Quantifying Variation in American School Safety

Using Explainable Machine Learning for the Social Sciences

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NYAAPOR/PANJAAPOR Young Public Opinion Stars Event, 27th April 2021

School Safety

Disadvantaged Students
(Chen, 2008;
Han & Akiba, 2011)

- Underperforming Students
- Minority Students
- Students in Poverty

Relationships and Environments
(Robinson, Leeb, Merrick, Forbes, 2016)

- Educational/Intervention Approaches
(Cueller, 2018)
- Parental and Community Involvement
(Lesneskie & Brock, 2017)
- Visible Security Features
(Perumean-Chaney & Sutton, 2013)

Demographic Controls

- Urbanicity
- School Size
- Neighbourhood Crime
- School Type (e.g. High School)

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Challenge: A lot of variables.
Can Explainable Machine Learning help us with this problem?

2017-18 School Survey of Crime and Safety

Stratified Random Sample of all Public Schools in America (n=84418)

Stratified according to School Level, Locale and Enrollment Size

Final Respondents (n=2762 School Leaders)

Contains Variables of Interest:

Disadvantaged Students
(Chen, 2008;
Han & Akiba, 2011)

Relationships and Environments
(Robinson, Leeb, Merrick, Forbes, 2016)

Demographic Controls

Four Steps: Using Explainable Machine Learning for Data Analysis.

Select
Learn
Filter
Measure

Four Steps: Using Explainable Machine Learning for Data Analysis.

Select

IVs:	Student Disadvantage	2 Ratio Var.	*percentacadnotimpt* *percentlowgrades*
	Education/Intervention Approaches	8 Binary Var.	*e.g., mentoring*
	Security Features	21 Binary Var.	*e.g., random_sweep*
	Community Involvement	7 Binary Var.	*e.g., religorg_help*
	Parental Involvement	3 Binary; 2 Ordinal Var.	*e.g., open_house*
	Demographic Controls	1 Binary; 4 Ordinal Var.	*e.g., school_size*
		48 Mixed-Type IVs	
DV:	School Safety	1 Ratio Var.	*total_incident*

Four Steps: Using Explainable Machine Learning for Data Analysis.

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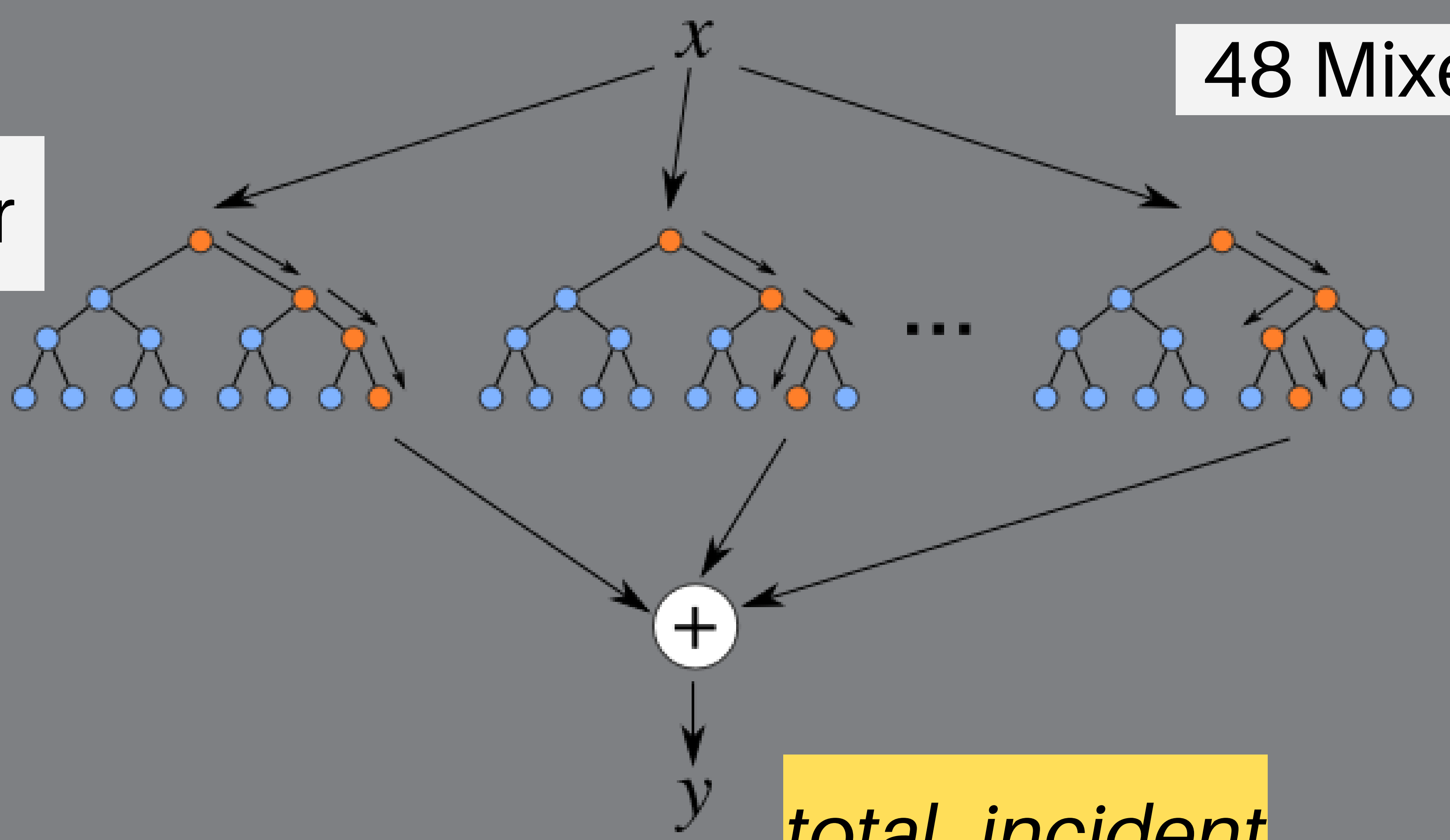
48 Mixed-Type IVs

Random Forest Regressor

Ensemble Model of Decision Trees



Hyperparameter Tuning Conducted

total_incident

Image Source: Chaya Bakshi, for *Gitconnected* on Medium

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Why Filter?

Shared variance between related features would result in each related feature contributing less individually

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Select **Learn** **Filter**

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How to Filter?

Recursive Feature Elimination, removing the feature with the lowest Permutation Feature Importance for this Random Forest Regressor

Four Steps: Using Explainable Machine Learning for Data Analysis.

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Why Filter?

How to Filter?

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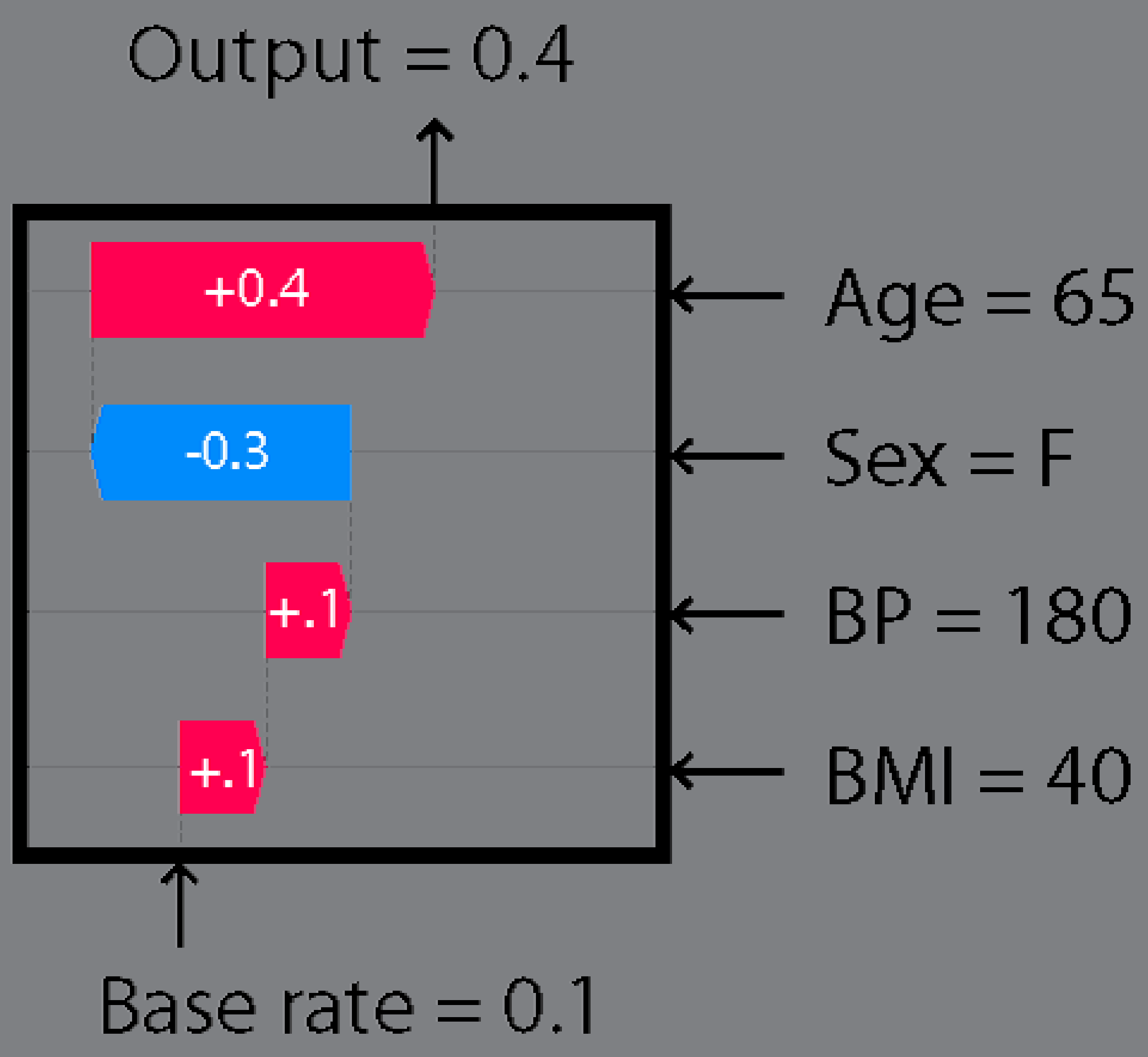
Recursive Feature Elimination, removing the feature with the lowest Permutation Feature Importance for this Random Forest Regressor

48 IVs to 24 IVs

Four Steps: Using Explainable Machine Learning for Data Analysis.

Select **Learn** **Filter** **Measure**

SHAP



1 Base Rate - average prediction of model

Image Source: Scott Lundberg, SHAP Repository on GitHub

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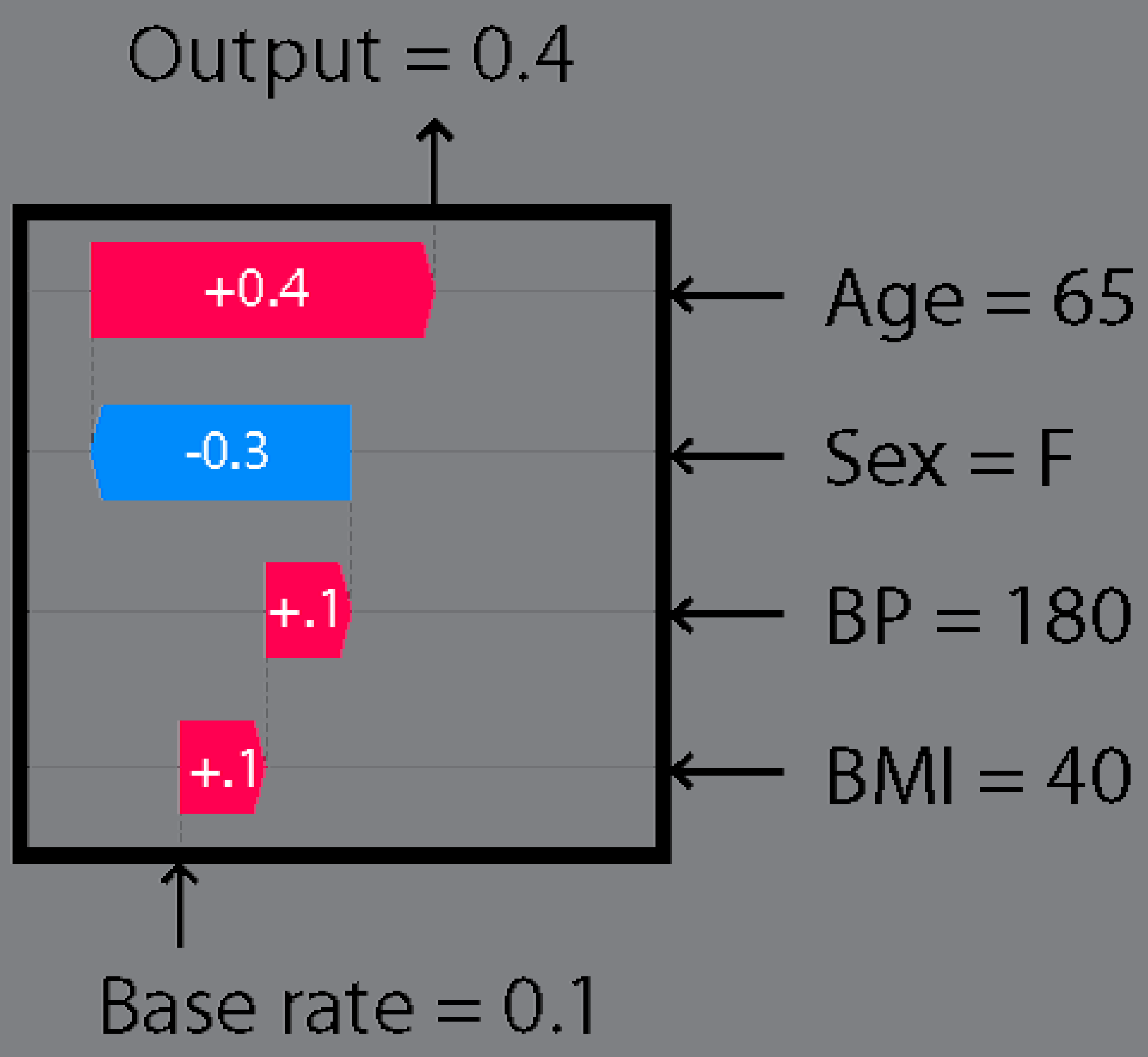
3 Output prediction for some combination of feature values



SHAP

2 Individual feature values, indicating contribution to output value

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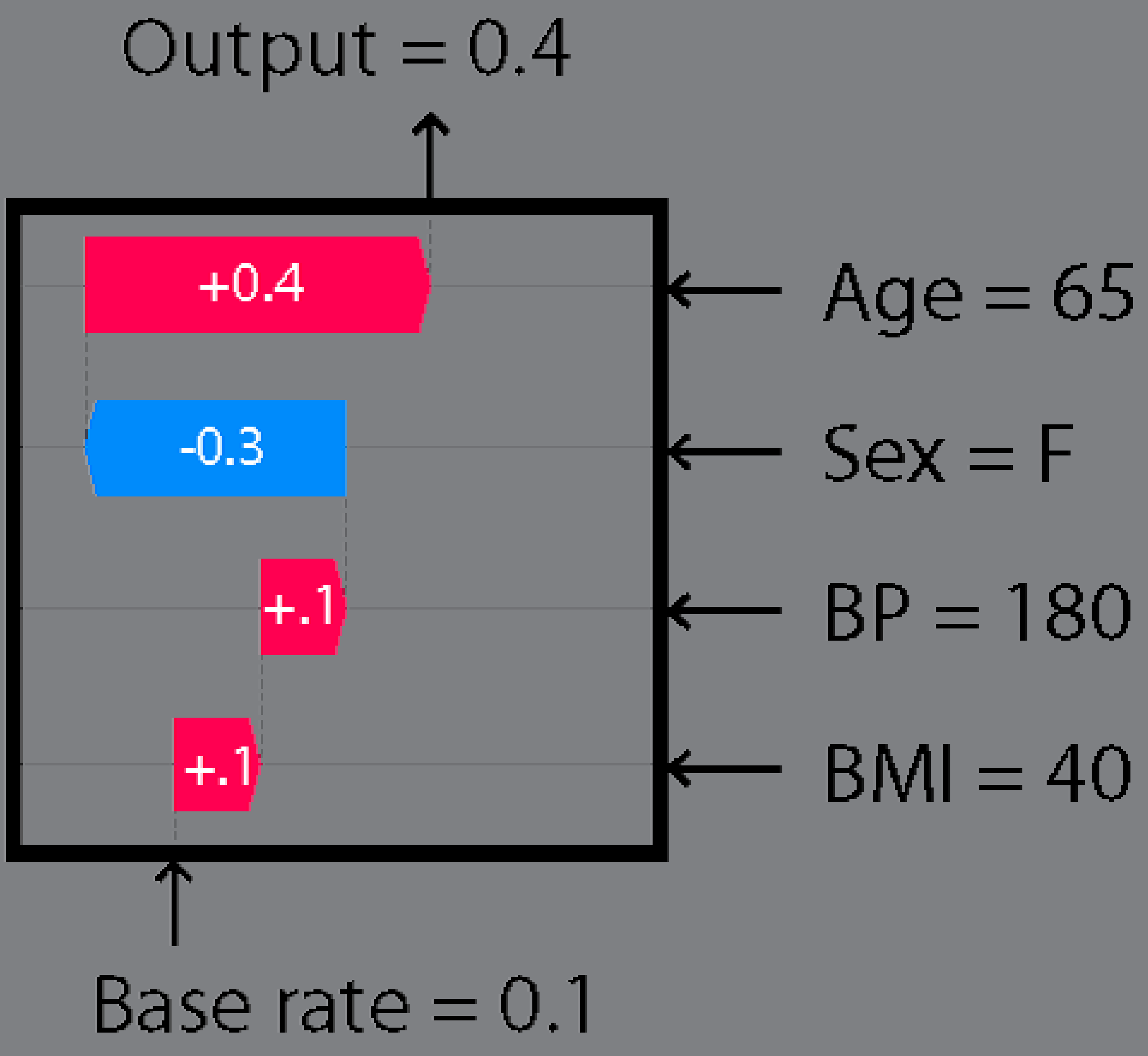

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Two Main Findings.

Magnitude
Direction

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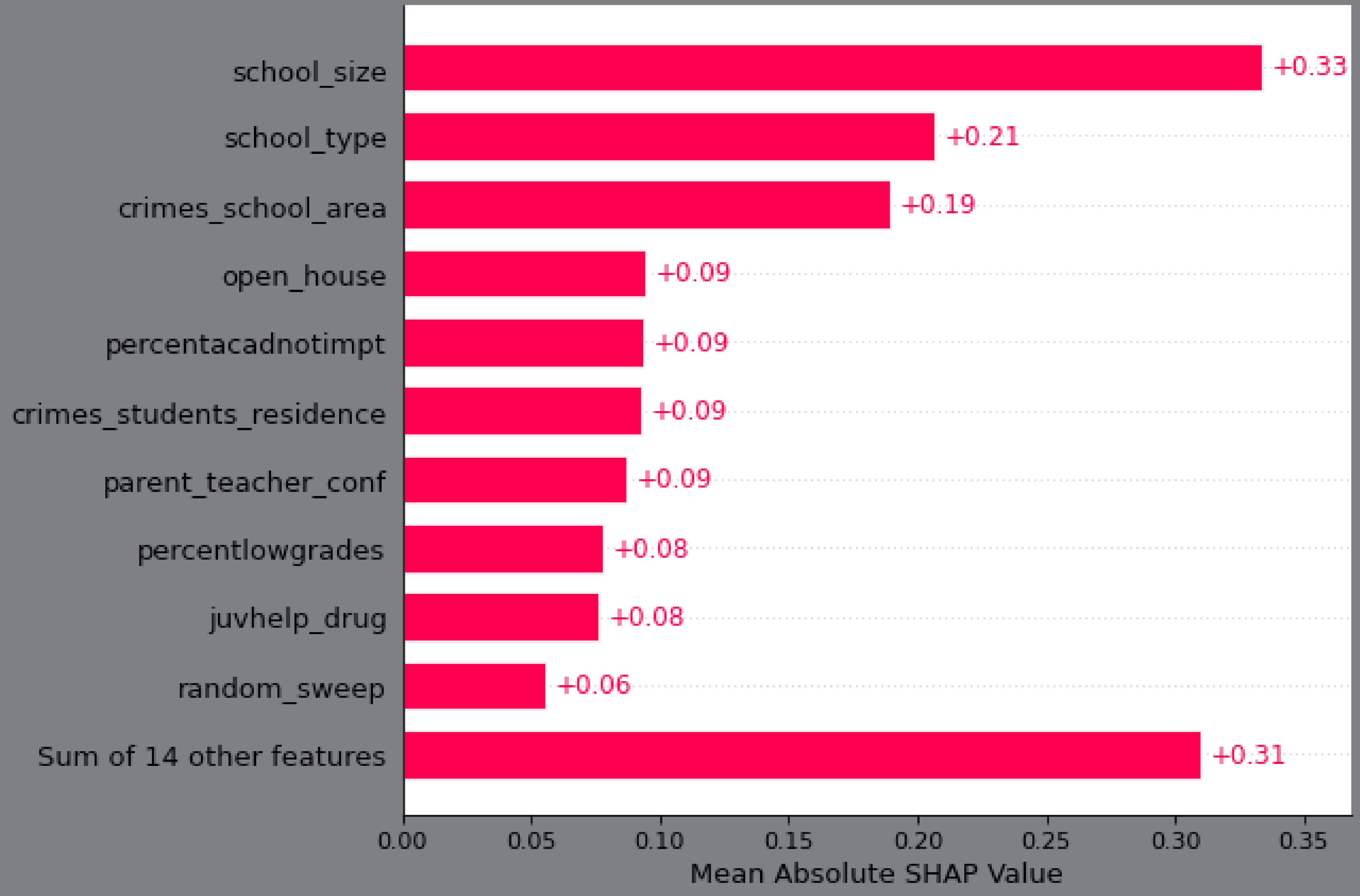
Magnitude

Direction

Top 10 Absolute SHAP Values



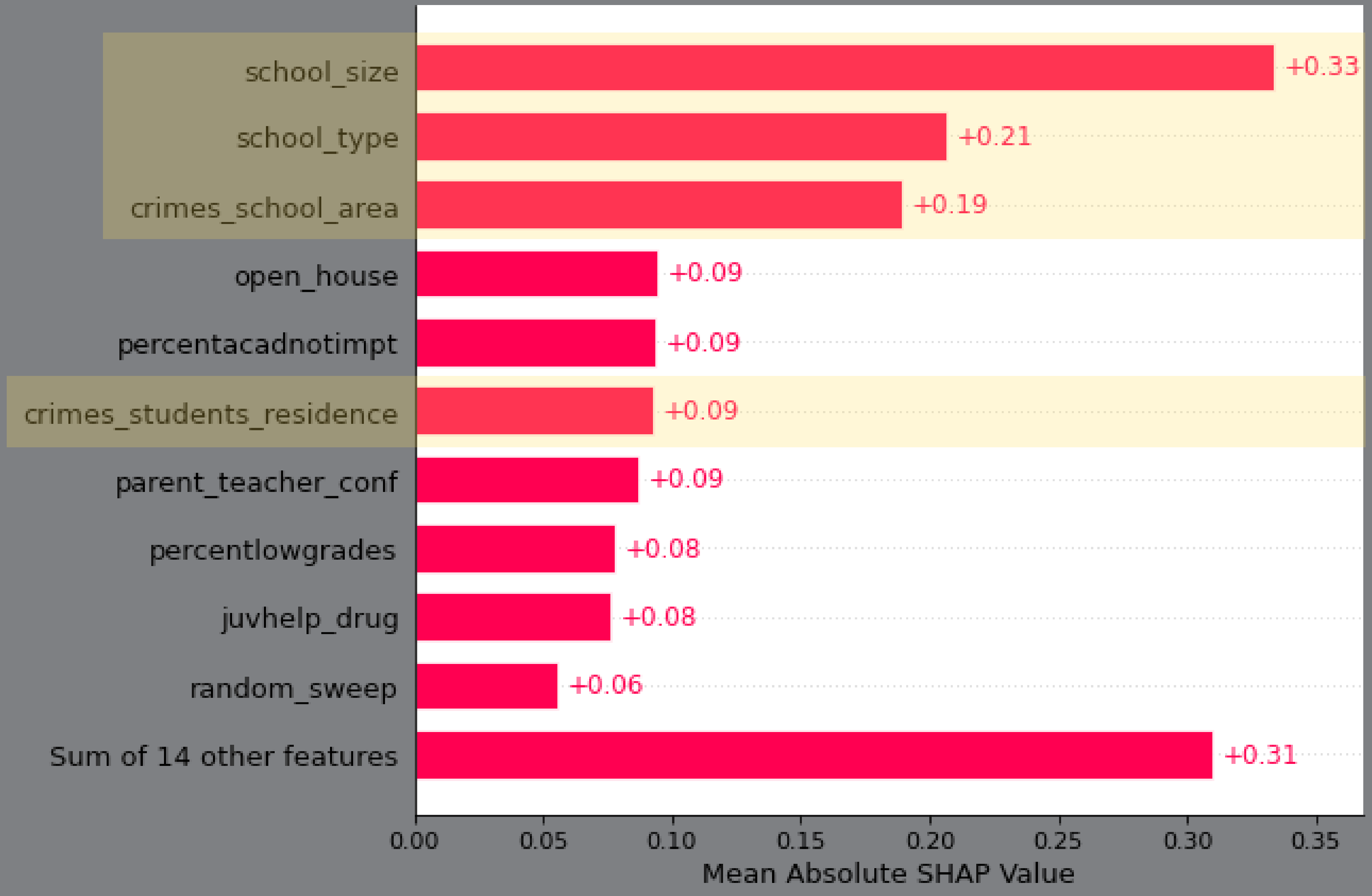
1. Demographic Controls had Highest Absolute SHAP Values
2. Markers of Student Disadvantage, and Parental Involvement too

Interpretation: Net of other variables, these contributed most of the variance in relation with total_incident. Not causal.

Two Main Findings.

Magnitude | **Direction**

Top 10 Absolute SHAP Values



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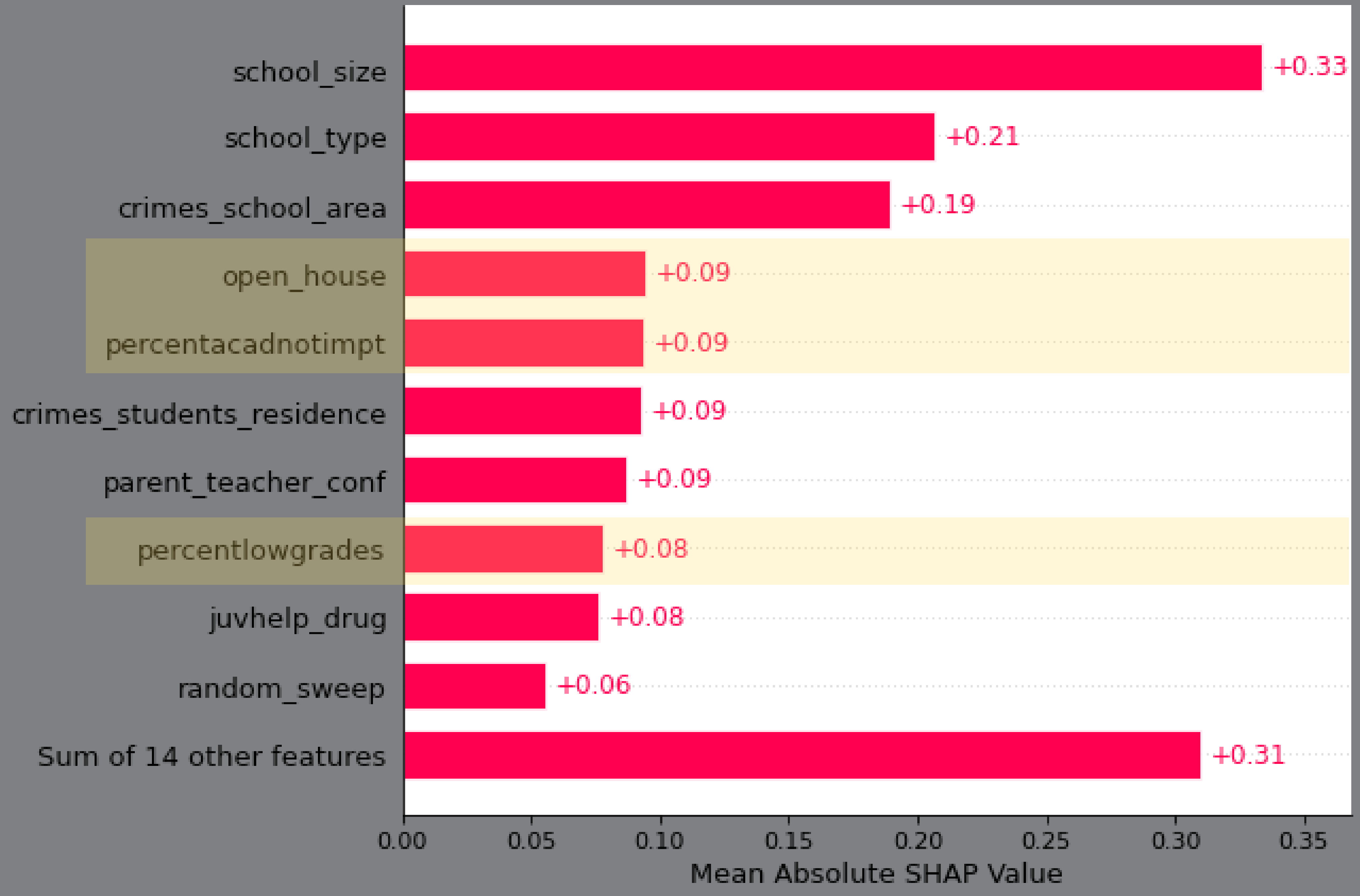

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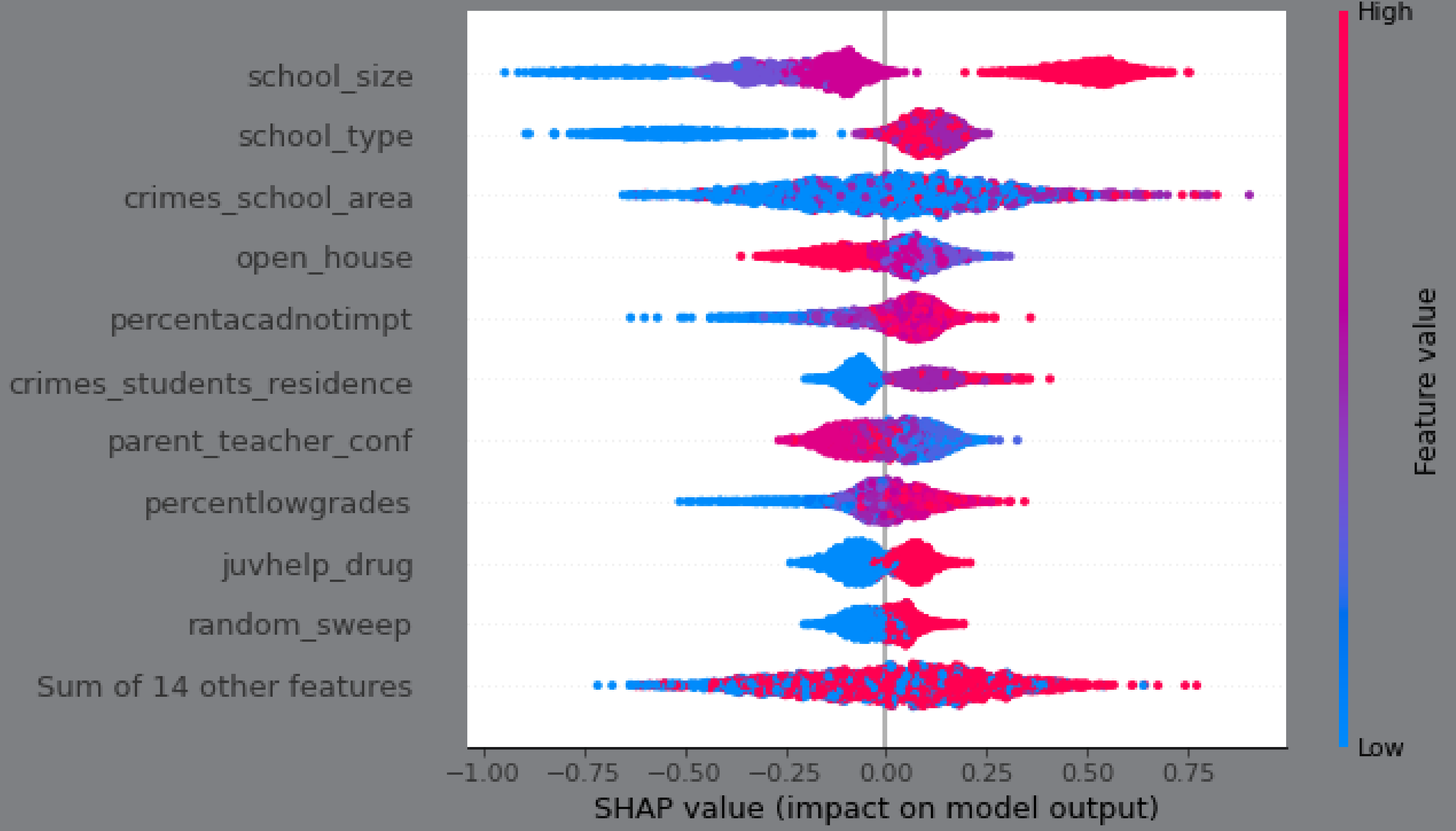

1. Associations between *total_incident* and variable values

2. Schools with more disadvantaged students are on average, less safe

Interpretation: Higher SHAP Values = Higher *total_incident,* net of variables; the opposite is true of lower SHAP Values.

Two Main Findings.

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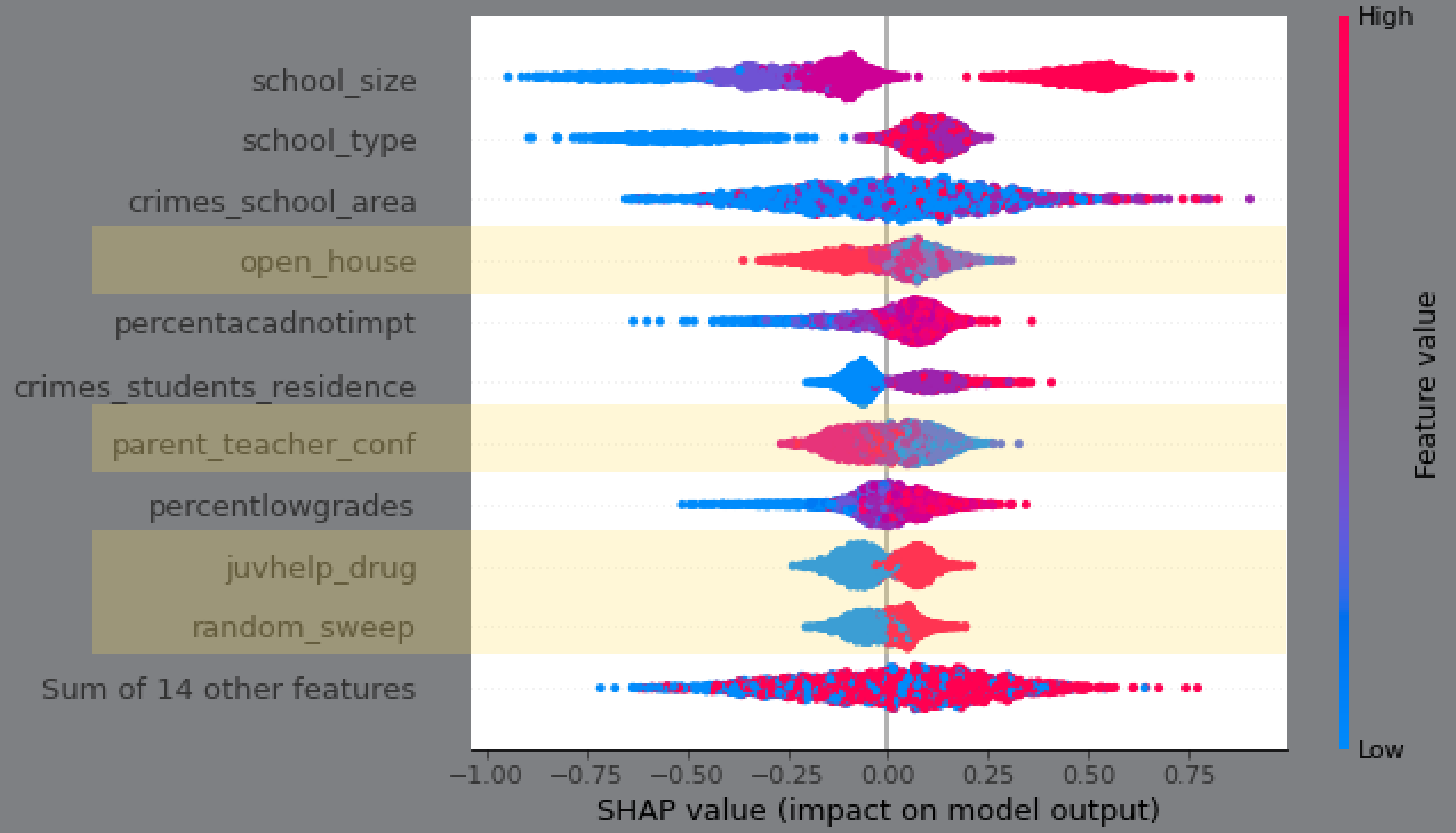
Top 10 Absolute SHAP Values



1

Associations between *total_incident* and variable values

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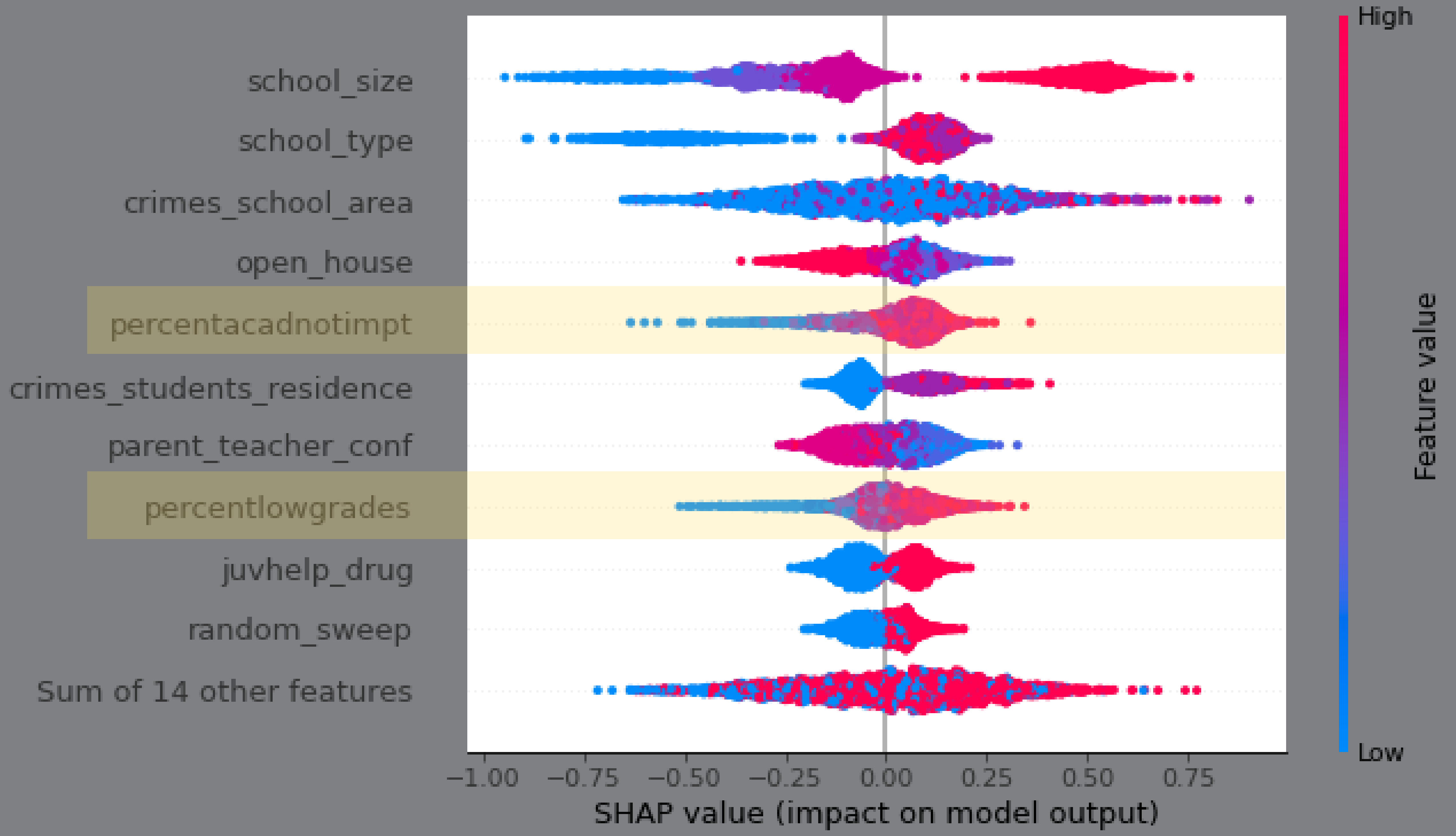

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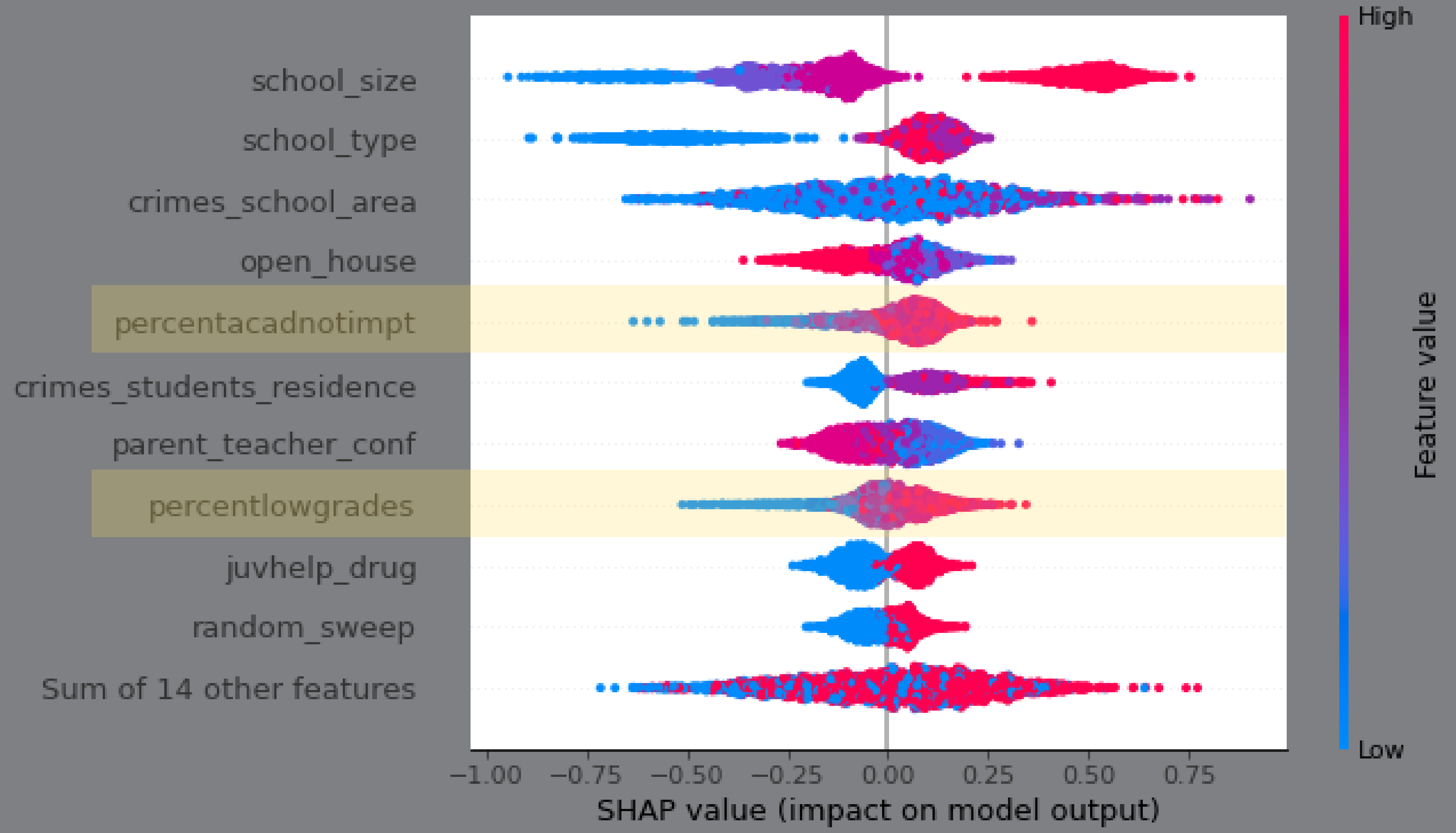

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In a Sentence.

We can jointly consider many variables at the same time using Explainable Machine Learning, and uncover directional relationships that important variables have with a given outcome variable.

Thank you for your time and attention!

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