## **Predicting Movie** Ratings using **Various ML Models**

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# Rating: 75/100

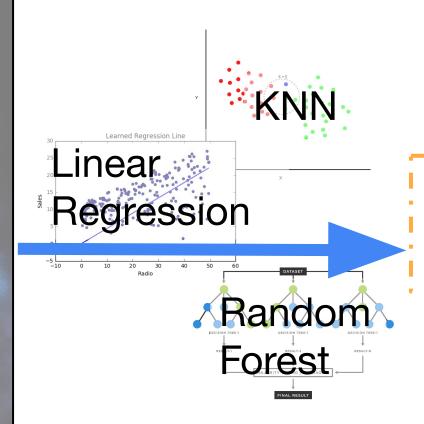
#### IMDB Database 10179 Movies

- Title
- Release Date
- Genre
- Description
- Status
- Language
- Budget
- Revenue
- Country

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## Methods

#### **K-Nearest Neighbors**

- non-parametric method
- Parameters used; Release date, Genre, Original Language, Budget, Country
- Release date = year, month, summer, valentines, halloween, christmas, new year
- Algorithm: Remember all of the training data. For new points: find the k
  closest points in the training data. For regression: typically take the average of
  the labels.
- Note, ALL SAME WEIGHT

#### **K-Nearest Neighbors**

Measuring accuracy: root-mean-square deviation

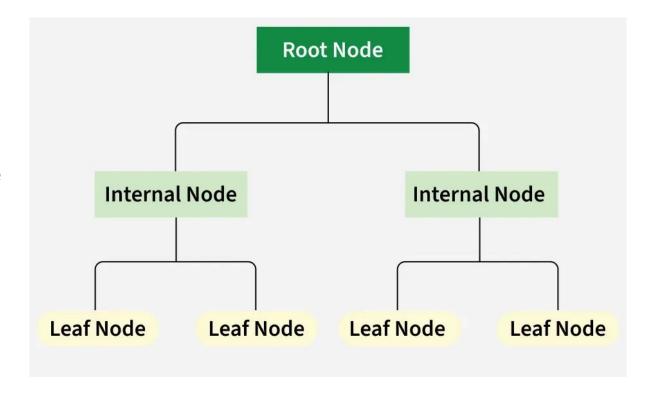
```
    i = variable i
    N = number of non-missing data points
    xi = actual observations time series
    \hat{xi} = estimated time series
```

80% training set 20% test set.

$$ext{RMSD} = \sqrt{rac{\sum_{i=1}^{N}\left(x_i - \hat{x}_i
ight)^2}{N}}$$

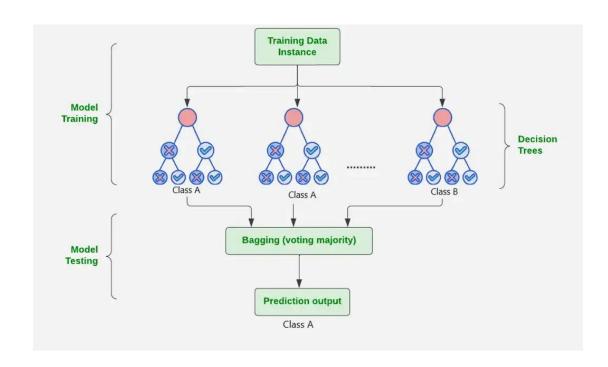
#### **Decision Tree**

- Uses data to classify the outcome of a certain data point
- Splits into two options based on the parameters of previous node



#### **Random Forest**

- Use several different decision trees to
- Best to use when importance of datapoints
- Meant to avoid overfitting and reduce bias



#### **Random Forest Parameters**

- Profit (Revenue-Budget)
- Vectorize valuation of Overview
- Genre
- Country
- Language
- Classification vs Regression
  - Majority for classification
  - Average for regression



Title, Release Date, Genre, Description, Status, Language, Budget, Revenue, Country

Title, Release Date, Genre, Description, Status, Language, Budget, Revenue, Country

Linguistic Aspects

- Description vs Rating
- Revenue/Budget vs Rating
- All Features vs Rating\*

#### Linear Regression: MLE

- 
$$\mathbf{F}$$
- Let  $\mathbf{X} = \begin{bmatrix} x_{11} & \cdots & x_{1k} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nk} \end{bmatrix}$ ,  $\mathbf{y} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}$ 
- Model
-  $\mathbf{F}$ 
-  $\mathbf{f}_{\widehat{\theta},\sigma}(y_i|\mathbf{x}_i) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(y_i - \mu_{\widehat{\theta}}(\mathbf{x}_i))^2}{2\sigma^2}\right)$ 

• 
$$f_{\widehat{\boldsymbol{\theta}},\sigma}(y_i|\boldsymbol{x_i}) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(y_i - \mu_{\widehat{\boldsymbol{\theta}}}(\boldsymbol{x_i}))^2}{2\sigma^2}\right)$$

• 
$$\mu_{\widehat{\boldsymbol{\theta}}}(\boldsymbol{x_i}) = \widehat{\boldsymbol{\theta}}^T \boldsymbol{x_i}$$

MLE

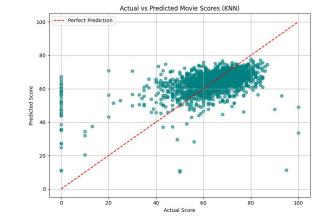
• 
$$\widehat{\boldsymbol{\theta}} = (\boldsymbol{X}^T \boldsymbol{X})^{-1} \boldsymbol{X}^T \boldsymbol{Y}$$

• 
$$\sigma^2 = \frac{1}{n} (Y - X\widehat{\theta})^T (Y - X\widehat{\theta})$$



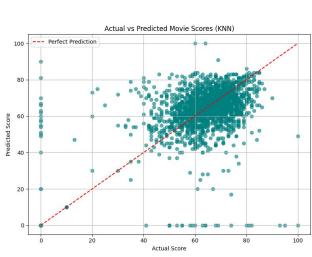
## Results

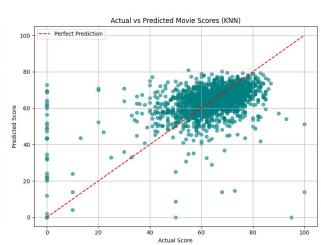
## **K-Nearest Neighbors**

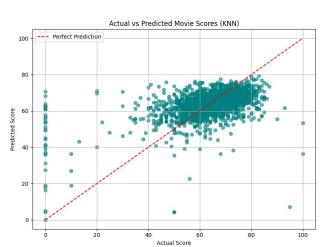


K=1, RMSE: 13.99, K=5, 11.43, K=10, 11.05,

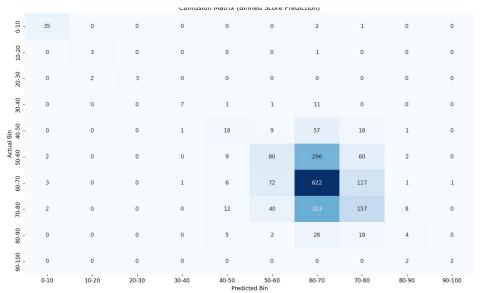
K=20 10.99



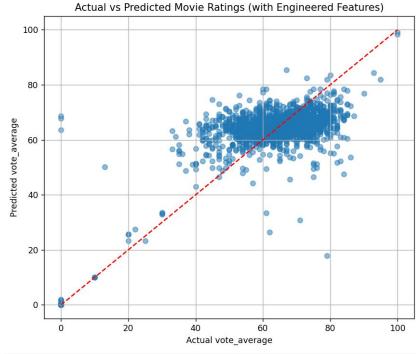




#### **Random Forest**

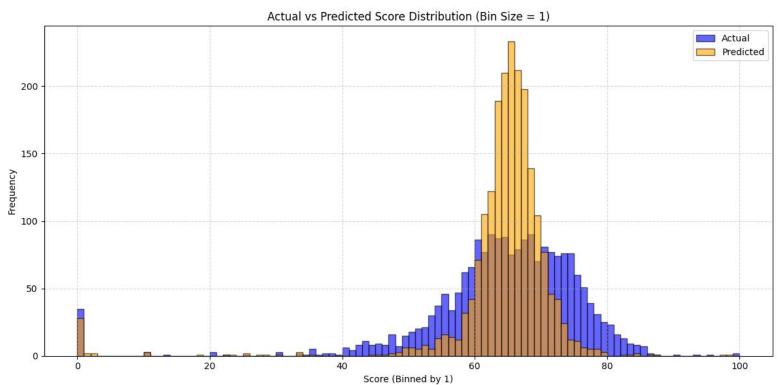


RMSE: 9.0952

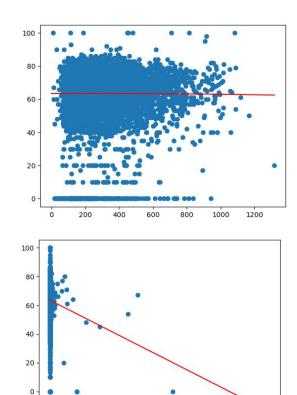


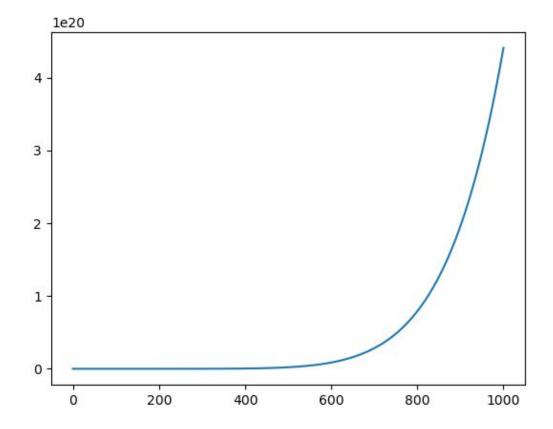
RMSE: 1.1171 bins

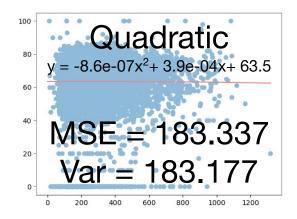
#### **Random Forest (Overfitting)**

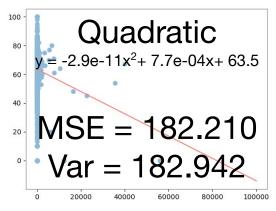


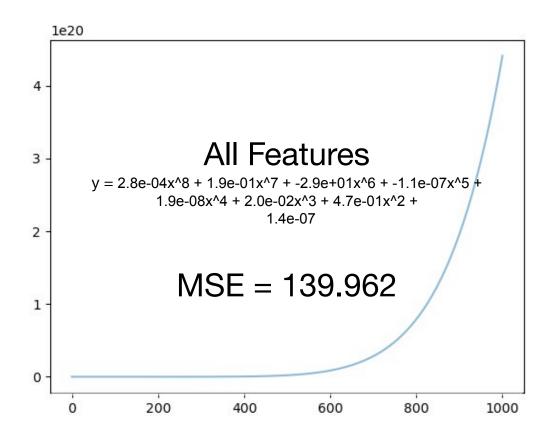
RMSE: 9.0952











## Conclusions

Our approach was ambitious...

Random Forest is the GOAT out of each of our models

But generally, this dataset has a couple factors which makes it difficult to use for prediction!

→ missing cultural factors which contribute to a movie's rating: cast, director, marketing, etc

## Thank You!

