# Foundations of Machine Learning Al2000 and Al5000

FoML-02 Probability - Bayes Theorem and Independence

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#### So far in FoML

• What is ML?





#### So far in FoML

- What is ML?
- Learning Paradigms









 Provides a consistent framework for the quantification and manipulation of "Uncertainty"





- Provides a consistent framework for the quantification and manipulation of "Uncertainty"
- Where does this 'Uncertainty' come from?





## Uncertainty in ML

Measurement Noise





## Uncertainty in ML

- Measurement Noise
- Finite size of the datasets





Frequentist Interpretation





- Frequentist Interpretation
  - Fraction of times the event occurs





Bayesian Approach





- Bayesian Approach
  - o Quantification of plausibility or strength of the belief of an event





- Bayesian Approach
  - o Quantification of plausibility or strength of the belief of an event
  - Modeling based approach





- Bayesian Approach
  - o Quantification of plausibility or strength of the belief of an event
  - Modeling based approach
  - Plays a central role in this course





#### Random Variable

• Stochastic variable sampled from a set of possible outcomes





#### Random Variable

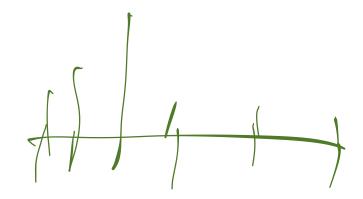
- Stochastic variable sampled from a set of possible outcomes
- Discrete or Continuous

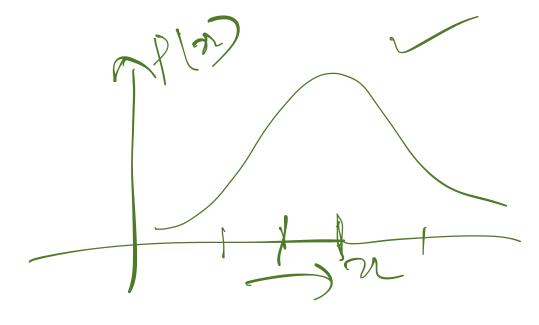




#### Random Variable

- Stochastic variable sampled from a set of possible outcomes
- Discrete or Continuous
- Probability distribution  $\rho(X)$



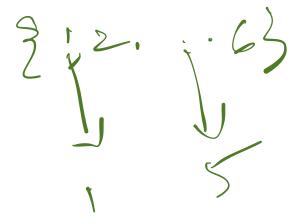






## Random Variable - Example (discrete)

Throwing a dice







## Random Variable - Example (discrete)

• Flipping a coin  $\{H, 7\}$ 



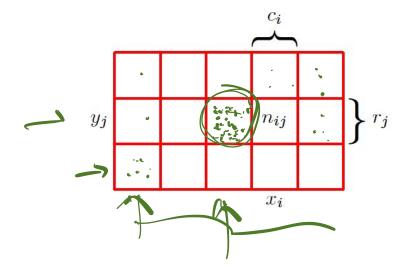


- X
- Y





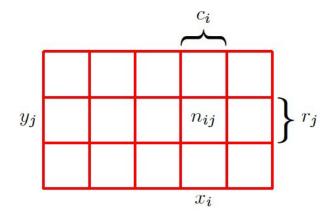
- N trails: sample both







Joint probability

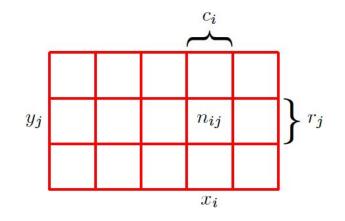






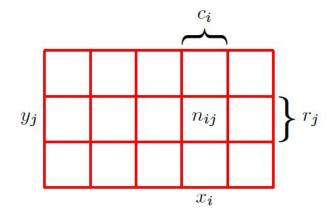
Joint probability

$$p(X = x_i, Y = y_j) = (ij)$$





• If I am interested only on X



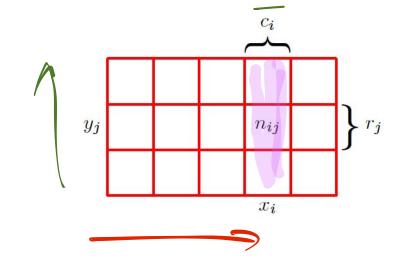




- If I am interested only on X
- Marginal probability of X

$$p(X = x_i) = \frac{\zeta_i}{N}$$

$$\zeta_i = \frac{\zeta_i}{N}$$

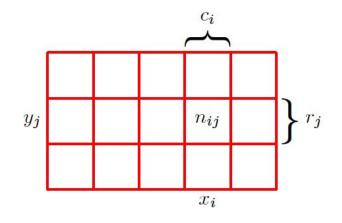






## Sum rule of Probability

$$p(X = x_i) = \sum_{j=1}^{3} p(X = x_i, Y = y_j)$$



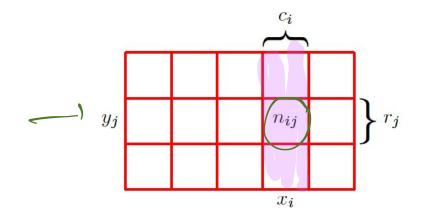




## Conditional Probability

Conditional probability of Y given X

$$p(Y = y_j(X = x_i)) =$$

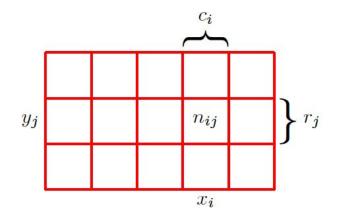






## Product Rule of probability

$$p(Y = y_j/X = x_i) =$$

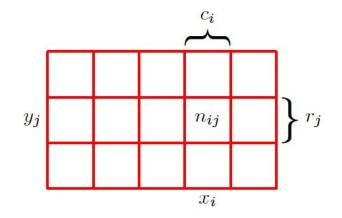






## Product Rule of probability

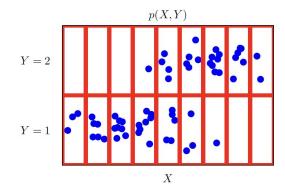
$$p(Y = y_j/X = x_i) =$$



$$p(Y = y_j, X = x_i) = p(Y = y_j/X = x_i) \cdot p(X = x_i)$$

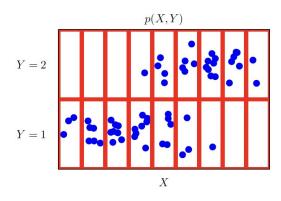






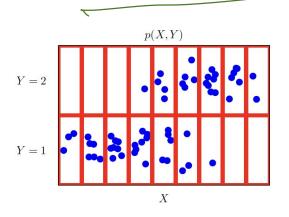






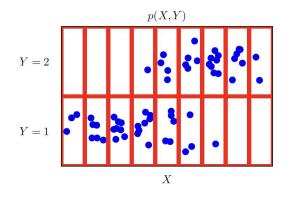
- X
- Y
- 60 trails sample both

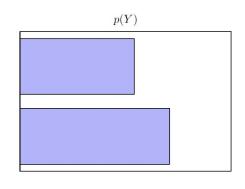




• Marginal distribution  $\rho(Y)$ 

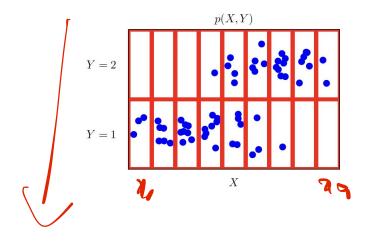




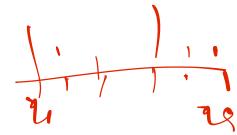






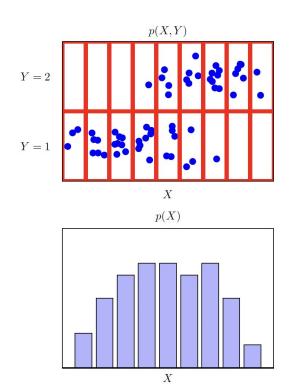


• Marginal distribution  $\rho(X)$ 



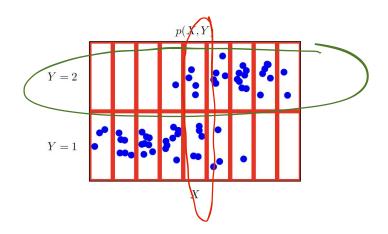




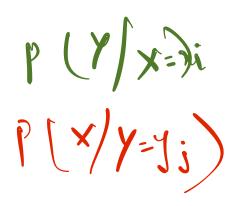








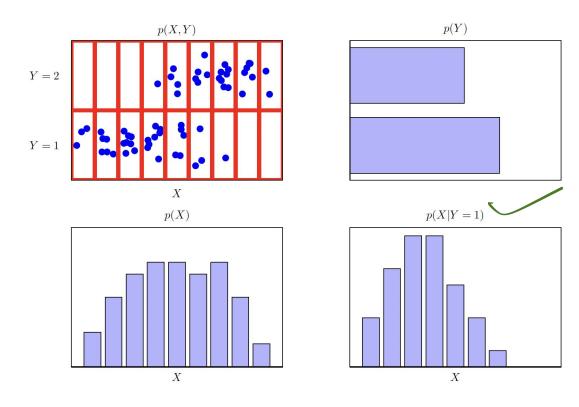
Conditional distribution of X







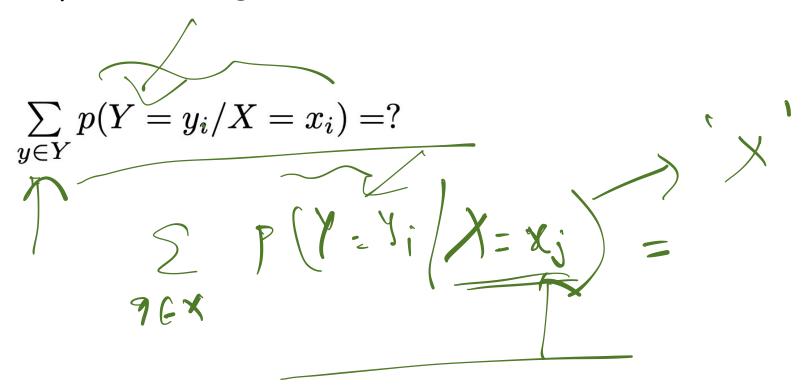
## Example: Marginal & Conditional distributions







## Example: Marginal & Conditional distributions









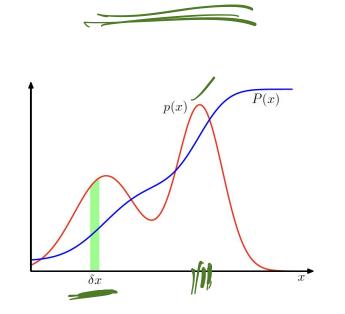


ρ(X): Probability density over X



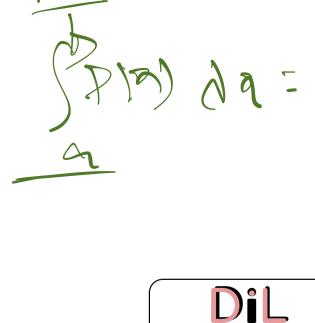


- ρ(X): Probability density over X
- Probability of x falling in (x, x+dx)
- Probability over a finite interval (a, b)



P(n)





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- Non-negativity
- Normalization





Change of variables

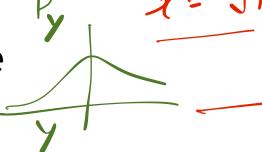




- Change of variables
- $\bullet \quad \times = O(\lambda)$







- Change of variables
- $\bullet \quad \times = O(\lambda) \quad \sim$
- Probabilities in (x, x+dx) must be transformed to (y, y+dy)

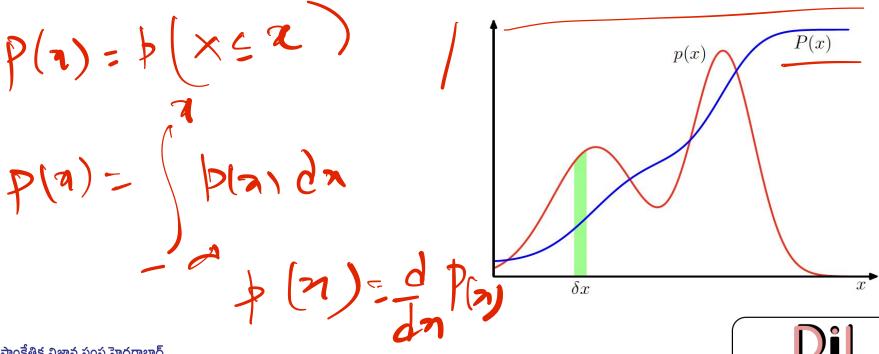
$$P(y) dy = P(x) dx$$

$$P(x) - P(y) dy$$



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Cumulative distribution function





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## Rules of Probability Theory

	Discrete	Continuous
Additivity	$p(X \in A) = \sum_{x \in A} p(x)$	pla) dr
Positivity	$p(x) \ge 0$	$p(x) \geq 0$
Normalization	2 p(n)=/	$\int_{\mathcal{X}} p(x) dx = 1$
Sum Rule	$p(x) = \sum_{y \in Y} p(x, y)$	)(n)= [p(my) dy
Product Rule	$p(x,y) = p(x/y) \cdot p(y)$	$p(x,y) = p(x/y) \cdot p(y)$





# Bayes theorem





## Bayes Theorem

Product rule

$$p(x,y) = p(x/y) \cdot p(y)$$

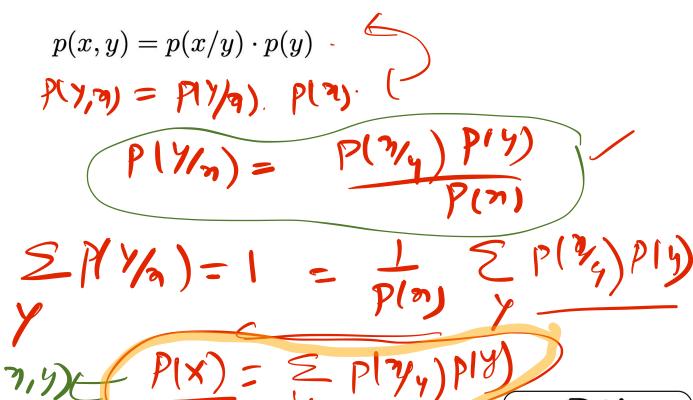






## Bayes Theorem

- Product rule
- Symmetry property
- Bayes rule
- Denominator



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 $p(y/x) = \frac{p(x/y) \cdot p(y)}{p(x)}$ 

- Prior probability
- Posterior probability of Y
- Likelihood of X = x given Y = y
- Evidence for X = x



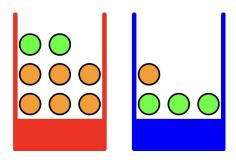


# Example





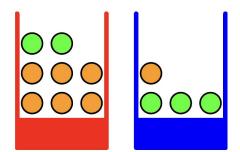
Random variables







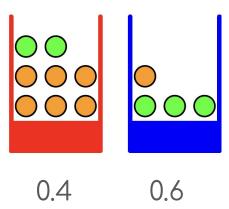
- Random variables
  - o Box B
  - o Fruit F







Prior Box distribution





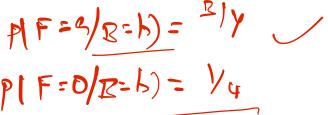






$$P(F=0) = \sum_{B} P(BF) = \sum_{B} P(BF)$$

$$P(F=0) = \sum_{B} P(BF)$$



Marginal of F

$$P(F=\alpha) = \sum_{B} P(BF) = \sum_{B} P(B) P(B) = \sum_{IO} \frac{1}{4} + \frac{1}{6} \frac{1}{3} = \frac{1}{20}$$

$$P(F=0) = \sum_{B} P(B,F)$$



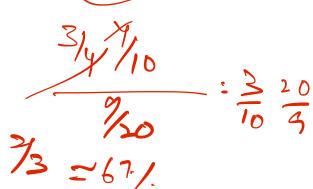
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0.6

0.4

- Marginals ρ(F=a) = 11/20 & ρ(F=0) = 9/20
- Posterior probability of Box given observed fruit

$$p(B=r/F=0) =$$







0.6

# Independence





## Independent Random variable

 Two random variables X and Y are independent iff measuring X gives no information about Y (and vice versa)

$$P(1/x) = P(1)$$

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$$P(1/x) = P(1/x)$$





## Next Expectation, Variance, and Gaussian Distribution



