

# **February 15th Expectation**

# Expectation

Suppose that a doctor get only two kinds of patients, those with insurance type `a` and one with insurance `b`. If a patient has insurance `a` the doctor gets 40 dollars per visit, if the patient is from insurance `b` he gets 55. Let INCOME be a random variable from the event space of insurance types to the space of dollars defined by  $f(A) = 40$  and  $f(B) = 55$ .  $P(\text{INCOME}=a)$  is  $1/3$  and  $P(\text{INCOME}=b)$  is  $2/3$ . How much money does the doctor get on average from every patient? The answer is

$$1/3 * 40 + 2/3 * 55 = 50$$

This value is known as the **expected value** or expectation of INCOME.

**MEAN: the value of a random variable that you expect, on average**

$$\mu_X = \sum_{\text{all possible values of } X} (\text{value of the R.V. } X) \times P(X)$$

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$$\mu = E(X)$$

# Expectation Value

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The expectation value of a function  $f(x)$  in a variable  $x$  is denoted  $\langle f(x) \rangle$  or  $E\{f(x)\}$ . For a single discrete variable, it is defined by

$$\langle f(x) \rangle = \sum_x f(x) P(x), \quad (1)$$

where  $P(x)$  is the probability function.

For a single continuous variable it is defined by,

$$\langle f(x) \rangle = \int f(x) P(x) dx. \quad (2)$$

The expectation value satisfies

$$\langle ax + by \rangle = a \langle x \rangle + b \langle y \rangle \quad (3)$$

$$\langle a \rangle = a \quad (4)$$

$$\langle \sum x \rangle = \sum \langle x \rangle. \quad (5)$$

# Expected word length

$$\begin{aligned} E(LENGTH) &= 3 \times 0.068 \\ &+ 2 \times 0.035 \\ &+ 3 \times 0.0284 \\ &+ 2 \times 0.0257 \\ &+ 1 \times 0.0229 \\ &\vdots \end{aligned}$$

Words listed by frequency: the first 2000 most frequent words from the Brown Corpus (1,015,945 words)

	Word	Instances	% Frequency
1.	<a href="#">The</a>	69970	6.8872
2.	<a href="#">of</a>	36410	3.5839
3.	<a href="#">and</a>	28854	2.8401
4.	<a href="#">to</a>	26154	2.5744
5.	<a href="#">a</a>	23363	2.2996
6.	<a href="#">in</a>	21345	2.1010
7.	<a href="#">that</a>	10594	1.0428
8.	<a href="#">is</a>	10102	0.9943
9.	<a href="#">was</a>	9815	0.9661
10.	<a href="#">He</a>	9542	0.9392
11.	<a href="#">for</a>	9489	0.9340
12.	<a href="#">it</a>	8760	0.8623
13.	<a href="#">with</a>	7290	0.7176
14.	<a href="#">as</a>	7251	0.7137
15.	<a href="#">his</a>	6996	0.6886
16.	<a href="#">on</a>	6742	0.6636
17.	<a href="#">be</a>	6376	0.6276
18.	<a href="#">at</a>	5377	0.5293
19.	<a href="#">by</a>	5307	0.5224
20.	<a href="#">I</a>	5180	0.5099

# Linearity of Expectation

## Linear Operator

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An operator  $\tilde{L}$  is said to be linear if, for every pair of functions  $f$  and  $g$  and scalar  $t$ ,

$$\tilde{L}(f + g) = \tilde{L}f + \tilde{L}g$$

and

$$\tilde{L}(tf) = t\tilde{L}f.$$

## SOME THEOREMS ON EXPECTATION

**Theorem 3-1:** If  $c$  is any constant, then

$$E(cX) = cE(X) \quad (8)$$

**Theorem 3-2:** If  $X$  and  $Y$  are any random variables, then

$$E(X + Y) = E(X) + E(Y) \quad (9)$$

**Theorem 3-3:** If  $X$  and  $Y$  are independent random variables, then

$$E(XY) = E(X)E(Y) \quad (10)$$



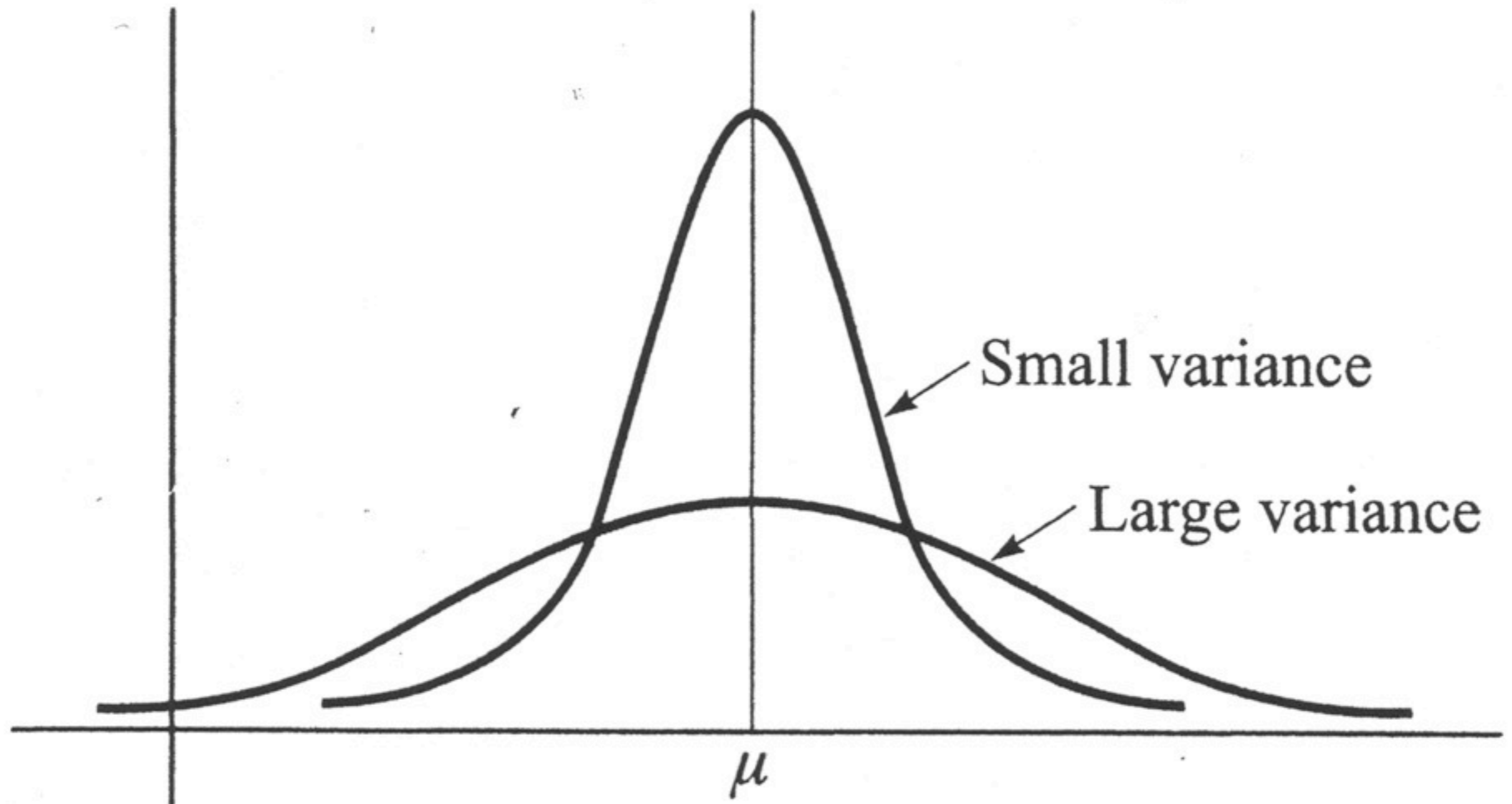


First die	Second die											
	1	2	3	4	5	6						
6	7	8	9	10	11	12						
5	6	7	8	9	10	11						
4	5	6	7	8	9	10						
3	4	5	6	7	8	9						
2	3	4	5	6	7	8						
1	2	3	4	5	6	7						
$x$	2		3	4	5	6	7	8	9	10	11	12
$p(X = x)$	$\frac{1}{36}$		$\frac{1}{18}$	$\frac{1}{12}$	$\frac{1}{9}$	$\frac{5}{36}$	$\frac{1}{6}$	$\frac{5}{36}$	$\frac{1}{9}$	$\frac{1}{12}$	$\frac{1}{18}$	$\frac{1}{36}$

**Figure 2.2** A random variable  $X$  for the sum of two dice. Entries in the body of the table show the value of  $X$  given the underlying basic outcomes, while the bottom two rows show the pmf  $p(x)$ .

**cf. Johnson page 39**

# Variance, the expected squared deviation



# Expected squared deviation

.... is just  $E(X^2) - (E(X))^2$

$$(130) \quad V(X) = E(X^2) - (E(X))^2$$

For a proof notice that

$$\begin{aligned} E(X - EX)^2 &= E(X - EX)(X - EX) \\ &= E(X^2 - 2X \cdot EX + (EX)^2) \\ (131) \quad &= E(X^2) - 2E((EX) \cdot X) + (EX)^2 \\ &= E(X^2) - 2(EX)(EX) + (EX)^2 \\ &= E(X^2) - (EX)^2 \end{aligned}$$

# Expected squared deviation

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*expected squared deviation*

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*Vasishth, appendix 4*

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## SOME THEOREMS ON VARIANCE

**Theorem 3-4:** 
$$\sigma^2 = E[(X - \mu)^2] = E(X^2) - \mu^2 = E(X^2) - [E(X)]^2 \quad (16)$$

where  $\mu = E(X)$ .

**Theorem 3-5:** If  $c$  is any constant,

$$\text{Var}(cX) = c^2 \text{Var}(X) \quad (17)$$

**Theorem 3-6:** The quantity  $E[(X - a)^2]$  is a minimum when  $a = \mu = E(X)$ .

**Theorem 3-7:** If  $X$  and  $Y$  are independent random variables,

$$\text{Var}(X + Y) = \text{Var}(X) + \text{Var}(Y) \quad \text{or} \quad \sigma_{X+Y}^2 = \sigma_X^2 + \sigma_Y^2 \quad (18)$$

$$\text{Var}(X - Y) = \text{Var}(X) + \text{Var}(Y) \quad \text{or} \quad \sigma_{X-Y}^2 = \sigma_X^2 + \sigma_Y^2 \quad (19)$$

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Vasishth 2.4.1

# Sample of size 5



$n=5$



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average bitterness

$$\bar{X} = \frac{1}{5} \sum_{i=1}^5 x_i$$



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⋮

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=  $\bar{X}$

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⋮

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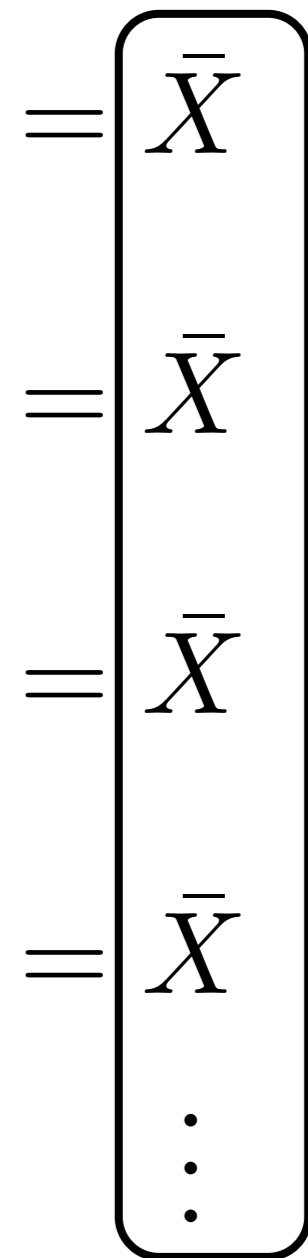


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the sampling distribution of the sample mean