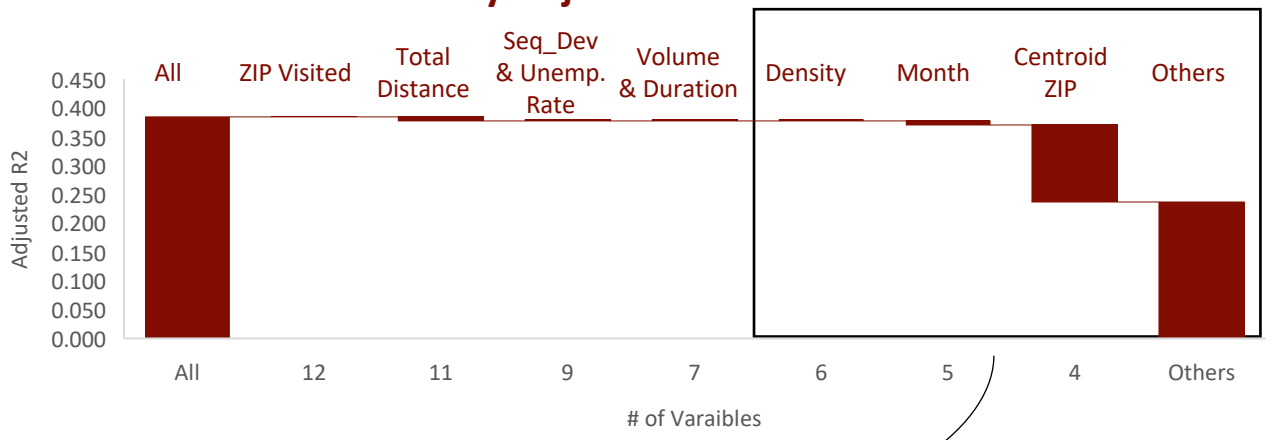
		Predicted 1	Predicted 0
Actual	1	a	b
	0	c	d

$$Accuracy = \frac{a+d}{a+b+c+d} \quad , \quad Sensitivity = \frac{a}{a+b} \quad , \quad Specificity = \frac{a}{a+c}$$

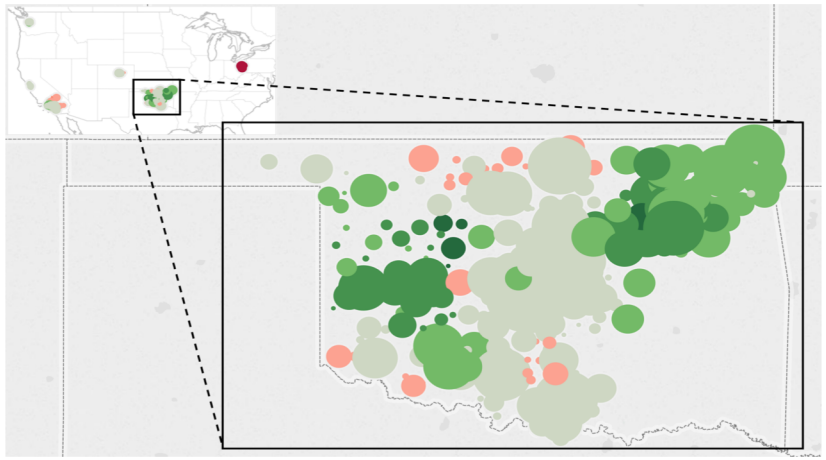
Results – *SLD_Deviation* by Regression Analysis

> Iterative Process of selecting significant variables

> Performance measured by Adjusted R^2



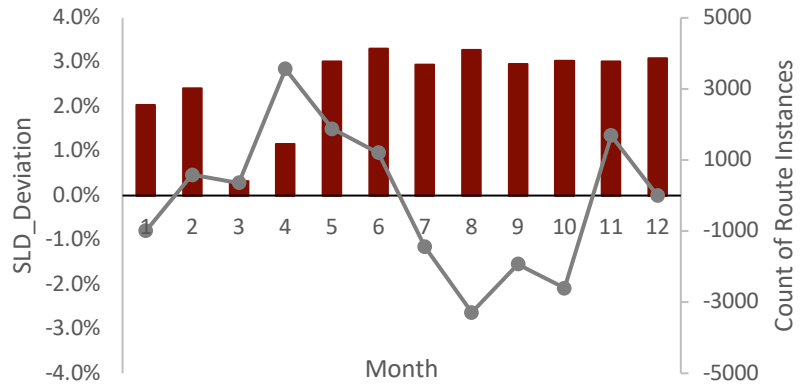
Centroid ZIP vs SLD_Deviation



> Sensitivity Analysis

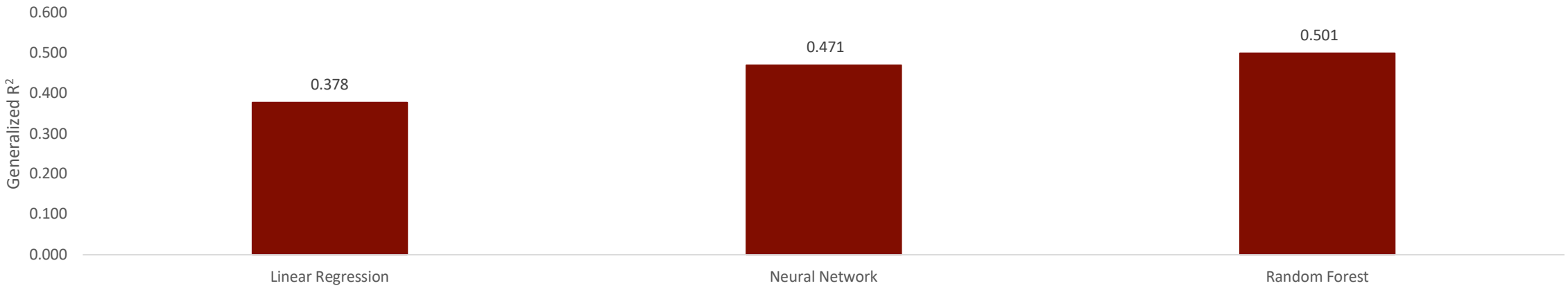
Variables	Adjusted R^2	Difference
Planned_SLD	0.220	-41.8%
Centroid ZIP	0.250	-33.9%
Route_ID	0.294	-22.2%
Number_Customers	0.367	-2.9%
Month	0.370	-2.1%
Area_Rectangular	0.370	-2.1%
All Included	0.378	0.0%

Seasonality of SLD_Deviation



Results – *SLD_Deviation* by Classification Methods

> Significantly Higher Generalized R^2 than Linear Regression



> Classification method, more variables ≠ better R^2

> Centroid ZIP and Route_ID are among the very significant variables in the linear regression but are the least significant in the neural network

Variables	Adjusted R^2	Difference
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Route_ID	0.294	-22.2%
Number_Customers	0.367	-2.9%
Month	0.370	-2.1%
Area_Rectangular	0.370	-2.1%
All Included	0.378	0.0%

Variables	Generalized R^2	Difference
Planned_SLD	0.231	-50.8%
Area_Rectangular	0.356	-24.3%
Month	0.435	-7.7%
Number_Customers	0.436	-7.3%
Route_ID	0.478	1.5%
Centroid ZIP	0.478	1.6%
All Included	0.471	0.0%

Variables	Generalized R^2	Difference
Route_ID	0.449	-10.3%
Centroid ZIP	0.453	-9.6%
Area_Rectangular	0.490	-2.2%
Planned_SLD	0.501	0.0%
Month	0.535	6.9%
Number_Customers	0.536	7.0%
All Included	0.501	0.0%

Conclusion

> Using environmental variables that describe the route, drivers' decision to deviate from the plan can be predicted with an accuracy of **84% in the US and 71% in Mexico**.

> The impact on distance of the deviations can be predicted with a coefficient of determination **R^2 of 0.54**.

> Drivers are more likely to deviate and increase the route's distance when **more customers** are visited.

> Customers' **geographical locations**, reflected in the ZIP codes and group of customers, are useful to predict deviations.