

**Будет Тервер... Но это неточно...**

**Прекрасный курс по терверу :)**

**[https://web.stanford.edu/class/archive/cs/cs109/  
cs109.1166//handouts/overview.html](https://web.stanford.edu/class/archive/cs/cs109/cs109.1166//handouts/overview.html)**

# Комбинаторные конструкции

## Перестановки

n элементов

n клеток

Порядок имеет значение

## Размещения

n элементов

k клеток

Порядок имеет значение

## Сочетания

n элементов

k клеток

Порядок не имеет значения

$$P_n = n!$$

$$A_n^k = \frac{n!}{(n-k)!}$$

$$C_n^k = \frac{n!}{(n-k)! \cdot k!}$$

## PIGEON HOLE PRINCIPLE

The pigeonhole principle states that if  $n$  items are put into  $m$  containers, with  $n > m$ , then at least one container must contain more than one item.

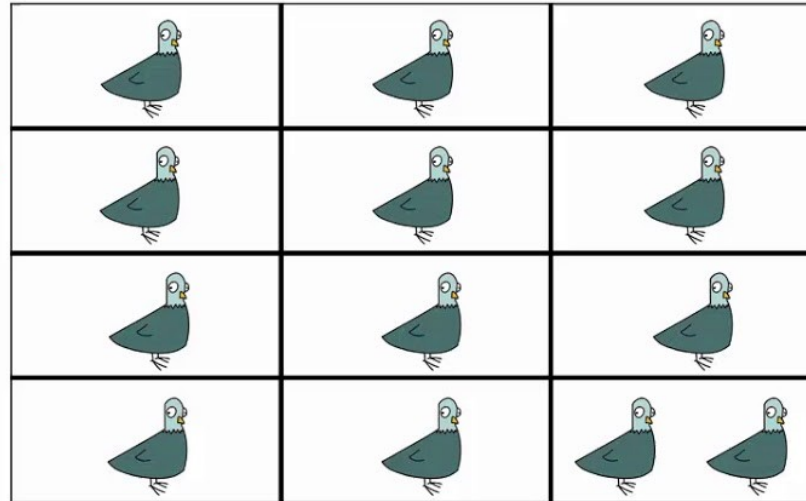
13 pigeons

3 billion

2 people

highest number

→ 150,000



## The Generalized Pigeonhole Principle

- The Principle

If  $n$  pigeons are allocated into  $k$  pigeonholes, then there is at least one pigeonhole which contains at least

$\left\lceil \frac{n}{k} \right\rceil$  pigeons.

# Вероятность

## Event Space and Sample Space

Sample space,  $S$ , is set of all possible outcomes of an experiment. For example:

1. Coin flip:  $S = \{\text{Head, Tails}\}$
2. Flipping two coins:  $S = \{(H, H), (H, T), (T, H), (T, T)\}$
3. Roll of 6-sided die:  $S = \{1, 2, 3, 4, 5, 6\}$
4. # emails in a day:  $S = \{x \mid x \in \mathbf{Z}, x \geq 0\}$  (non-neg. ints)
5. YouTube hrs. in day:  $S = \{x \mid x \in \mathbf{R}, 0 \leq x \leq 24\}$

Event Space,  $E$ , is some subset of  $S$  that we ascribe meaning to. In set notation ( $E \subseteq S$ ).

1. Coin flip is heads:  $E = \{\text{Head}\}$
2.  $\geq 1$  head on 2 coin flips:  $E = \{(H, H), (H, T), (T, H)\}$
3. Roll of die is 3 or less:  $E = \{1, 2, 3\}$
4. # emails in a day  $\leq 20$ :  $E = \{x \mid x \in \mathbf{Z}, 0 \leq x \leq 20\}$
5. Wasted day ( $\geq 5$  YT hrs.):  $E = \{x \mid x \in \mathbf{R}, 5 \leq x \leq 24\}$

$$P(E) = \lim_{n \rightarrow \infty} \frac{n(E)}{n}$$

Axiom 1:  $0 \leq P(E) \leq 1$

Axiom 2:  $P(S) = 1$

Axiom 3: If  $E$  and  $F$  mutually exclusive ( $E \cap F = \emptyset$ ),  
then  $P(E) + P(F) = P(E \cup F)$

# Совместные и несовместные события

## Independence

Two events  $E$  and  $F$  are called independent if:  $P(EF) = P(E) P(F)$ . Or, equivalently:  $P(E | F) = P(E)$ . Otherwise, they are called dependent events

Three events  $E$ ,  $F$ , and  $G$  independent if:

$$P(EFG) = P(E) P(F) P(G), \text{ and}$$

$$P(EF) = P(E) P(F), \text{ and}$$

$$P(EG) = P(E) P(G), \text{ and}$$

$$P(FG) = P(F) P(G)$$

## Conditional Independence

Two events  $E$  and  $F$  are called conditionally independent given  $G$ , if

$$P(E F | G) = P(E | G) P(F | G)$$

Or, equivalently:  $P(E | F G) = P(E | G)$

# Условная вероятность

$$P(E|F) = \frac{P(EF)}{P(F)}$$

Here is the general form of the Chain Rule:

$$P(E_1 E_2 \dots E_n) = P(E_1)P(E_2|E_1) \dots P(E_n|E_1 \dots E_{n-1})$$

In the case where the sample space has equally likely outcomes:

$$P(E|F) = \frac{\# \text{ outcomes in } E \text{ consistent with } F}{\# \text{ outcomes in } S \text{ consistent with } F} = \frac{|EF|}{|SF|} = \frac{|EF|}{|F|}$$

approximation of probability we get:

$$P(E|F) = \frac{P(EF)}{P(F)} = \frac{\frac{\text{people who liked both}}{\text{people who watched both}}}{\frac{\text{people who liked amelie}}{\text{people who watched amelie}}}$$

# Теорема Байеса

Most Common Version:

$$P(F|E) = \frac{P(E|F)P(F)}{P(E)}$$

Expanded Version:

$$P(F|E) = \frac{P(E|F)P(F)}{P(E|F)P(F) + P(E|F^c)P(F^c)}$$

**Пример**

**([cs109.stanford.edu/demos/naturalBayes.html](http://cs109.stanford.edu/demos/naturalBayes.html))**



# Random Variable and Expectation

- $P(Y = 0) = 1/8$  (T, T, T)
- $P(Y = 1) = 3/8$  (H, T, T), (T, H, T), (T, T, H)
- $P(Y = 2) = 3/8$  (H, H, T), (H, T, H), (T, H, H)
- $P(Y = 3) = 1/8$  (H, H, H)
- $P(Y \geq 4) = 0$

## Probability Mass Function

Probability mass functions (PMF) is a function that maps possible outcomes of a random variable to the corresponding probabilities. We can plot PMF graphs:

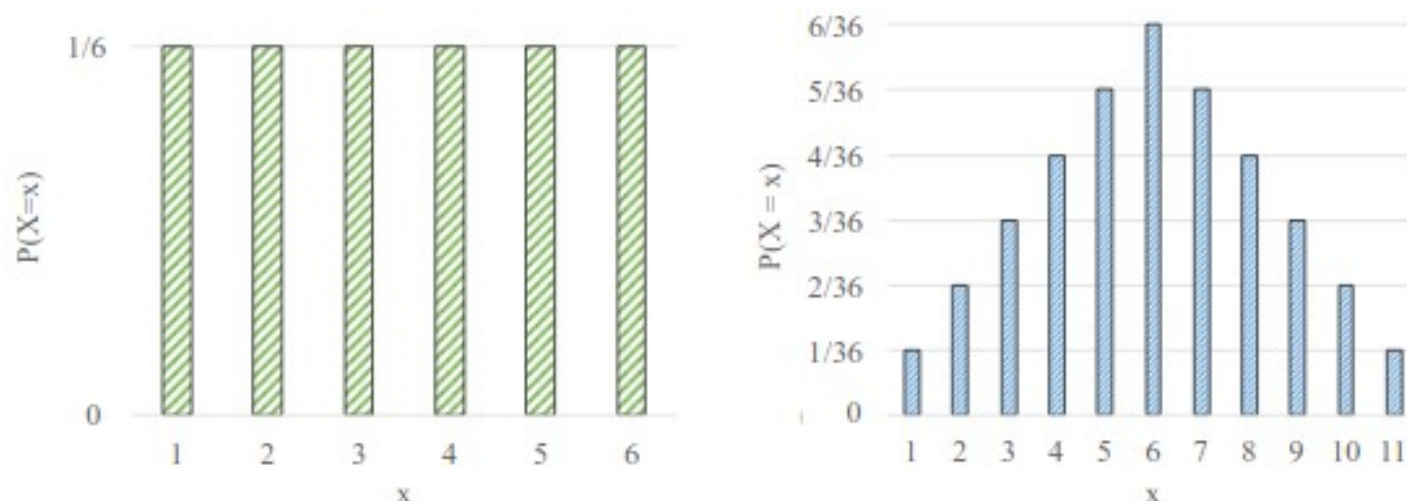


Figure: On the left, the PMF of a single 6 sided die roll. On the right, the PMF of the sum of two dice rolls.

## Cumulative Distribution Function

For a random variable  $X$ , the Cumulative Distribution Function (CDF) is defined as:

$$F(a) = P(X \leq a) \text{ where } -\infty < a < \infty$$

## Expected Value

The Expected Value for a discrete random variable  $X$  is defined as:

$$E[X] = \sum_{xP(x)>0} xP(x)$$

It goes by many other names: Mean, Expectation, Weighted Average, Center of Mass, 1st Moment.

# Variance (дисперсия)

Here are some useful identities for variance:

- $Var(aX + b) = a^2 Var(X)$
- Standard deviation is the root of variance:  $SD(X) = \sqrt{Var(X)}$

# Continuous Random Variables

## Cumulative Distribution Function

For a continuous random variable  $X$  the Cumulative Distribution Function, written  $F(a)$  or as (CDF) is:

$$F(a) = P(X \leq a) = \int_{-\infty}^a f(x)dx$$

## Expectation and Variance

For continuous RV  $X$ :

$$E[X] = \int_{-\infty}^{\infty} xf(x)dx$$

$$E[g(X)] = \int_{-\infty}^{\infty} g(x)f(x)dx$$

$$E[X^n] = \int_{-\infty}^{\infty} x^n f(x)dx$$

For both continuous and discrete RVs:

$$E[aX + b] = aE[X] + b$$

$$Var(X) = E[(X - \mu)^2] = E[X^2] - (E[X])^2$$

## Uniform Random Variable

$X$  is a Uniform Random Variable  $X \sim Uni(\alpha, \beta)$  if:

$$f(x) = \begin{cases} \frac{1}{\beta - \alpha} & \text{when } \alpha \leq x \leq \beta \\ 0 & \text{otherwise} \end{cases}$$

The key properties of this RV are:

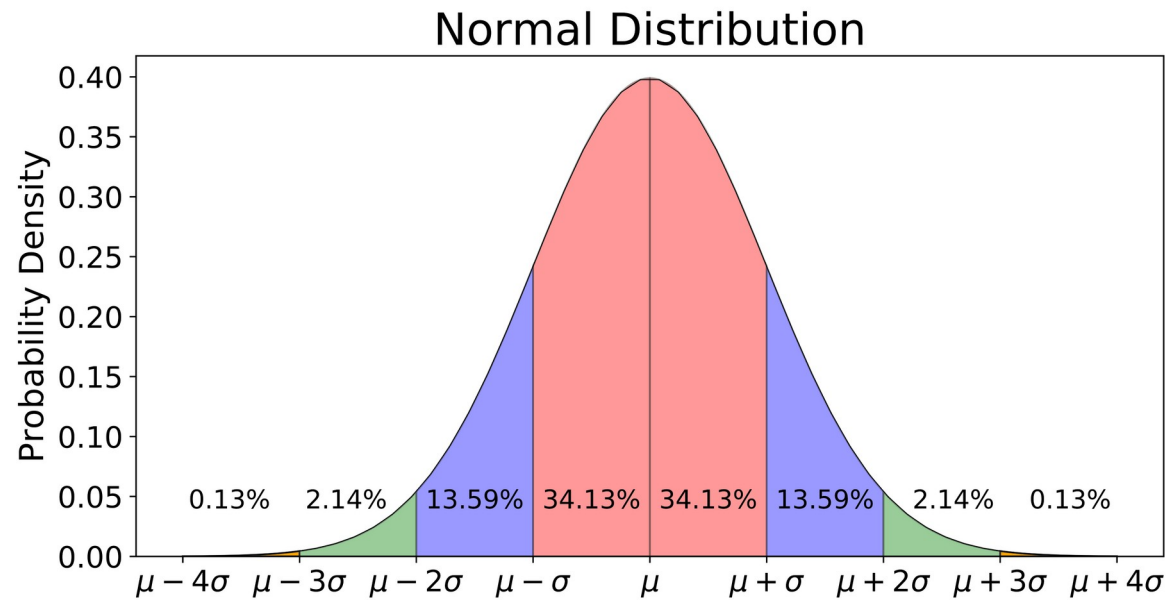
$$P(a \leq X \leq b) = \int_a^b f(x)dx = \frac{b - a}{\beta - \alpha} \text{ (for } \alpha \leq a \leq b \leq \beta)$$

$$E[X] = \int_{-\infty}^{\infty} xf(x)dx = \int_{\alpha}^{\beta} \frac{x}{\beta - \alpha} dx = \frac{x^2}{2(\beta - \alpha)} \Big|_{\alpha}^{\beta} = \frac{\alpha + \beta}{2}$$

$$Var(X) = \frac{(\beta - \alpha)^2}{12}$$

# Normal (aka Gaussian) Random Variable

If  $X$  is a normal variable we write  $X \sim \mathcal{N}(\mu, \sigma^2)$ .



<https://www.youtube.com/watch?v=rzFX5NWojp0>

# Maximizing Likelihood


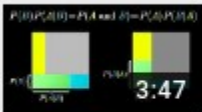


$$L(\theta) = \prod_{i=1}^n f(X_i|\theta)$$

$$LL(\theta) = \log \prod_{i=1}^n f(X_i|\theta) = \sum_{i=1}^n \log f(X_i|\theta)$$

# Naive Bayes

<https://web.stanford.edu/class/archive/cs/cs109/cs109.1166//pdfs/39%20NaiveBayes.pdf>

# Несколько полезных видео к просмотру.

0		<b>Bayes theorem</b> 3Blue1Brown 15:46
1		<b>The quick proof of Bayes' theorem</b> 3Blue1Brown 3:47
2		<b>Binomial distributions   Probabilities of probabilities, part 1</b> 3Blue1Brown 12:34
3		<b>Why "probability of 0" does not mean "impossible"   Probabilities of probabilities, part 2</b> 3Blue1Brown 10:01

<https://www.youtube.com/watch?v=HZGCoVF3YvM&list=WL&index=10>

<https://www.youtube.com/watch?v=8idr1WZ1A7Q&list=WL&index=12>

[https://www.youtube.com/watch?v=U\\_85TaXbelo&list=WL&index=11](https://www.youtube.com/watch?v=U_85TaXbelo&list=WL&index=11)

<https://www.youtube.com/watch?v=ZA4JkHKZM50&list=WL&index=13>