Regression metrics optimization

Metrics optimization: our plan

1) **Regression**
   - MSE, (R)MSE, R-squared
   - MAE
   - (R)MSPE, MAPE
   - (R)MSLE
2) **Classification:**
   - Accuracy
   - Logloss
   - AUC
   - Cohen's Kappa

RMSE, MSE, R-squared

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

How do you optimize them?

Just fit the right model!

$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}} \qquad R^2 = 1 - \frac{MSE}{\frac{1}{N}\sum_{i=1}^{N}(y_i - \bar{y})^2}$$

RMSE, MSE, R-squared

- **Tree-based**

  `XGBoost, LightGBM`

  `sklearn.RandomForestRegressor`

- **Linear models**

  `sklearn.<>Regression`

  `sklearn.SGDRegressor`

  `Vowpal Wabbit` *`(quantile loss)`*

- **Neural nets**

  `PyTorch, Keras, TF,` etc.

Synonyms: L2 loss

Read the docs!

MAE

$$\mathrm{MAE} = \frac{1}{N} \sum_{i=1}^{N} |y_i - \hat{y}_i|$$

How do you optimize it?

Again, just run the right model!

MAE

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  `~~XGBoost~~, LightGBM`

  `sklearn.RandomForestRegressor`

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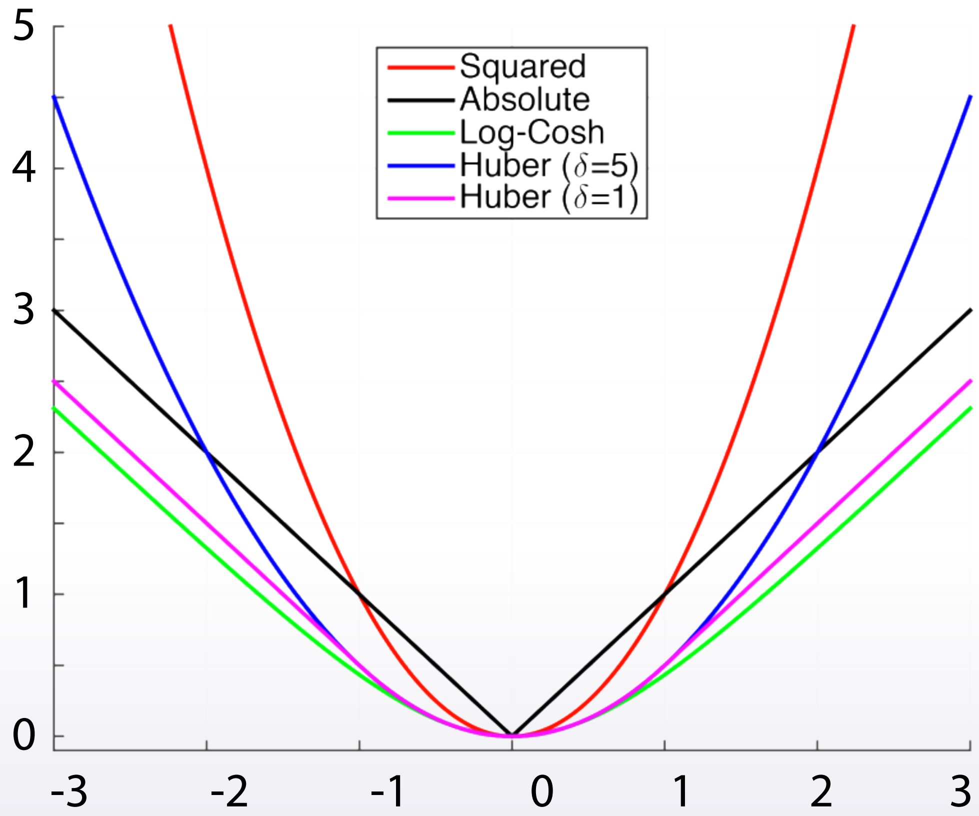
Synonyms: L1, Median regression

Read the docs!

MAE: optimal constant

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}_i|$$



MSPE and MAPE

$$\text{MSPE} = \frac{100\%}{N}\sum_{i=1}^{N}\left(\frac{y_i - \hat{y}_i}{y_i}\right)^2 \qquad \text{MAPE} = \frac{100\%}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$$

How do you optimize them?

~~Just run the right model!~~

MSPE (MAPE) as weighted MSE (MAE)

Sample weights

$$\text{MSPE} = \frac{100\%}{N} \sum_{i=1}^{N} \left(\frac{y_i - \hat{y}_i}{y_i} \right)^2$$

$$w_i = \frac{1/y_i^2}{\sum_{i=1}^{N} 1/y_i^2}$$

$$\text{MAPE} = \frac{100\%}{N} \sum_{i=1}^{N} \left| \frac{y_i - \hat{y}_i}{y_i} \right|$$

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  - Usually need to resample many times and average

RMSLE

$$\text{RMSLE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\log(y_i+1) - \log(\hat{y}_i+1)\right)^2} =$$

$$= \sqrt{MSE\left(\log(y_i+1), \log(\hat{y}_i+1)\right)}$$

Train:

1. Transform target:

$$z_i = \log(y_i + 1)$$

2. Fit a model with MSE loss

Test:

- Transform predictions back:

$$\hat{y}_i = \exp(\hat{z}_i) - 1$$

Conclusion

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