Modeling Voter Turnout in Local Elections With Housing Data

Elliott Day

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Odd Year Elections

In the State of Washington, elections for local office are held in odd-numbered years.

This results in an electorate for local offices that is different than the one for congressional seats and president.

An Example

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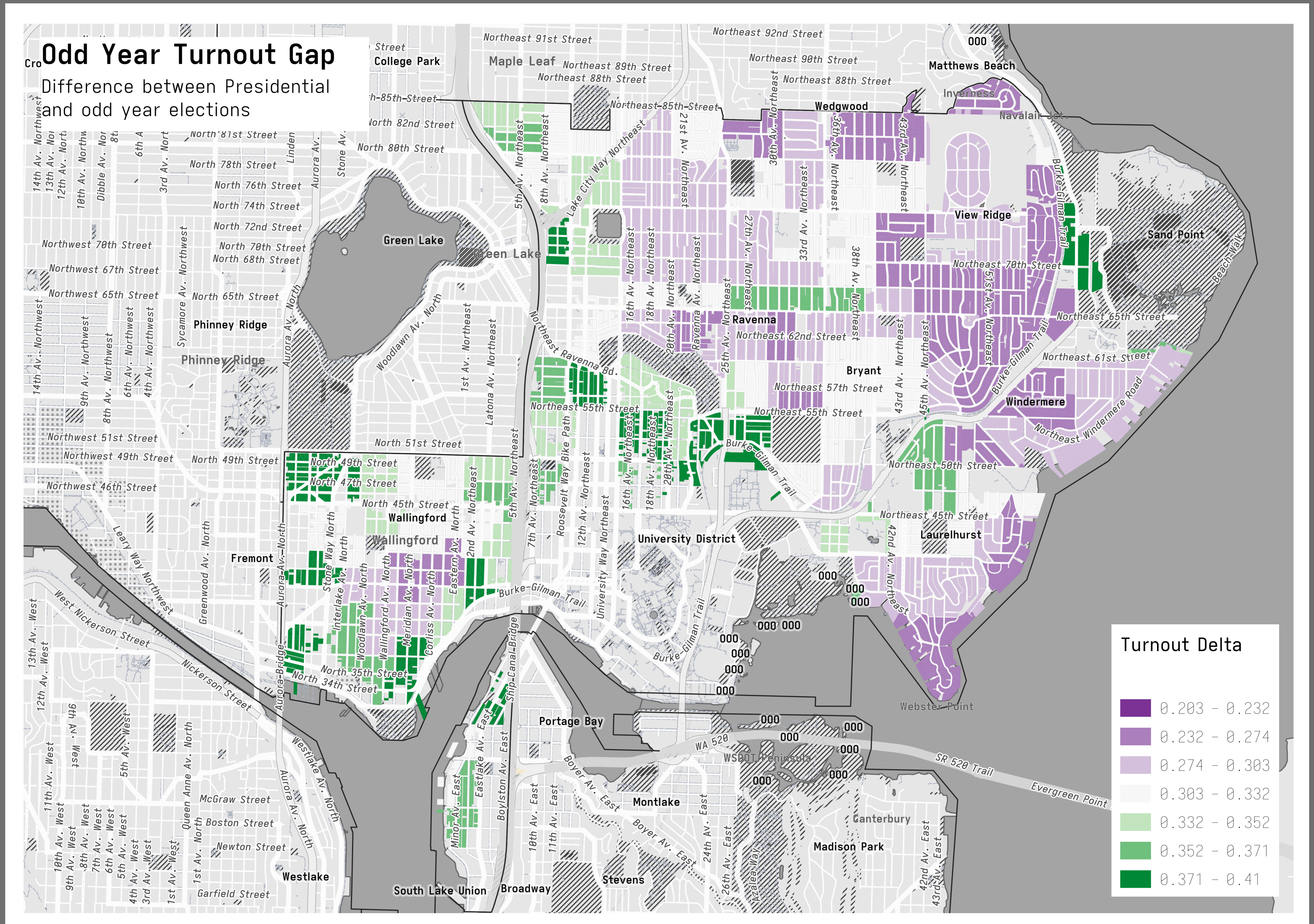
Shaun Scott, candidate for City Council in Seattle Council District 4



An Example

Shaun Scott, candidate for City Council in Seattle Council District 4

Lost by more than 4 points in an odd year

If precincts had voted with the same preference (conservative assumption) at the rate of the 2020, that margin shrinks to less than a percent

2019 Seattle City Council District 4

	Actual	Presidential Turnout
Shaun Scott	15568	24548
	45.84%	47.33%
Alex Pedersen	16954	24982
	49.92%	48.16%
Votes Cast	33962	51871
Registered Voters	61367	61367

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(And either way if you want to win local elections you need to be prepared for the electorate that will be participating.)

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- Using housing data to build a durable estimator of hypothetical voter turnout scenarios based on previous turnout patterns.
- Of interest to campaigns, election administrators, researchers, and nonprofits
- The dataset is extensive and has many potential other applications

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— Using housing data to build a durable estimator of hypothetical voter turnout scenarios based on historical turnout patterns and future landscapes.

— Of interest to campaigns, election administrators, researchers, and nonprofits

— The dataset is extensive and has many potential other applications

The Data

King County Assessor

A record for every residence in the county (~989,000)
Seattle and surrounding area; relatively diverse demographically and in terms of housing across the county

King County Assessor

A record for every residence in the county (~989,000)

The Voter File

A record for every voter in the county (~1.4 million)

The Targets

— Registered Voters Per Parcel

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— Votes cast in 2019 Per Parcel

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— Registered Voters Per Parcel
— Votes cast in 2019 Per Parcel
— Votes cast in 2020 Per Parcel

The Models

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— RandomForestRegressor

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— Keras Neural Network

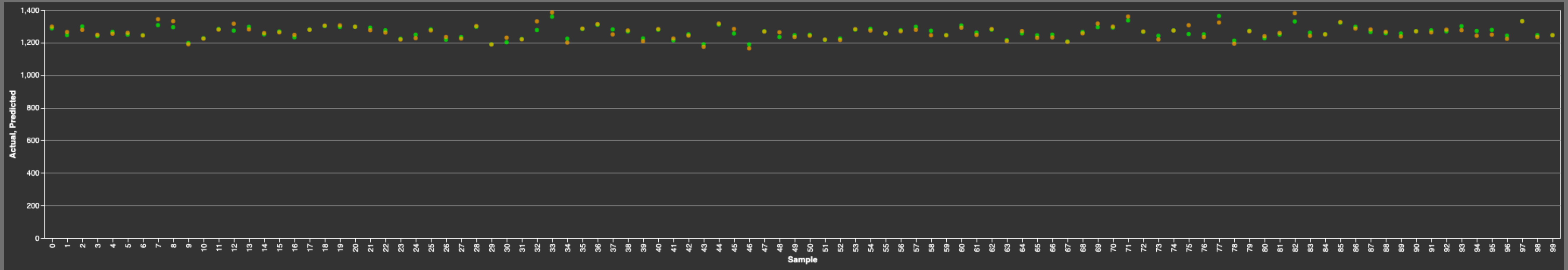
Random Forest

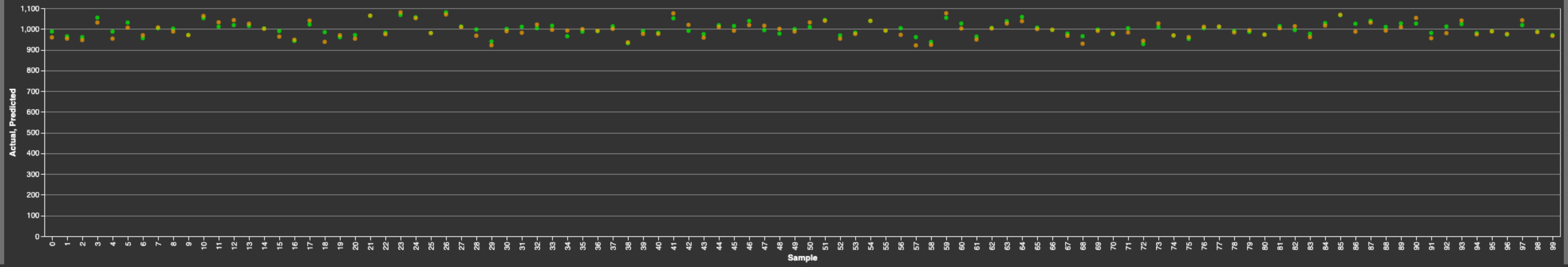
— RandomizedSearchCV
— Then trained on full dataset

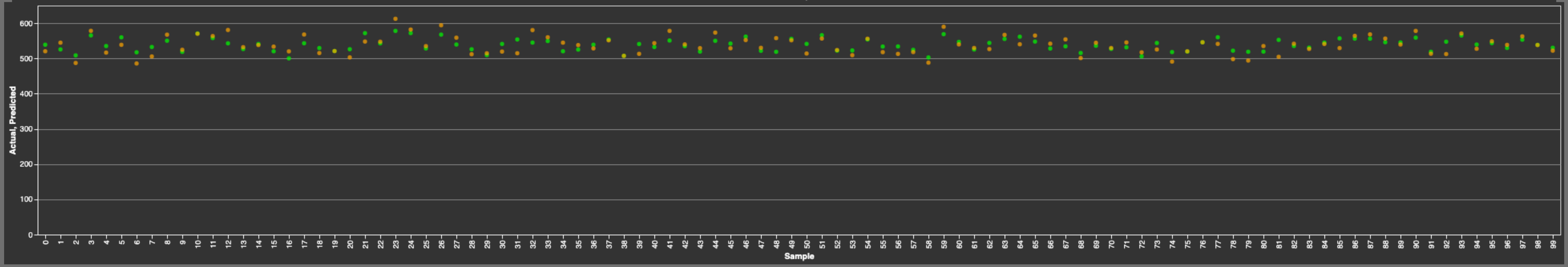
Neural Regressor

— Early stopping
— Lots of trial and error

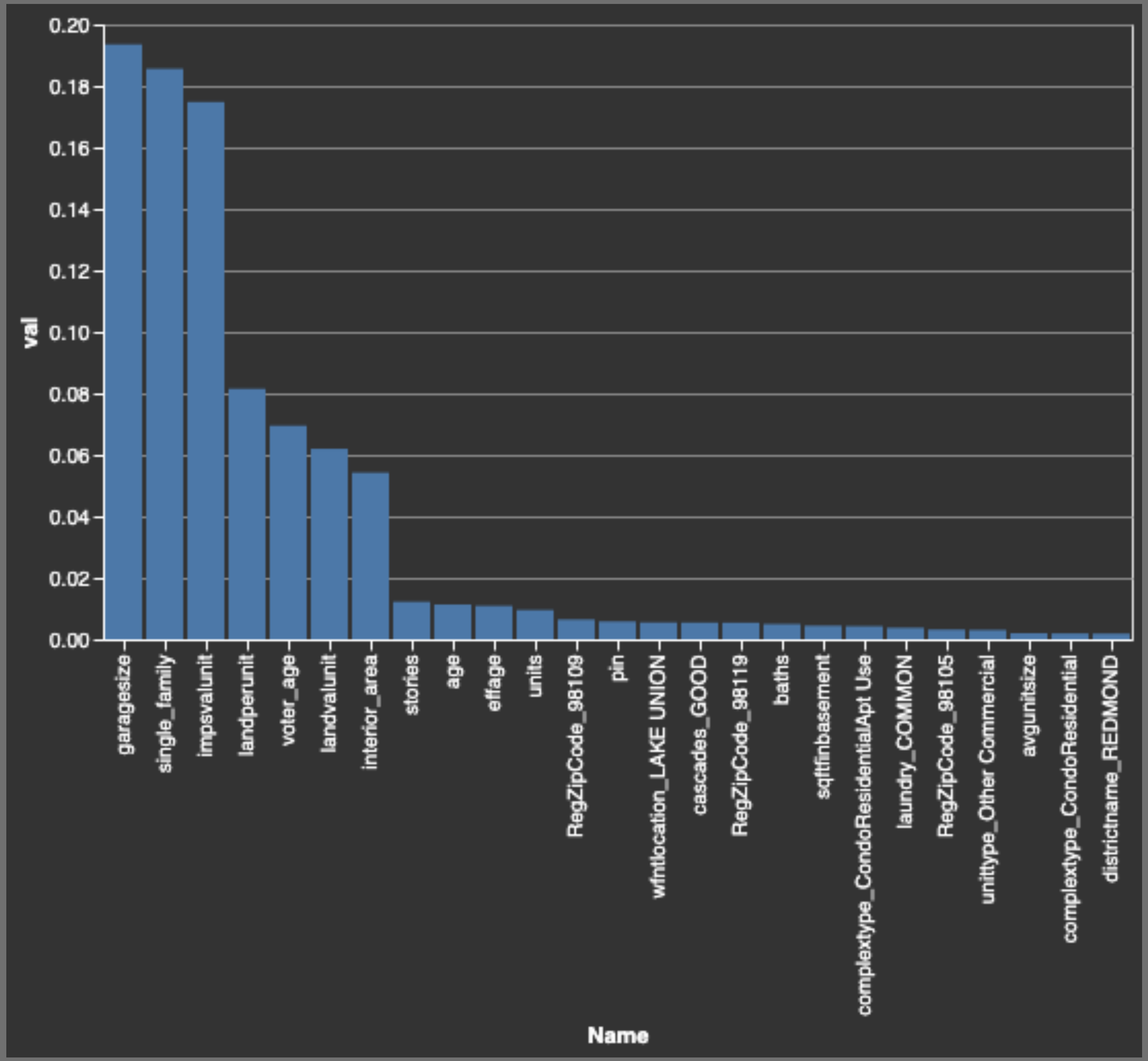
Aggregate Accuracy







Feature Importances



Evaluation

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Goal:

Evaluation

Goal: Compare model performance on different forms and sizes of aggregation

Evaluation

	Random Forest Regression - 2020 Voters				Neural Regression - 2020 Voters		
	Actual	Predicted	RMSE		Actual	Predicted	RMSE
senior_housing	2032.964824	2033.171594	0.000102	fourplex	1567.817949	1557.450270	0.006613
fourplex	1567.817949	1569.035525	0.000777	apartment	41987.903225	42298.559992	0.007399
apartment	41987.903225	41882.981701	0.002499	single_family	202247.673392	197756.910856	0.022204
single_family	202247.673392	202818.624523	0.002823	duplex	2966.606277	3036.821827	0.023669
duplex	2966.606277	2991.836718	0.008505	senior_housing	2032.964824	1982.716823	0.024717
triplex	1210.083333	1230.755636	0.017083	triplex	1210.083333	1242.919038	0.027135
townhouse	5618.548988	5489.541046	0.022961	townhouse	5618.548988	5289.885259	0.058496
mobile_home	259.421984	251.634855	0.030017	mobile_home	259.421984	219.275274	0.154754

What's Next

— Error analysis

— New Features (e.g. gated communities)

— Analyzing and modeling candidate preference, including measuring for when such a preference is expressed in patterns related to housing