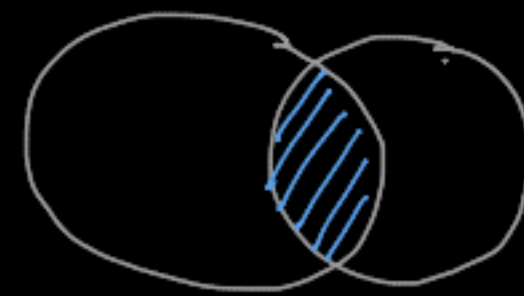
Naive Bayes' Algorm

1. Conditional Probability

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



$$P(A \cap B) = P(A|B) \cdot P(B).$$

$$P(A, B) \qquad \text{—(1)}.$$

$P(A \cap B) = P(B \cap A)$

$P(A, B)$ $P(B, A)$

2. A & B are mutually 'independent'.

$$P(A|B) = P(A).$$

|||ly $P(A|B, C, D) = P(A|D).$ —(2).

if A is indep. of B, C.

zoom.us Meeting View Edit Window Help

3. Mutually Exclusive.

$P(A|B) = 0$.

- if A & B are exclusive Events.

Bayes' Theorem.

Likelihood.

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)} \quad \text{--- (3)}$$

Prior.

Posterior.

Evidence.

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Classification can be expressed as Conditional probability

$$P(C_k|x) \Rightarrow \left.\begin{array}{l} P(C_0|x) \\ P(C_1|x) \end{array}\right\} \text{whichever is greater}$$

x_1	x_2	x_3	y
-	-	-	C_0
-	-	..	C_1

$$P(C_k|x) = \frac{P(x|C_k) \cdot P(C_k)}{P(x)}$$

$P(x) \rightarrow$ Constant.

$$\simeq P(x|C_k) \cdot P(C_k).$$

$$\simeq P(x, C_k) \quad \text{from (1)}.$$

$$\Rightarrow P(x_1, x_2, x_3, \ldots x_d, C_k).$$

From (1).

✓ $P(A,B) = P(A|B)\cdot P(B)$.

$P(A|B,C,D) \Rightarrow P(A|D)$.

$$P(C_k|x) = P(x, C_k)$$

$$= P(\underbrace{x_1}_{A}, \underbrace{x_2, x_3, x_4, \ldots x_d, C_k}_{B}).$$

Chain Rule.

$$= P(x_1 | x_2, x_3, x_4 \cdots x_d, C_k) \cdot P(\underbrace{x_2}_{A}, \underbrace{x_3, x_4 \cdots x_d, C_k}_{B})$$

$$\cdot P(x_2 | x_3, x_4, \cdots x_d, C_k) \cdot P(\underbrace{x_3}_{A}, \underbrace{x_4, \cdots x_d, C_k}_{B})$$

$$P(x_3 | x_4, \cdots x_d, C_k) \cdot$$

$$P(x_4, \cdots x_d, C_k)$$

$\leftarrow x \rightarrow$

x_1	x_2	x_3	y

$$P(x_d|C_k)\cdot P(C_k)$$

$$P(x_1|C_k) \times P(x_2|C_k) \cdot P(x_3|C_k) \cdots P(x_d|C_k) \cdot P(C_k)$$

$$P(C_k \mid \vec{x}) = P(x_1 \mid C_k) \cdot P(x_2 \mid C_k) \cdot P(x_3 \mid C_k) \cdots P(x_d \mid C_k) \cdot \underline{P(C_k)}.$$

$\rightarrow$ Bayes' Theorem

$x_1 \quad x_2 \quad x_3 \quad x_1 \qquad y$

Sunny High Mild Strong $\rightarrow$? yes / No.

$$P(\text{yes} \mid (S, H, M, s)) \rightarrow P(\text{Sunny} \mid \text{yes}) \cdot P(\text{High} \mid \text{yes}) \cdot P(\text{Mild} \mid \text{yes}) \cdot P(\text{Strong} \mid \text{yes}) \cdot \underline{P(\text{y}}$$

$$P(\text{No} \mid (S, H, M, s)) \rightarrow \left(\tfrac{2}{9}\right) \cdot \left(\tfrac{3}{9}\right) \cdot \left(\tfrac{4}{9}\right) \left(\tfrac{3}{9}\right) \cdot \left(\tfrac{9}{14}\right) =$$

$$\hookrightarrow P(\text{Sunny} \mid \text{No})\, P(\text{High} \mid \text{No})\, P(\text{Mild} \mid \text{No}) \cdot P(\text{Strong} \mid \text{No}) \cdot P(\text{No}).$$

$$\left(\tfrac{3}{5}\right)\left(\tfrac{4}{5}\right)\left(\tfrac{2}{5}\right)\left(\tfrac{3}{5}\right)\left(\tfrac{5}{14}\right) =$$

Multinomial NB → Counts / discrete.

BoW → 2 4 3 1 0

Continuous → GaussianNB.

Categorical NB → Cat. data.

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Forecasting   Univariate.

— time related.

— Predicting into the future.

x_1	x_2	x_3	y
.	..	.	.

	Time (t)	Sales (y)
Jan 2000	1	—
Feb 2000	2	.
March 2000	3	.
	:	y_{t-2}
Nov 2021	$n-1$	y_{t-1}
→ Dec 2021	n^{th}	y_t
Jan 2022		— y_{t+1}
Feb 2022		— y_{t+2}

Past Data

} Forecast

Period → days
→ months
— weeks
→ seconds
→ years.
— ms

y_{t+k}

↳ No. of Periods

Chronology should be maintained.

	x_1	x_2	x_3	y
1				
2				
3				
⋮				
$n=1000$				

Randomly
Choose 80% → train
20% → test.

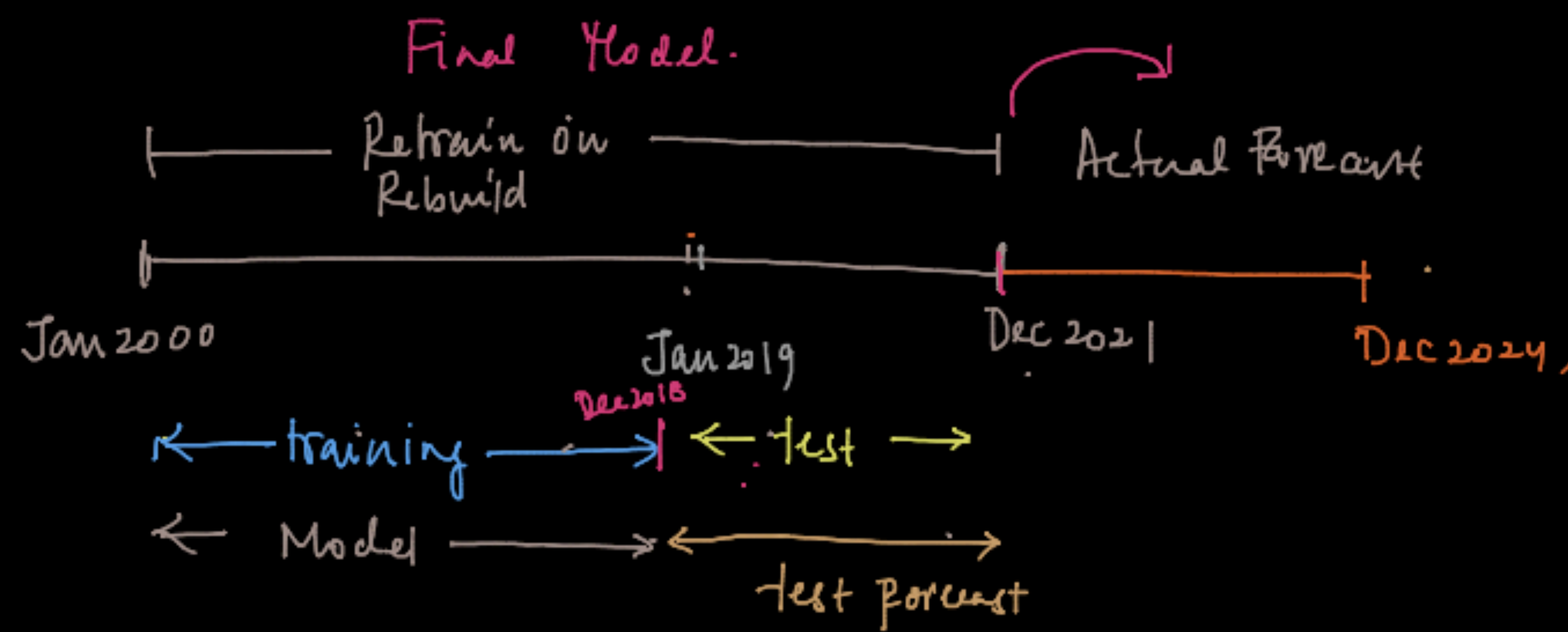
240 → Months
264 → Months

Time (t)	Sales (y)
Jan 2002 1	⋮
2	⋮
⋮	⋮
Dec 2021 n	⋮

228 months
36 months Test.

Future
Jan 2022
Feb 2022
⋮
Dec 2025

36 months test


Final Model.
Retrain on Rebuild
Actual Forecast
Jan 2000
Jan 2019
Dec 2021
Dec 2024.
Dec 2018
training
test
Model
test forecast