

# Motivation and Basics

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# Weekly Objectives

- Motivate the study on
  - Machine learning, AI, Datamining....
  - Why? What?
  - Overview of the field
- Short questions and answers on a story
  - What consists of machine learning?
  - MLE
  - MAP
- Some basics
  - Probability
  - Distribution
  - And some rules...

# BASICS

MLE: prior knowledge X. Data update - frequentist  
MAP: " 0. - Bayesian

# What we just saw is...

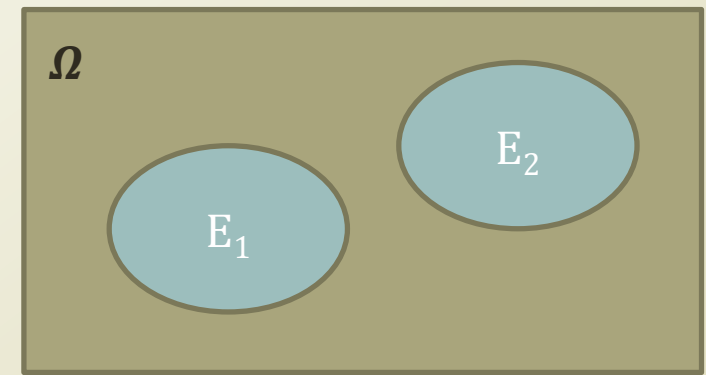
## Bayes says

### Why not use the Beta distribution?

← From the knowledge of probability, distribution, and statistics

- A struggle
  - Billionaire
    - To earn money by analyzing a small dataset out of huge possibilities
  - You
    - To give the billionaire the best probable and approximate answers from the small dataset
  - Bayes
    - To convince you that the prior knowledge can be incorporated to the answers
- Eventually
  - Trying to find out the nature of the thumbtack game
  - The key is the probability of the thumbtack outcome, either head or tail
- Underlying knowledge to solve the problem
  - Probability
  - Distribution
  - Some mathematical tricks
- To go further, you need to know these

# Probability



- Philosophically, Either of the two
  - Objectivists assign numbers to describe states of events, i.e. counting
  - Subjectivists assign numbers by your own belief to events, i.e. betting
- Mathematically
  - A function with the below characteristics

*이항변수, 이항 분포, with 2 events*

$$P(E) \in R_{\text{event}} \quad P(E) \geq 0 \quad P(\Omega) = 1$$

*Conf.*

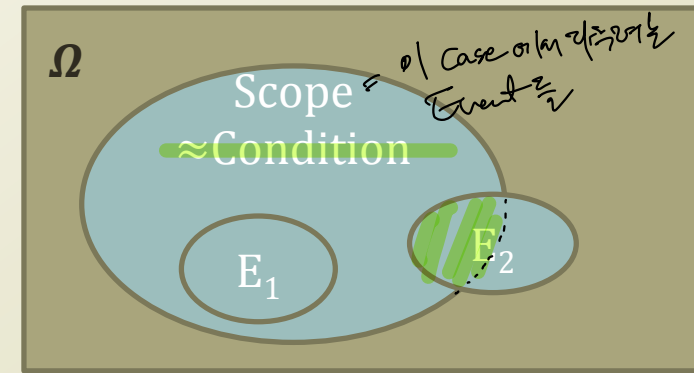
$$P(E_1 \cup E_2 \cup \dots) = \sum_{i=1}^{\infty} P(E_i) \text{ when a sequence of mutually exclusive}$$

- Subsequent characteristics

$$\text{if } A \subseteq B \text{ then } P(A) \leq P(B) \quad P(\emptyset) = 0 \quad 0 \leq P(E) \leq 1$$

$$P(A \cup B) = P(A) + P(B) - P(A \cap B) \quad P(E^c) = 1 - P(E)$$

# Conditional Probability



- We often do not handle the universe,  $\Omega$
- Somehow, we always make conditions
  - Assuming that the parameters are  $X, Y, Z, \dots$
  - Assuming that the events in the scope of  $X, Y, Z, \dots$

$$P(A|B) = \frac{P(A \cap B)}{P(B)} \rightarrow \text{scope}$$

이 case에서 각 event를

- The conditional probability of A given B

- Some handy formula

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

Nice to see that we can switch the condition and the target event

$$\text{Posterior} = \frac{\text{Likelihood} \times \text{Prior Knowledge}}{\text{Normalizing Constant}}$$

$$P(A) = \sum_n P(A|B_n)P(B_n)$$

Nice to see that we can recover the target event by adding the whole conditional probs and priors

# Probability Distribution

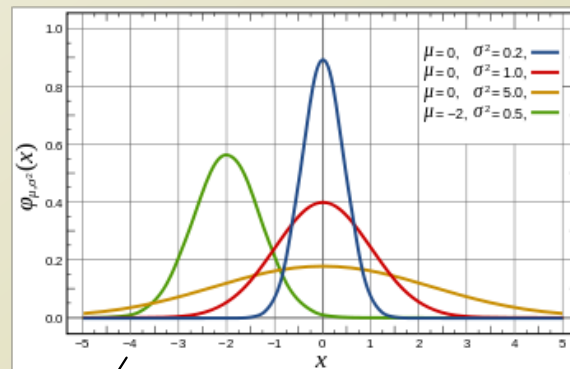
"Mapping."

- Probability distribution assigns
  - A probability to a subset of the potential events of a random trial, experiment, survey, etc.
- A function mapping an event to a probability
  - Because we call it a probability, the probability should keep its own characteristics (or axioms)
  - An event can be
    - A continuous numeric value from surveys, trials, experiments...
    - A discrete categorical value from surveys, trials, experiments...
- For example,

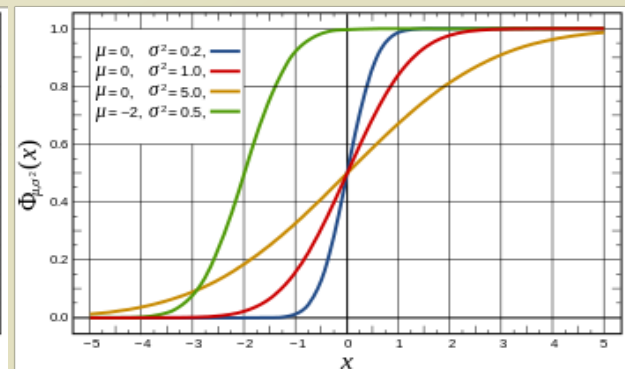
$$f(x) = \frac{e^{-\frac{1}{2}x^2}}{\sqrt{2\pi}}$$

Event  $\leftarrow$

f: a probability  
distribution function  
x: a continuous value  
f(x): assigned probs



Probability Density Function  
(PDF) =  $f(x)$



Cumulative Distribution Function  
(CDF) =  $\int_{-\infty}^x f(x) dx$

# Normal Distribution

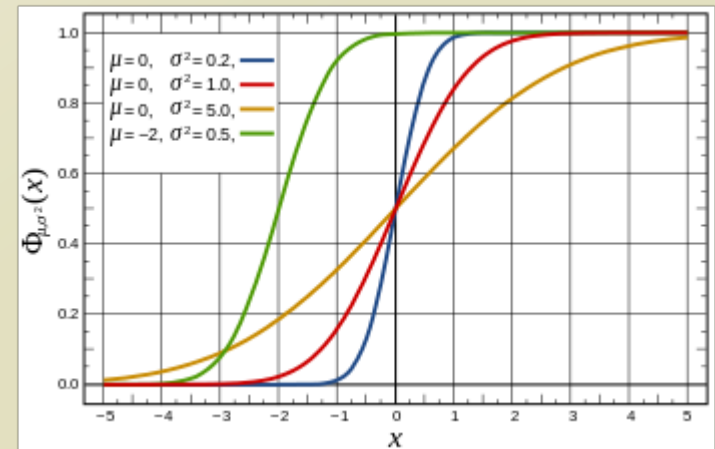
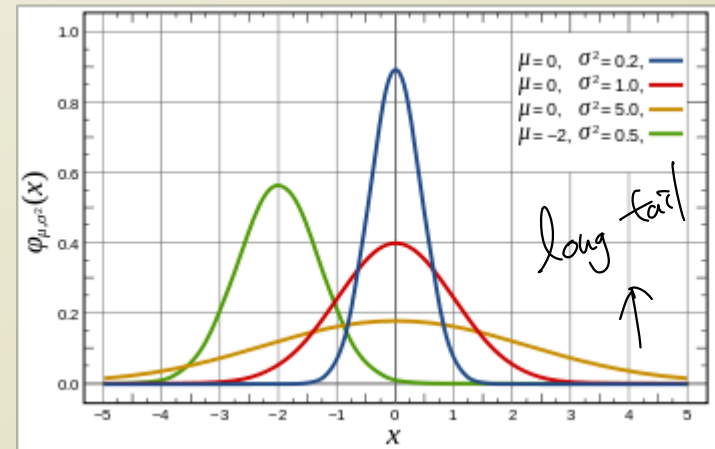
- Very commonly observed distribution
  - Continuous numerical value

- $f(x; \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$

- Notation:  $N(\mu, \sigma^2)$

- Mean:  $\mu$

- Variance:  $\sigma^2$





# Beta Distribution

- Supports a closed interval
  - Continuous numerical value
  - $[0,1]$
  - Very nice characteristic
  - Why?
    - Matches up the characteristics of probs

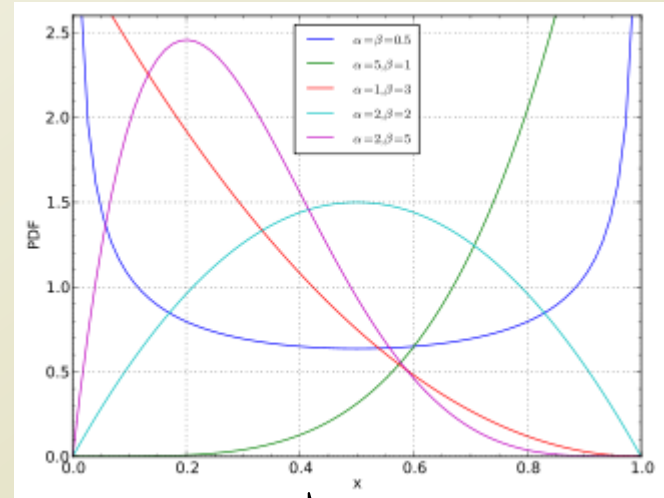
$$f(\theta; \alpha, \beta) = \frac{\theta^{\alpha-1}(1-\theta)^{\beta-1}}{B(\alpha, \beta)}, B(\alpha, \beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)},$$

$$\Gamma(\alpha) = (\alpha - 1)!, \alpha \in \mathbb{N}^+$$

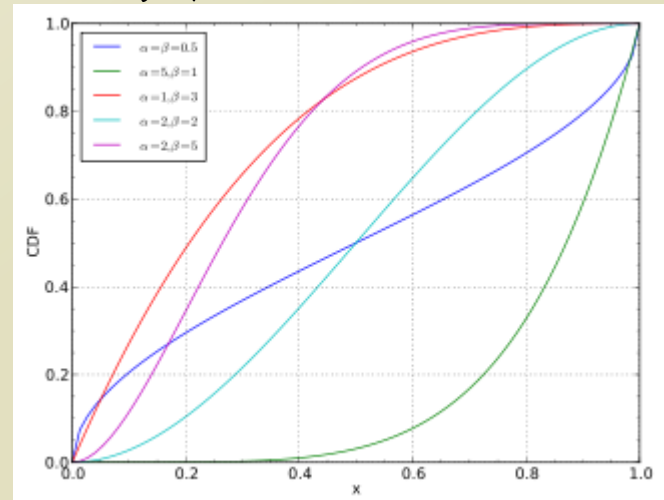
• Notation: Beta( $\alpha, \beta$ )

• Mean:  $\frac{\alpha}{\alpha+\beta}$

• Variance:  $\frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$

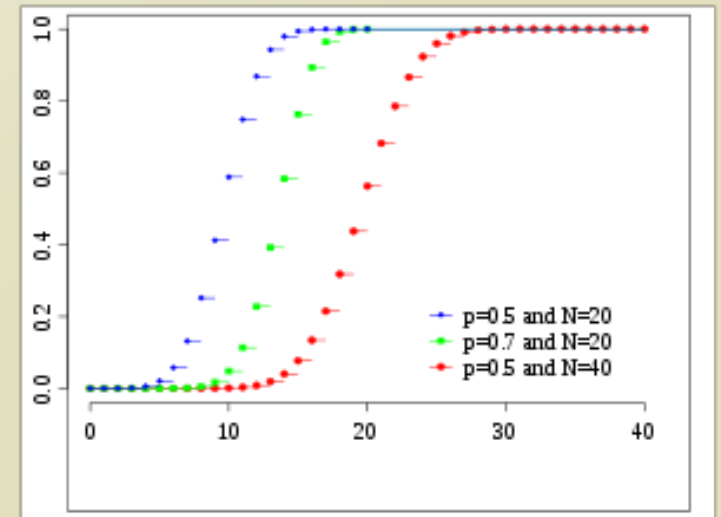
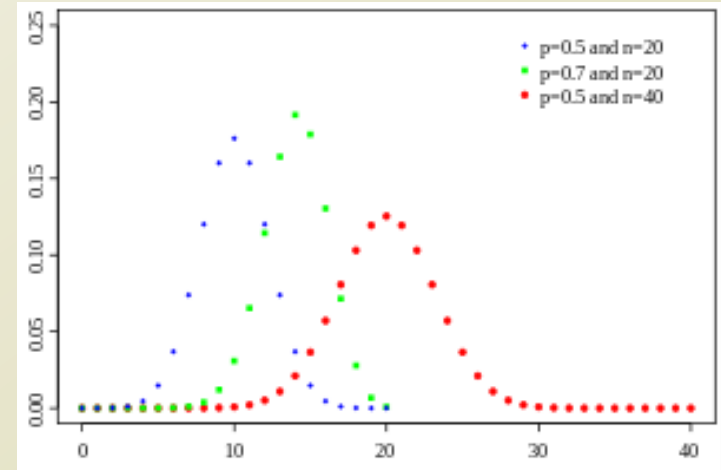


$[0, 1]$  Continuous  
 → 범위가 정해졌는데 모양이 변할 수 있음



# Binomial Distribution

- Simplest distribution for discrete values
  - Bernoulli trial, yes or no
  - 0 or 1
  - Selection, switch....
- $f(\theta; n, p) = \binom{n}{k} p^k (1 - p)^{n-k}, \binom{n}{k} = \frac{n!}{k!(n-k)!}$
- Notation:  $B(n, p)$
- Mean:  $np$
- Variance:  $np(1 - p)$



# Multinomial Distribution

still discrete

text mining  
word selection

- The generalization of the binomial distribution
  - Beyond yes/no
  - Choose A, B, C, D, E, ..., Z
  - Word selection, cluster selection, ...

- $$f(x_1, \dots, x_k; n, p_1, \dots, p_k) = \frac{n!}{x_1! \dots x_k!} p_1^{x_1} \dots p_k^{x_k}$$

- Notation:  $\text{Mult}(P), P = \langle p_1, \dots, p_k \rangle$
- Mean:  $E(x_i) = np_i$
- Variance:  $\text{Var}(x_i) = np_i(1 - p_i)$

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