Contents

Statistics For Data Science

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1 Basic Terminologies

1.1 Population

An entire set of items you want to study

1.2 Sample

A subset of population used to estimate statistical behavior of the whole population

1.3 Histogram

A histogram is a graphical representation of numerical data that groups the data into bins and displays the frequency of data points within each bin as bars

1.4 Law of large numbers

As the number of trials (or samples) increases, the sample average (or empirical mean) will converge to the expected value (or population mean).

1.4.1 Weak Law of large numbers

The weak law states that the sample average of a sequence of independent identically distributed(i.i.d.) random variables converges in probability to

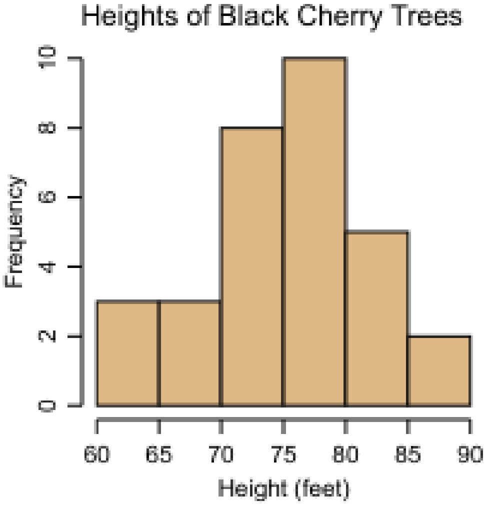

Figure 1: Example of a Histogram

the expected value as the number of samples goes to infinity

$$\bar{X}_n = \frac{1}{n}\sum_{i=1}^{n} X_i \xrightarrow{p} \mu \quad as\ n \to \infty$$

which means,

$$\forall \varepsilon > 0, \lim_{n\to\infty}^{n} \mathbf{p}(|\bar{X}_n - \mu| > \varepsilon) = 0$$

1.4.2 Strong Law of large numbers

The strong law states that the sample average of a sequence of i.i.d. random variables converges almost surely to the expected value as the number of samples goes to infinity

$$\bar{X}_n = \frac{1}{n}\sum_{i=1}^{n} X_i \xrightarrow{a.s.} \mu \quad as\ n \to \infty$$

Which means,

$$\mathrm{P}(\lim_{n\to\infty} \bar{X}_n = \mu) = 1$$

2 Measure of Central Tendency

2.1 Mean

Average of all data points, sensitive to outliers since a single large outlier could easily skew mean

$$\mu = \frac{\sum x_i}{n}$$

2.2 Median

The middle data point when data are stored, robust to outliers

2.3 Mode

The most frequent data point of the dataset

3 Measure of Spread

Range: Difference between minimum value and maximum value

$$Range = x_{max} - x_{min}$$

3.1 Variance

Average squared deviation

$$\sigma^2 = \frac{\sum (x_i - \mu)^2}{n} (Population)$$

$$s^2 = \frac{\sum (\bar{x_i} - \mu)^2}{n-1} (Sample)$$

3.2 Standard Deviation

Root of Variance

$$\sigma = \sqrt{\sigma^2}$$

3.3 Inter Quartile Range(IQR)

Difference between 75th Percentile/3rd Quartile and 25th Percentile/1st Quartile, it is used for outlier detection

$$IQR = Q_3 - Q_1$$

4 Probability Distributions

4.1 Discrete Distributions

A discrete probability distribution describes the probability of occurrence of each value of a discrete random variable

- Discrete random variable: Countable values like 1,2,3
- Each individual value has an associated probability
- The sum of probabilities for all possible values is 1

$$\sum_i \mathrm{P}(X = x_i) = 1$$

4.2 Continuous Distributions

5 Shape fo the Distributions

5.1 Skewness

Measure of Asymmetry

5.1.1 Right-skewed

tail on the right ($mean > median$)

5.1.2 Left-skewed

tail on the left ($mean < median$)

6 Evaluation Metrics

6.1 Mean Absolute Error

$$MAE = \frac{1}{n} \sum |y_i - \hat{y}_i|$$

- Robust to outliers, treats all errors equally doesn't square the errors like RMSE,MSE..etc
- It's used when your model can tolerate moderate outliers
- Interpretability - Has same unit as the thing you are predicting/easy to understand
- Gives out constant gradient (bad for gradient based loss function)

6.1.1 Gradient of MAE

$$\frac{d}{d\hat{y}}|y - \hat{y}| = \begin{cases} +1 & \text{if } \hat{y} < y \\ -1 & \text{if } \hat{y} > y \\ \text{undefined} & \text{if } \hat{y} = y \end{cases}$$

As you can see no matter how far the error is from true value it always gives a constant gradient as it treats every error as same stics

6.2 Mean Squared Error

$$MAE = \frac{1}{n} \sum (y_i - \hat{y}_i)^2$$

- Penalizes large errors/outliers
- Gives out strong gradient signals

6.2.1 Gradient of MSE

$$\frac{dMSE}{d\hat{y}} = -\frac{2}{n}(y - \hat{y})$$

It points in the direction of the error, and it grows linearly with size of the error Larger the gradient, when prediction are more wrong $\longrightarrow$ model adjusts faster

6.3 Root Mean Squared Error(RMSE)

$$RMSE = \sqrt{MSE}$$

- It combines interpretability of MAE and sensitive to errors of MSE
- It has smooth gradient curves just like MSE, and it's preferred for gradient descent

6.3.1 Gradient of RMSE

$$\frac{dRMSE}{\hat{y_i}} = \frac{1}{n * RMSE}(\hat{y_i} - y_i)$$

1. The gradient strength changes with RMSE, if your RMSE is very large the gradient becomes small, and if your RMSE is very small the gradient becomes large.
2. It makes RMSE a Non-constantly scaled loss
3. MSE is preferred over RMSE in training, but RMSE is preferred while reporting for interpretability

6.4 R-Square(R^2)

6.5 Adjusted R^2

6.6 Huber Loss

6.7 MAPE

7 TODO

1. other eval metrics precision, recall, f1 etc..