

# Machine learning-based approach for filling gaps in data on plasma-related processes

## Prediction of Sputtering Yields

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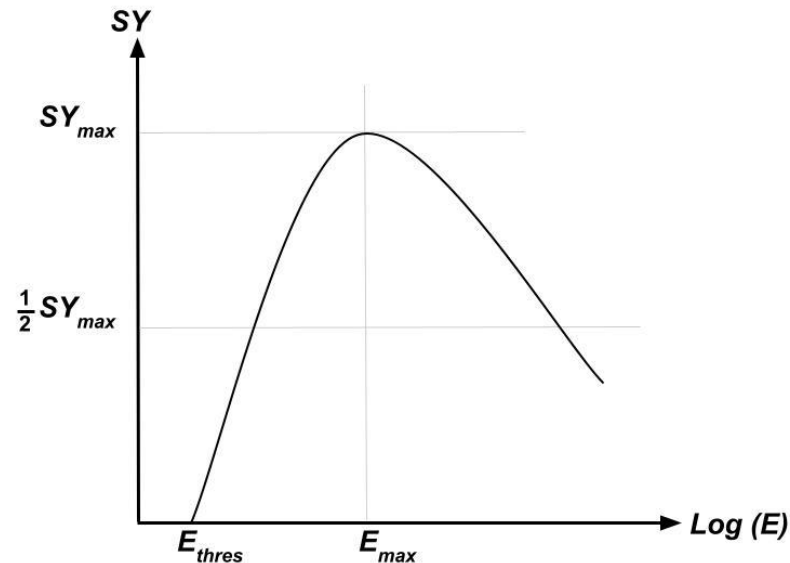
**Sputtering** is the removal of atoms from a lattice by particle (ion) impact

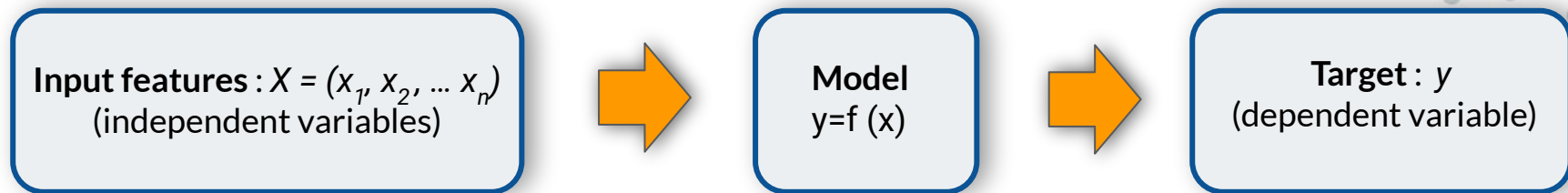
**Sputtering yield (SY)** is the number of atoms removed from the surface by a single impact

**Sputtering Yield** depends on impact energy, angle and target-projectile combination

Experiments and MD simulation are used to measure or estimate sputtering yields, but both these approaches are time consuming and difficult to implement

We can use existing sputtering yield data to train a machine learning model capable of predicting sputtering yields for target-projectile combinations that has never been studied before.





A supervised machine learning algorithm learns relationships between input data (input features) and known responses to the data (target) so it can generate reasonable predictions for the response to new data.

# Dataset to predict Sputtering Yield for single-element targets



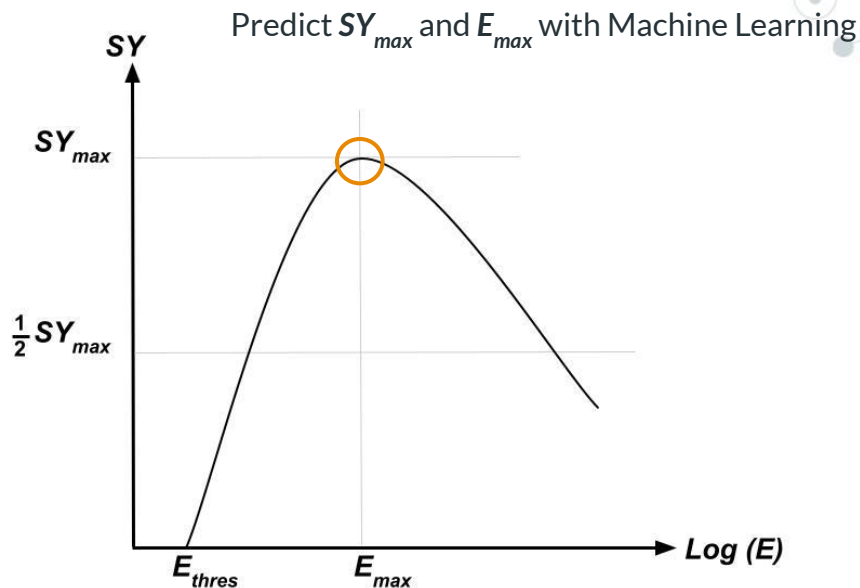
Target dependent variables:

$SY_{max}$  and  $E_{max}$  values at normal incidence

267 single-element target-ion combinations

Input descriptors  
(independent variables):

Easily accessible data describing chemical and physical properties of projectile ions and target materials



# Dataset to predict Sputtering Yield for single-element targets



19 descriptors

Target dependent variables:

$SY_{max}$  and  $E_{max}$  values at normal incidence

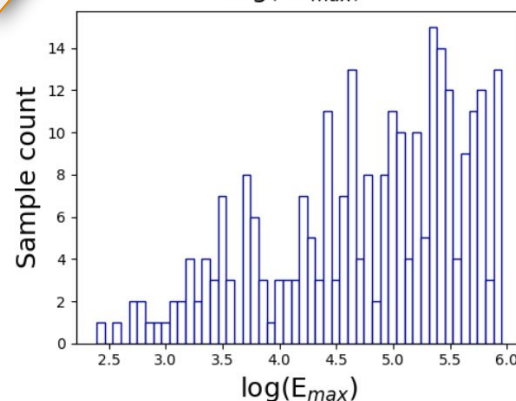
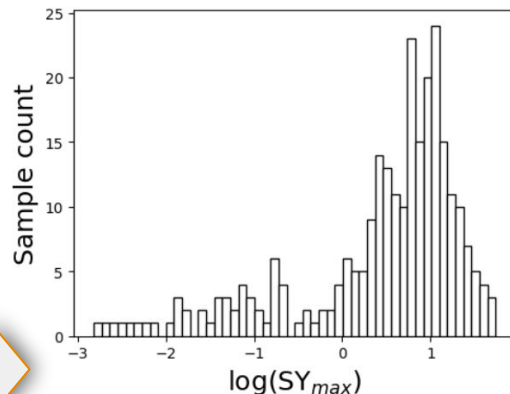
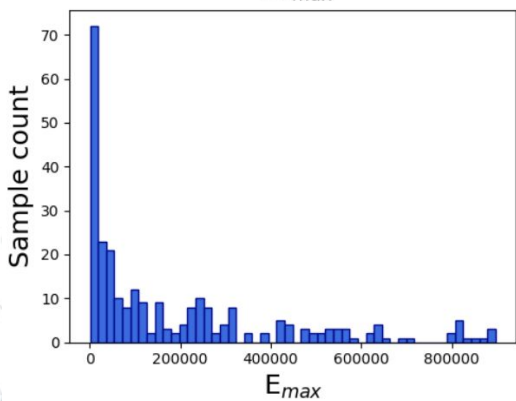
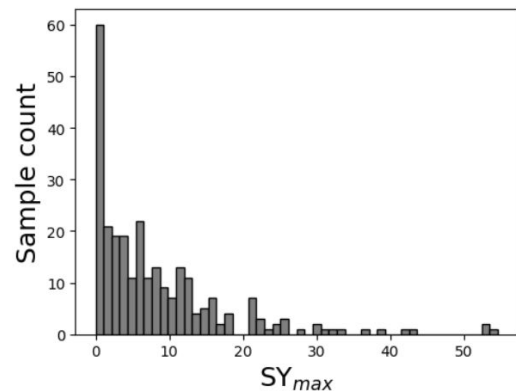
267 single element target-ion combinations

**Input descriptors (independent variables):**

Easily accessible data describing chemical and physical properties of projectile ions and target materials

| Target   | Projectile  |
|--|---|
| Atomic number, Atomic mass                         | Atomic number, Atomic mass  |
| Melting point, Boiling point                       | Melting point, Boiling point  |
| Energy of evaporation, Enthalpy of formation (gas) | Energy of evaporation (neutral), Energy of formation (neutral, gas phase) |
| Density  | —   |
| First ionization potential                         | First ionization potential (neutral particle)                             |
| Atomic, Covalent and VdW radii                     | Atomic, Covalent and VdW radii  |

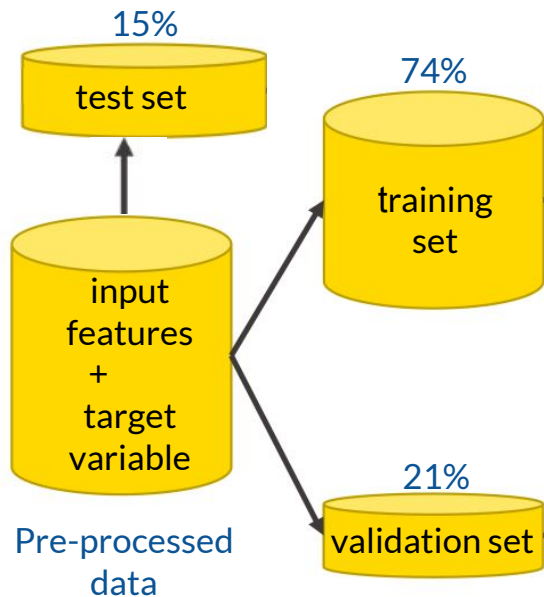
## 1. Log-transformation of the target variables



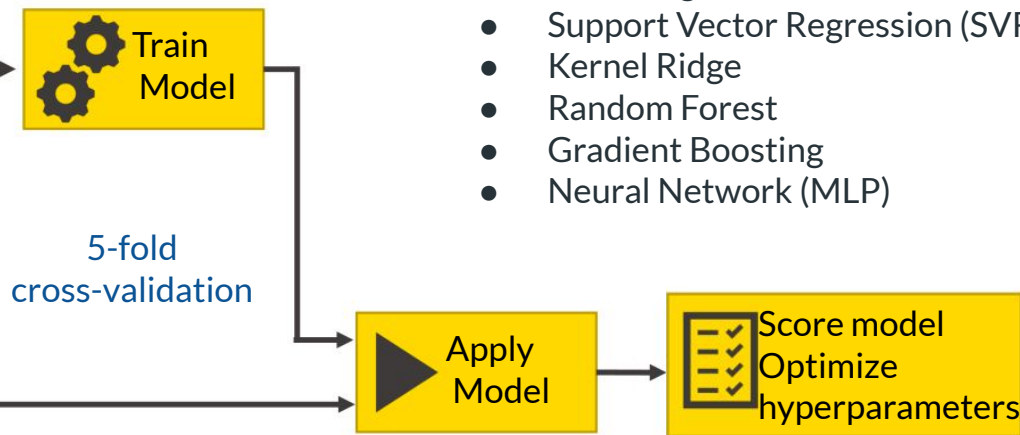
2. Missing value imputation with a simple Machine Learning algorithm

3. Normalization on the input data to bring all the descriptors to the same scale

## Data partitioning



## Model training and validation



### Considered models:

- Lasso Regression
- Support Vector Regression (SVR)
- Kernel Ridge
- Random Forest
- Gradient Boosting
- Neural Network (MLP)

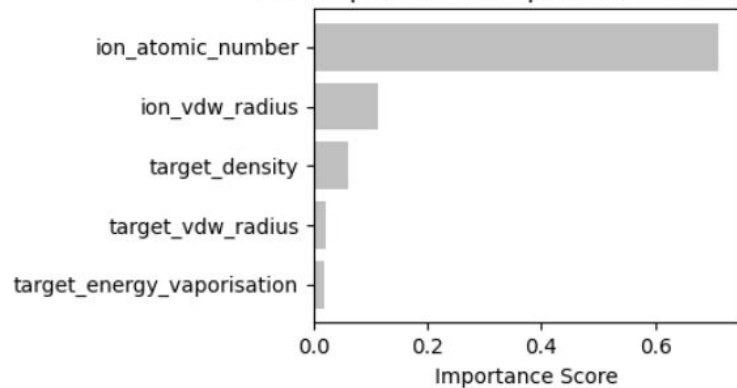
**Best predictions:** Voting regressors combining different machine learning models

$$\log(SY_{max}) = 50\% \text{ XGBoost} + 20\% \text{ Random\_Forest} + 20\% \text{ SVR} + 10\% \text{ Kernel\_Ridge}$$

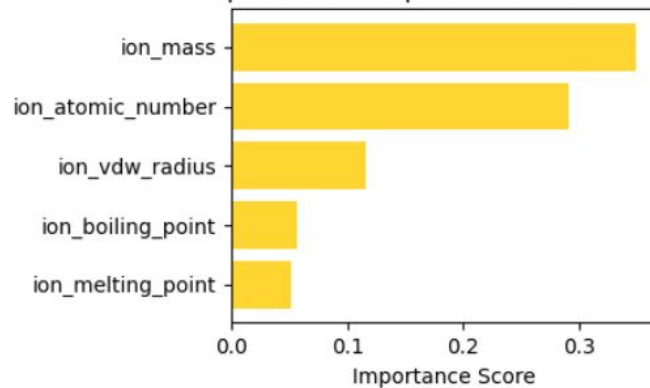
$$\log(E_{max}) = 40\% \text{ XGBoost} + 40\% \text{ Random\_Forest} + 20\% \text{ SVR}$$

# Most important descriptors

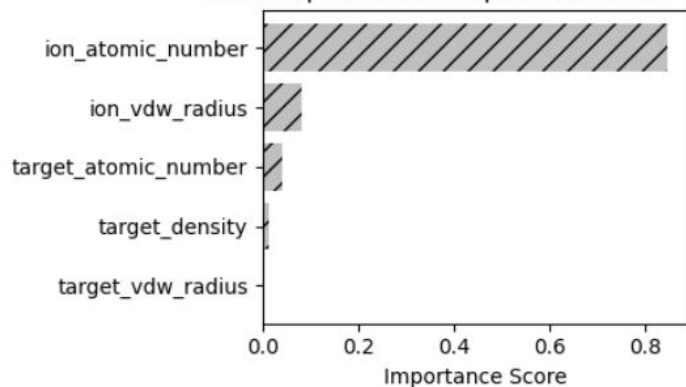
Most Important Descriptors XGBoost -  $SY_{max}$



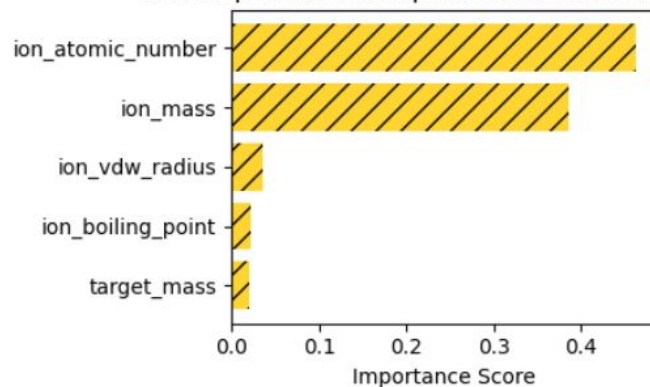
Most Important Descriptors Random Forest -  $SY_{max}$



Most Important Descriptors XGBoost -  $E_{max}$



Most Important Descriptors Random Forest -  $E_{max}$

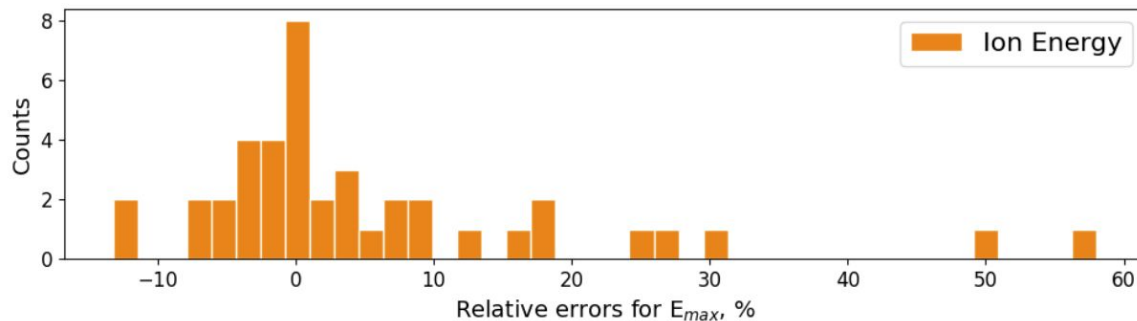
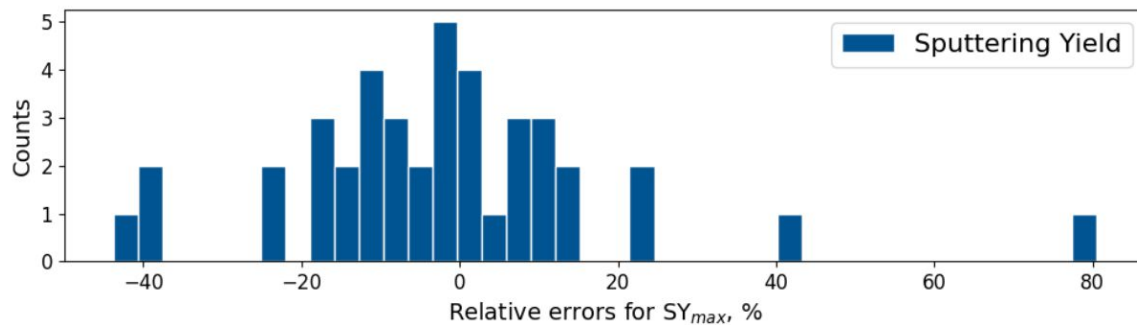




# Machine Learning predictions for test target-ion pairs

| Target                               | Mean Absolute Error Validation sets | Mean Absolute Error Test set |
|--------------------------------------|-------------------------------------|------------------------------|
| Sputtering Yield<br>$\log(SY_{max})$ | 0.0712                              | 0.0653                       |
| Ion energy<br>$\log(E_{max})$        | 0.0382                              | 0.0366                       |

Test set: 41 target-ion pairs



# SY predictions for targets composed of multiple elements

## New data set

### Sputtering yield data for

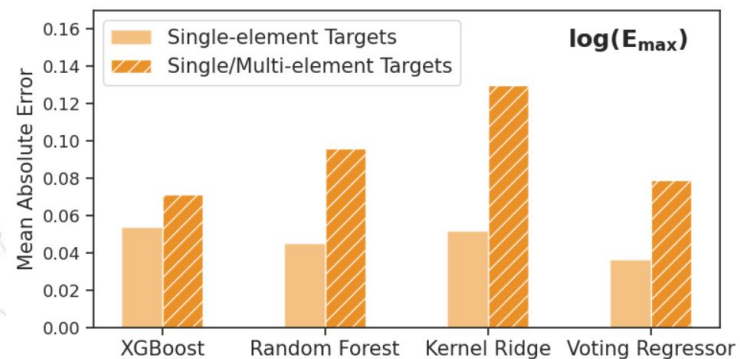
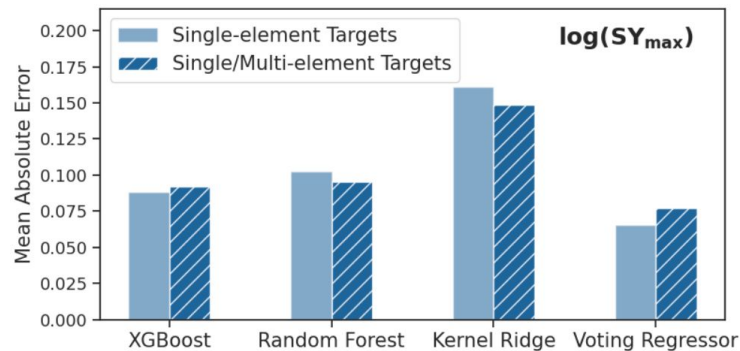
- **51** target - ion pairs with target materials composed of multiple atoms ( $N_{\text{atoms}} = 1...7$ )
- **284** single - element target - ion pairs

## Updated descriptors

| Target   | Projectile                                    |
|--|---|
| Total atomic number, Average atomic number, Molecular mass     | Atomic number, Atomic mass                    |
| Melting point, Boiling point                                   | Melting point, Boiling point                  |
| Enthalpy of formation (gas)                                    | Energy of formation (neutral, gas phase)      |
| Density  | —   |
| —  | First ionization potential (neutral particle) |
| Bulk Modulus, Lattice Volume, Lattice Type                     | —   |
| VdW radius   | Atomic, Covalent and VdW radii                |
| N atoms from different groups and blocks in the periodic table | Group and block in the periodic table         |

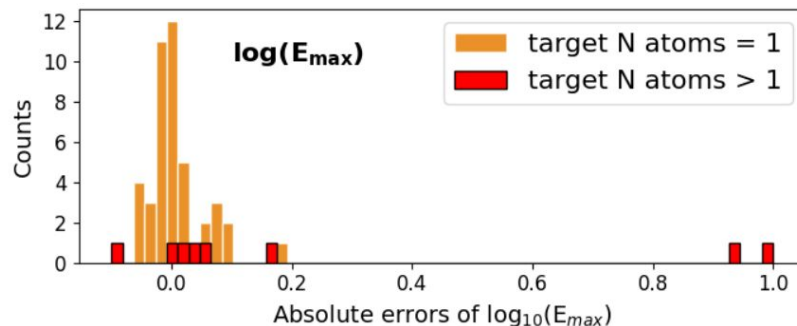
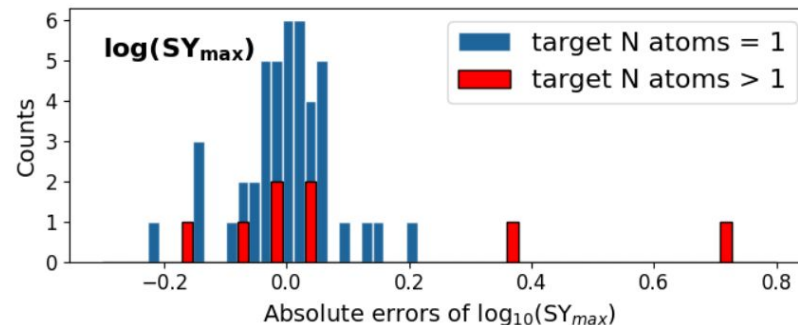
# Machine Learning predictions for test target-ion pairs

## Test data error comparison: single-element vs. mixed targets

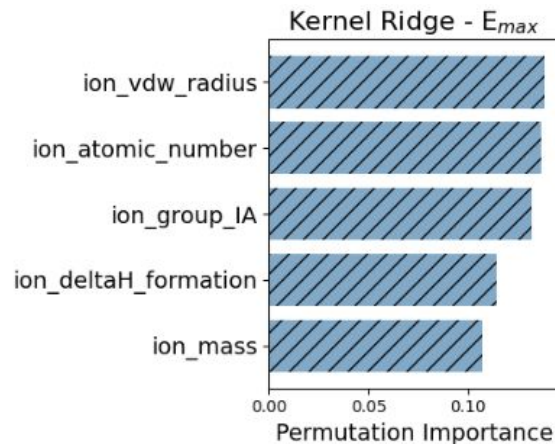
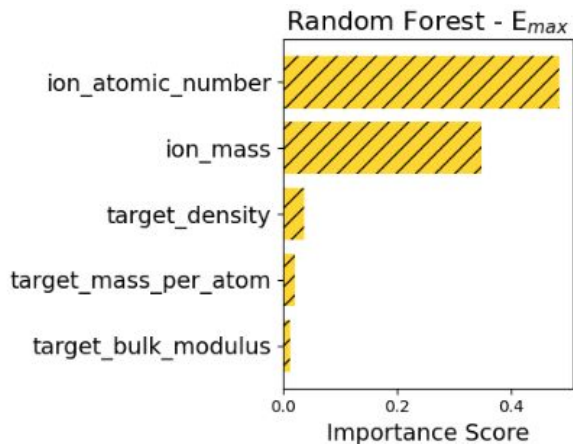
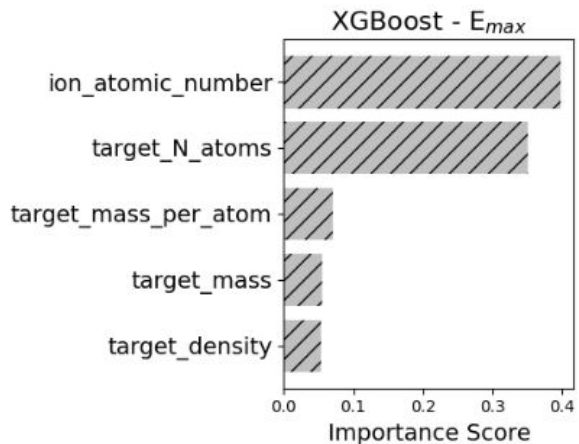
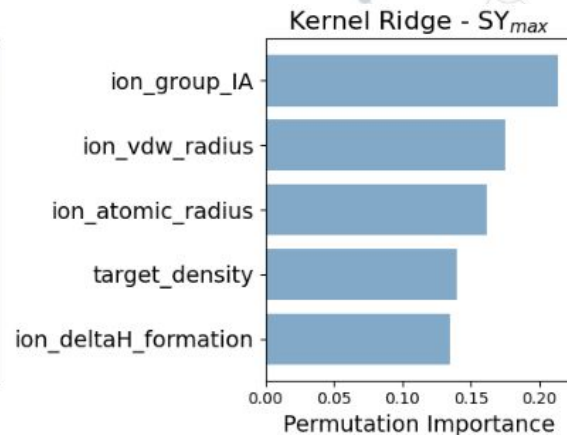
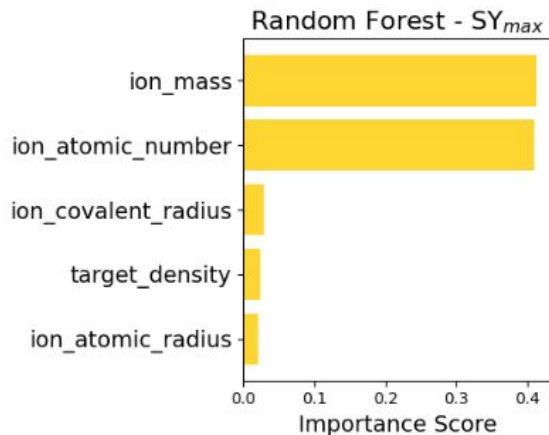
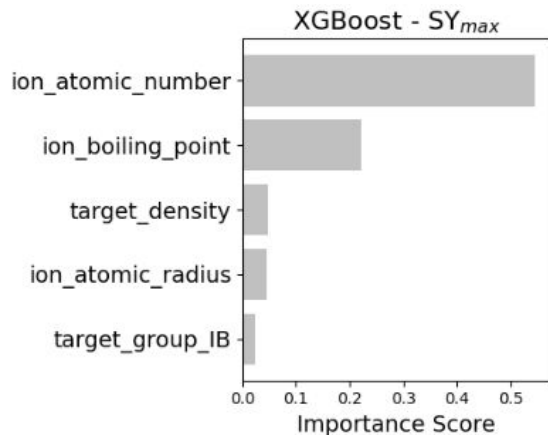


Mixed targets test set: 51 target-ion pairs

## Mean Absolute Error distribution for Voting Regressor



# Most important descriptors - targets composed of multiple elements



- ❑ Machine learning provides a cost-effective and efficient alternative to traditional experiments and simulations for predicting complex outcomes.
- ❑ We have developed a machine learning-based algorithm capable of accurately predicting sputtering yields using readily available data on the chemical and physical properties of target materials and projectile ions.