MACHINE LEARNING

Classification

Muhammad Afif Hendrawan, S.Kom., M.T.

Outlines

- Callback - Probability
- Bayes Theorem
- Naive Bayes Intuition
- Discriminative vs. Generative Models
- Types of Naive Bayes

Callback - Probability

Bayes Theorem

Bayes Theorem - Concept

"is a way to find a probability value of an event based on the probability values of another known event"

Likelihood

Prior Probability

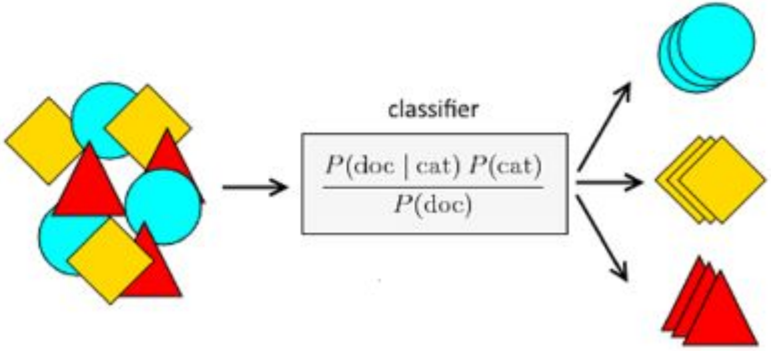
$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

Posterior Probability

Marginal Likelihood

Bayes Theorem - Formal Definition

- A machine learning model based on **Bayesian theorem** (rule) to classify objects based on specific features.
- Attempting to find the label of object 'A' based on feature 'B'.

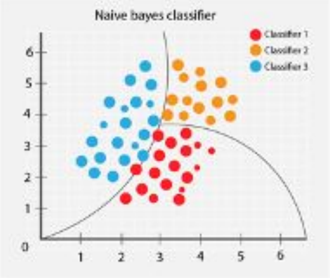


In machine learning, naive Bayes classifiers are a family of simple "probabilistic classifiers" based on applying Bayes' theorem with strong (naive) independence assumptions between the features.

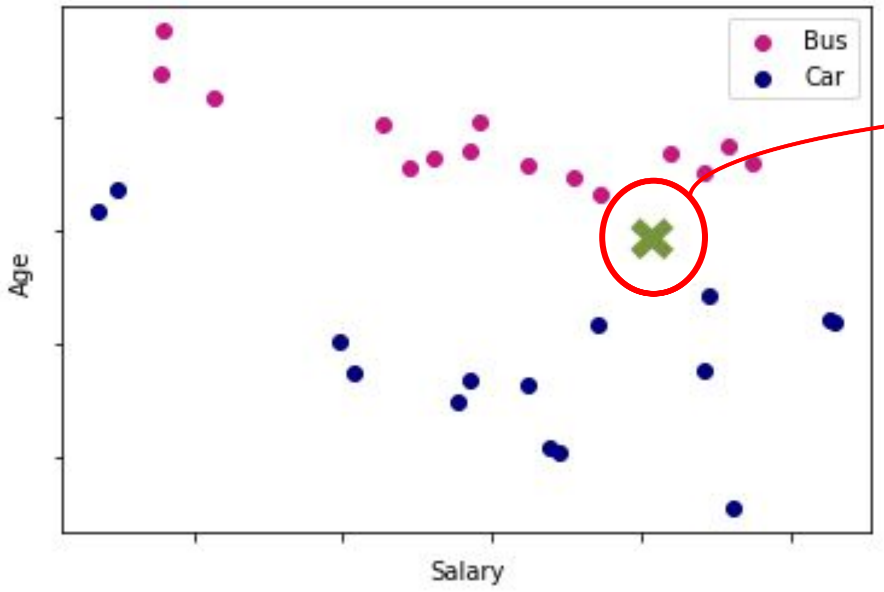
$$P(A|B) = \frac{P(B|A)\,P(A)}{P(B)}$$

using Bayesian probability terminology, the above equation can be written as

$$\text{Posterior} = \frac{\text{prior x likelihood}}{\text{evidence}}$$



Bayes Theorem - Intuition #1



What happen with “X”?
Is “X” a bus or a car?

Bayes Theorem - Intuition #2

Find the probability of the bus

$$P(Bus|X) = \frac{P(X|Bus)P(Bus)}{P(X)}$$

Bayes Theorem - Intuition #3

Find the probability of the car

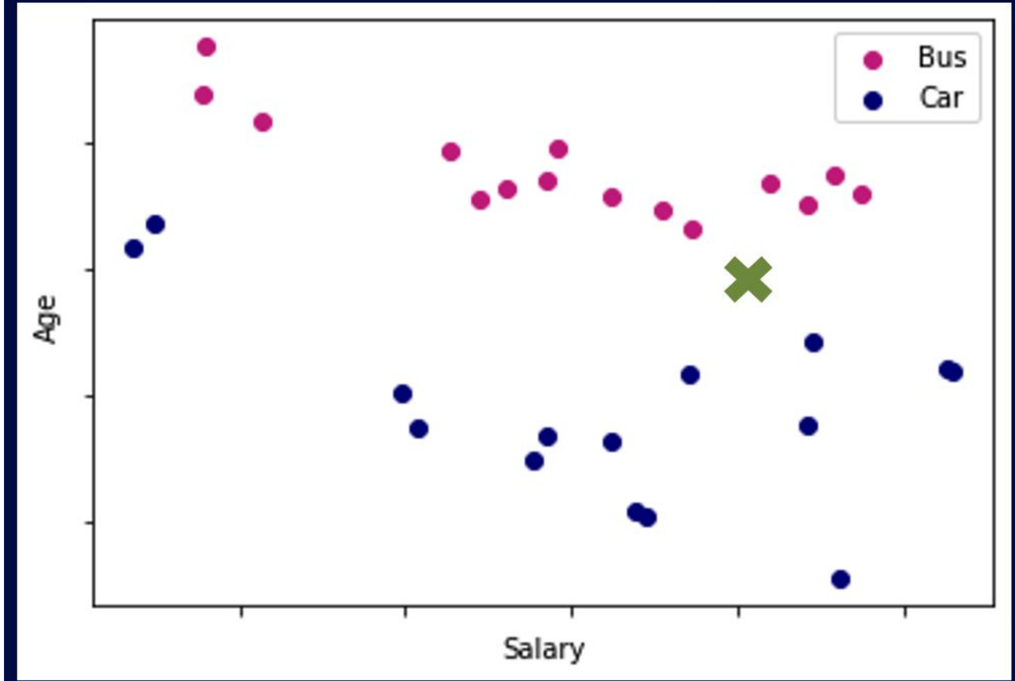
$$P(Car|X) = \frac{P(X|Car)P(Car)}{P(X)}$$

Bayes Theorem - Intuition #4

Compare the probability of bus and car

$$P(Bus|X)\ vs.\ P(Car|X)$$

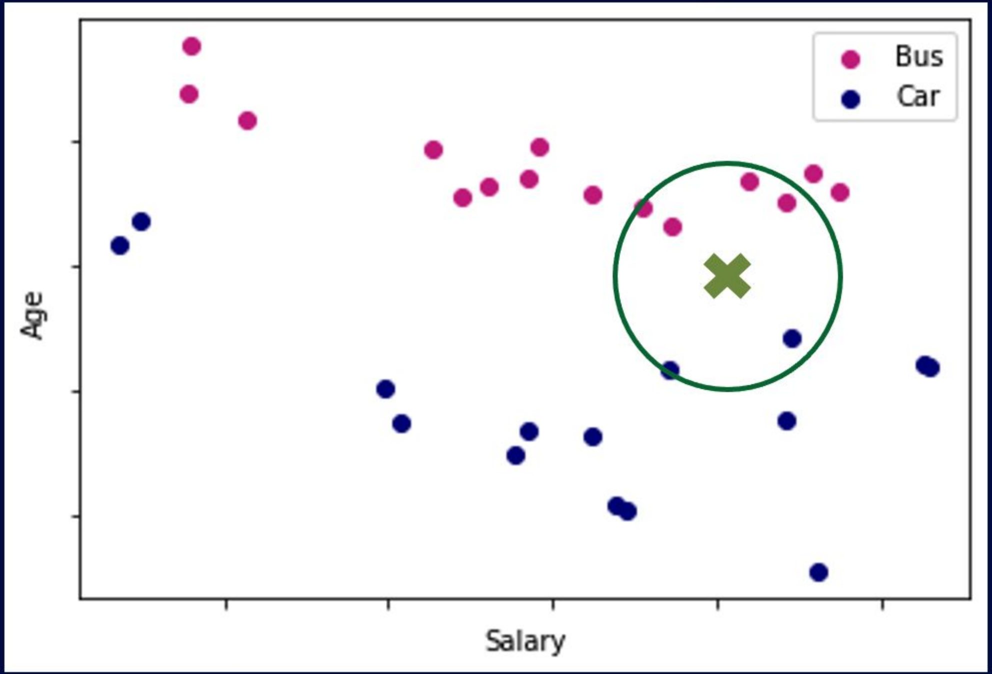
Bayes Theorem - Solution #1



$$P(Bus) = \frac{Total\ of\ Bus}{Total\ of\ Data}$$

$$P(Bus) = \frac{15}{30} = 0.5$$

Bayes Theorem - Solution #2



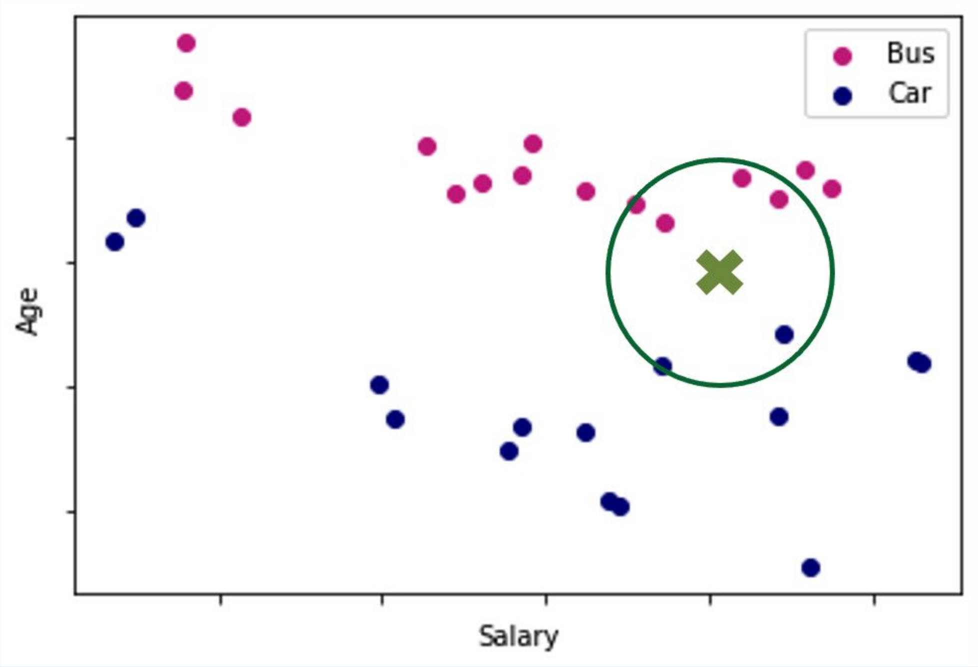
$$P(X) = ???$$

Think about the circle

$$P(X) = \frac{Total\ Observation}{Total\ of\ Data}$$

$$P(X) = \frac{6}{30} = 0.2$$

Bayes Theorem - Solution #3



$$P(X|Bus) = ???$$

Think about the circle (again)

Think the person who ride a bus within the circle

$$P(X|Bus) = \frac{Total\ Observation\ of\ Bus}{Total\ of\ Bus}$$

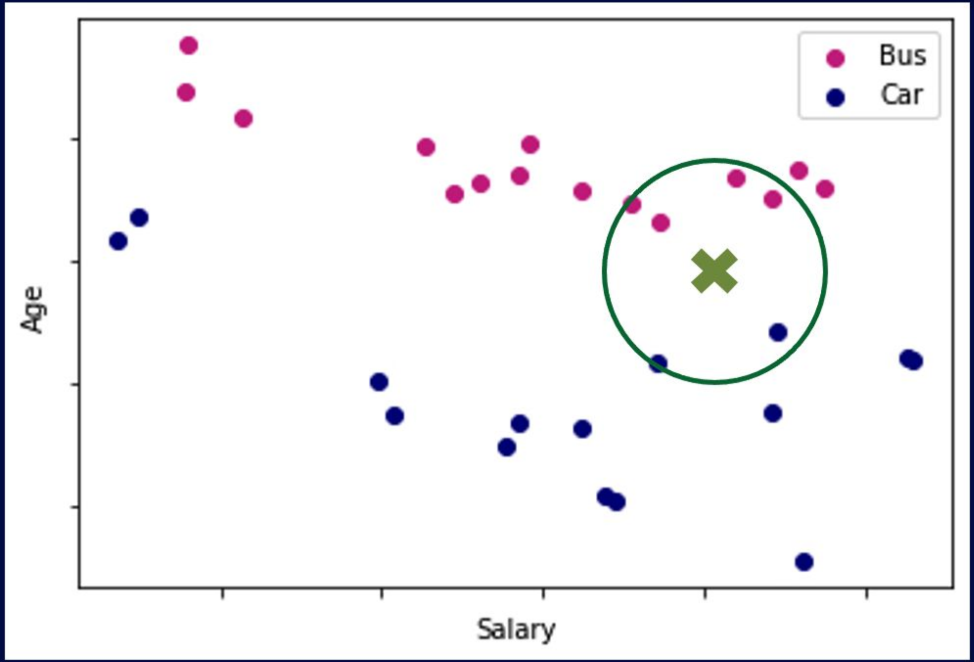
$$P(X|Bus) = \frac{4}{15} = 0.267$$

Bayes Theorem - Solution #4

$$P(Bus|X) = \frac{P(X|Bus)P(Bus)}{P(X)}$$

$$P(Bus|X) = \frac{0.267 * 0.5}{0.2} = 0.6675 \approx 66.75\%$$

Bayes Theorem - Solution #5



$$P(Car) = \frac{15}{30} = 0.5$$

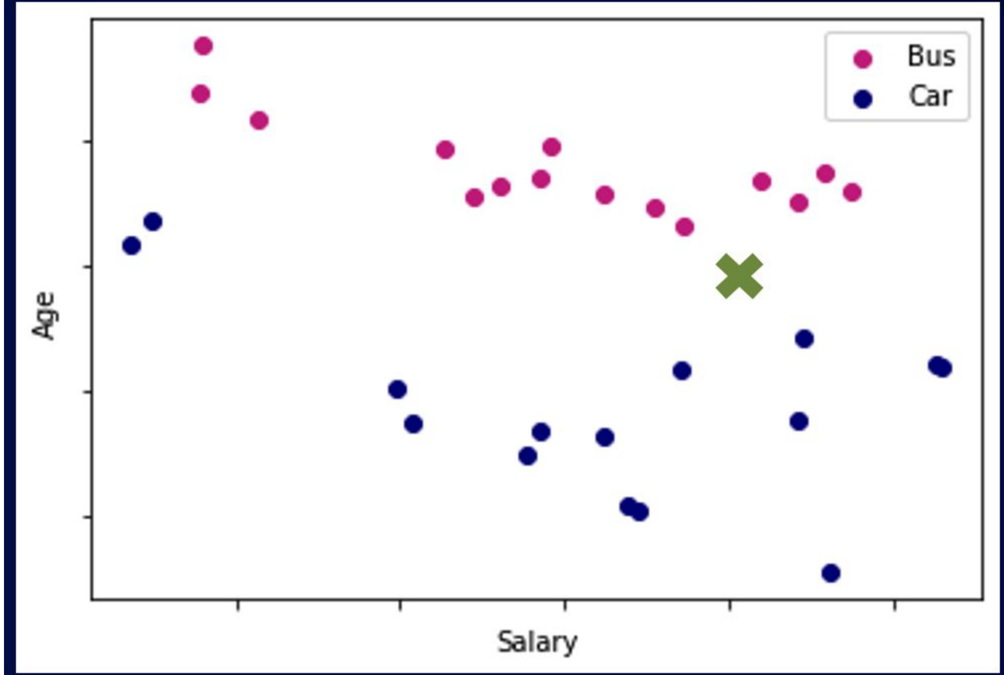
$$P(X) = \frac{6}{30} = 0.2$$

$$P(X|Car) = \frac{2}{15} = 0.133$$

$$P(Car|X) = \frac{0.133 * 0.5}{0.2} = 0.3325$$

$$P(Car|X) \approx 33.25\%$$

Bayes Theorem - Solution #6 (FINAL)



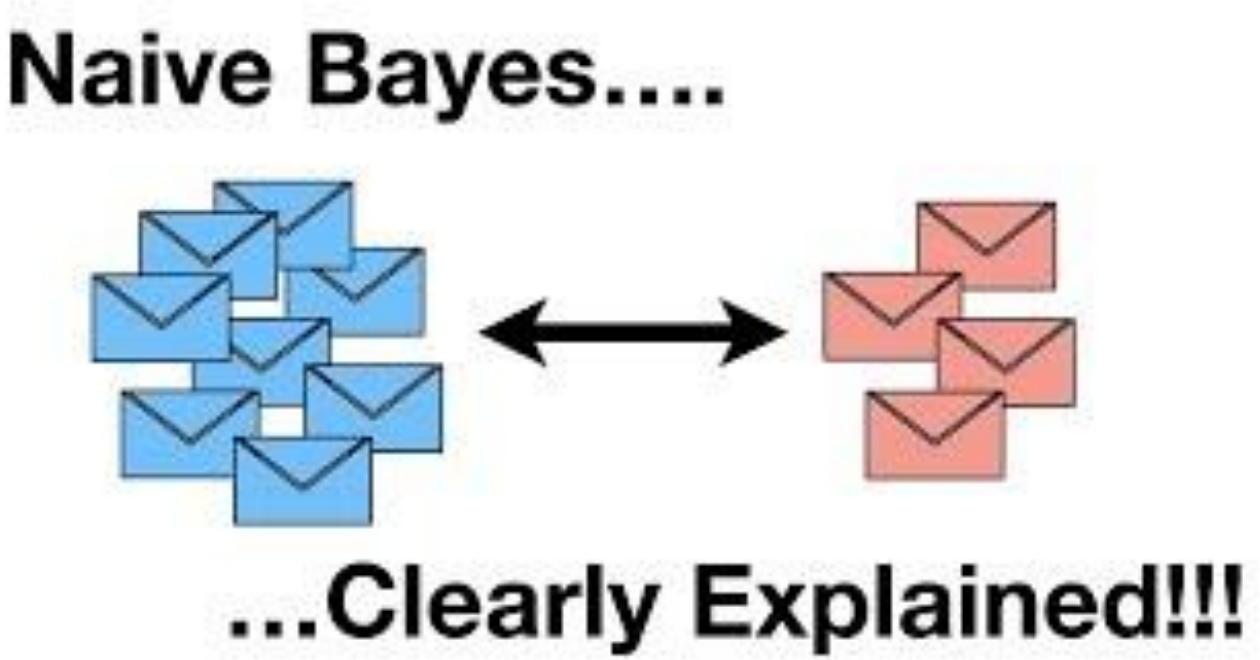
$$P(Bus|X)\ vs.\ P(Car|X)$$

$$66.75\%\ vs.\ 33.25\%$$

$$66.75\% > 33.25\%$$

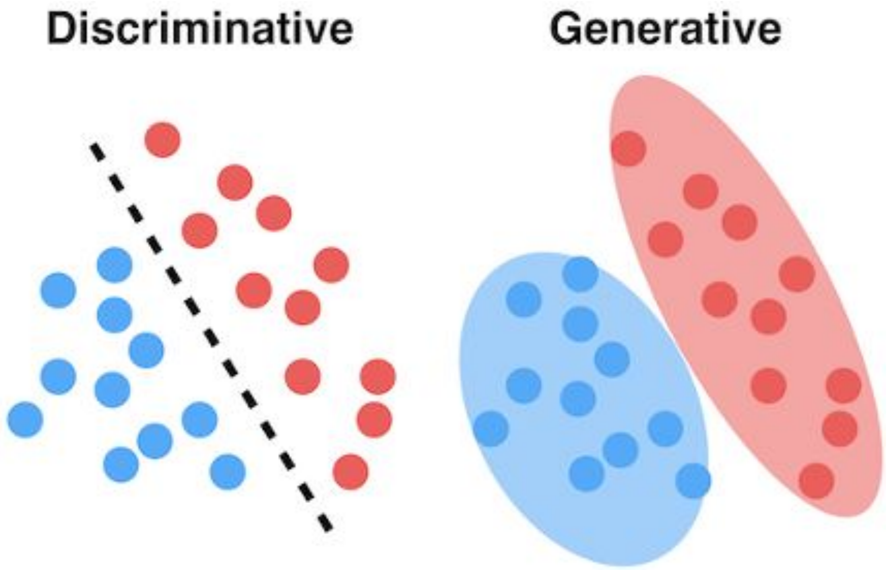
$$X\ is\ Bus$$

Great Explanation from StatQuest!



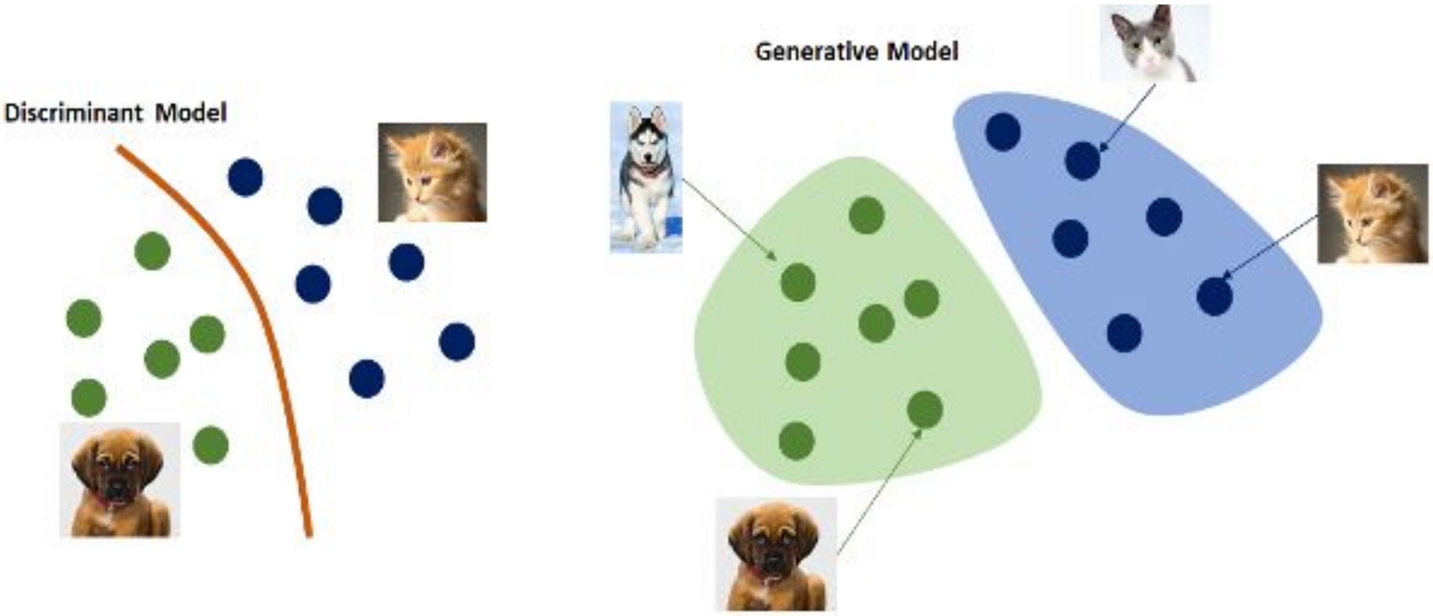
Discriminative vs. Generative Models

Discriminative vs. Generative Models



- A **Discriminative** model based on decision boundaries that differentiate each class.
- A **Generative** models are constructed based on the joint probability distribution of features and classes, P(x, y).

Discriminative vs. Generative Models - Example



What is Generative Models?

- A machine learning model based on the probability of a class and the probability of features that describe a specific class.
- Machine learning models depict how classes directly generate new features or examples from data but can lead to more biased calculations.
- Generative models produce models that perform sufficiently well with limited training data and are more 'resilient' to overfitting conditions.
- The drawback of generative models is their reliance on assumptions, which can hinder the model's ability to 'learn' more effectively.

So,
What do you think about Naive Bayes?

Types of Naive Bayes

Types of Naive Bayes

- Multinomial Naïve Bayes - For features with **discrete** values.
- Binomial Naïve Bayes - Similar to multinomial Naïve Bayes, but for **boolean features**.
- Gaussian Naïve Bayes - For **continuous features** assumed to follow a **normal distribution**.


рахмат
danke
謝謝
spas
ngiyabonga
شكراً جزيلاً
Баярлалаа
mersi
kia ora
barka
welalin
tack
teşekkür ederim
mahalo
tapadh leat
спасибо
faafetai lava
vinaka
спасибі
blagodaram
dank je
misaotra
matondo
paldies
grazzi
gracias
хвала
kiitos
dankie
nanni
nandri
dhanyavad
thank you
asante
manana
obrigada
tenki
bedankt
bayarlalaa
gràcie
hvala
mauruuru
köszönöm
aciū
dankon
akun
enkosi
djiere dieuf
tau
mochchakkeram
murakoze
dziękuję
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mamnun
chnorakaloutioun
gratias ago
gràcies
sulpáy
go raibh maith agat
chokrane
sobodi
dėkuji
sagolun
sukriya
kop khun krap
taiku
arigatô
takk
dakujem
trugarez
obrigado
mèsi
didi madloba
ありがとう
najis tuke
tanemirt
grazie
rahmet
terima kasih
kam sah hamnida
rahmat
ευχαριστώ
diolch
dhanyavadagalu
shukriya
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мерси
তোমাকে ধন্যবাদ
감사합니다
xièxie
merci