

# Lecture 13 Notes

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## Setup

- We are going to consider the problem of estimating the size of a subpopulation.
- Suppose, for example, that we have a population of known size, and we want to estimate the number of individuals infected with some disease.
- To make this concrete, I have a bag containing 140 mints of which an unknown number are “diseased” (mint chocolate).
- Our goal is to estimate the number of “diseased” candies in the entire population.
- How can we do this?

## Activity

### Sampling without Replacement

#### 1. Estimation

- Students sample 20 candies without replacement. Let  $x$  be the number of diseased candies in the sample.
- Ask them to estimate the number of diseased candies in the entire population. The obvious value is

$$\hat{M} = \frac{140x}{20}.$$

- Ask them why?
- Provide mathematics:
  - Given that we are sampling without replacement,  $X \sim \text{Hypergeometric}(20, M, 140)$ . Then

$$E(X) = \frac{20M}{140}.$$

- If we rearrange and solve for  $M$  this provides

$$M = \frac{140E(X)}{20}.$$

- Replacing  $E(X)$  with the observed value yields

$$\hat{M} = \frac{140x}{20}.$$

- Compute estimate for the specific sample obtained by the class.
  - Round to nearest integer.

## 2. Precision

- Before continuing, enter value of  $x$  in `Slide/lecture_13_slides.Rnw` and recompile.
- Ask: “Who believe that there are exactly  $\hat{M}$  diseased candies in the bag?”
- Even though  $\hat{M}$  may be our best guess, and it may be right, there is uncertainty in this experiment. If we repeated the experiment, then we would likely draw a different number of diseased candies in our sample. This would lead to different estimates.
- More importantly, there are different values of  $M$  that could lead to the same value of  $x$ .
  - Use calculator at [stattrek](http://stattrek.com) to compute  $P(X = x|M = \hat{M})$  and  $P(X = x|M = \hat{M}+1)$ .
  - The probabilities should be similar. This implies that the true value of  $M$  could easily be  $\hat{M}$  or  $\hat{M} + 1$ .
  - In fact, there is a range of values for which  $P(X = x|M)$  is close to  $P(X = x|M = \hat{M})$ .
- How big this range is tells us about the precision of the estimate. The precision is the opposite of variance. If the precision is big then the range of possible values is small and we can be confident that the true value is close to  $\hat{M}$ . On the other hand, if the range is big then the precision is small and we will have less confidence in our estimate.
- Show plot of  $P(X = x|M)$  vs  $M$ .
  - One way to measure the precision is to consider the values of  $M$  for which  $P(X = x|M)$  is above a certain value.
  - We’ll consider the values for which  $P(X = x|M) > .05$ . (Show next plot with line.)
  - For our sample, the values are... see following table for the values given the observed  $x$ .

## Sampling with Replacement

### 1. Estimation

- Why did we sample without replacement?
  - The answer seems intuitive. If we sample with replacement then we risk sampling the same individuals multiple time, which would give us less information about the population. How can we see this?

- Suppose that we were to sample with replacement. Let  $Y$  be the number of diseased candies sampled.

- If we sample with replacement,  $Y \sim \text{Binomial}(20, M/140)$ . Then

$$E(Y) = \frac{20M}{140}.$$

- If we rearrange and solve for  $M$  this provides

$$M = \frac{140E(X)}{20}.$$

- Replacing  $E(Y)$  with the observed value yields exactly the same estimator

$$\hat{M} = \frac{140y}{20}.$$

- This means that if we observe the same number of diseased candies then our estimate will be the same regardless of whether or not we sample with replacement.
- So, where does sampling with replacement matter?

## 2. Precision

- Sampling with replacement affects the precision of the estimate.
- Suppose that we consider the values of  $M$  for which  $P(Y = y|M) > .05$ . (Show plot)
- In this case, the range of plausible values is... see Table 2 for values.
- The relative precision is...see Table 2 for values.
- The range of values is slightly wider when we sample without replacement than when we sample with replacement.
- This is why sampling without replacement is better.

## Variances

- Computing the range of values such that  $P(X = x|M) > .05$  or  $P(Y = y|M) > .05$  is not trivial. However, there is a better way to measure the precision.
- The precision measures the uncertainty of the estimate, and uncertainty is measured by the variance. In fact, precision in statistics is defined to be the inverse of the variance.
- Consider the case of the hypergeometric:

$$\hat{M} = \frac{NX}{n},$$

– Then

$$\text{Var}(\hat{M}) = \frac{N^2}{n} \text{Var}(X)$$

and since  $X$  is hypergeometric

$$\text{Var}(\hat{M}) = \frac{N^2}{n^2} \left( \frac{N-n}{N-1} \right) \left( \frac{nM}{N} \right) \left( 1 - \frac{M}{N} \right).$$

-Similarly, if we sample without replacement then

$$\hat{M} = \frac{NY}{n},$$

is a linear transformation of the random variable  $Y$ . Then

$$\text{Var}(\hat{M}) = \frac{N^2}{n} \text{Var}(Y)$$

and since  $Y$  is binomial

$$\text{Var}(\hat{M}) = \frac{N^2}{n^2} n \left( \frac{M}{N} \right) \left( 1 - \frac{M}{N} \right).$$

The ratio of these two is

$$\frac{\frac{N^2}{n^2} \left( \frac{N-n}{N-1} \right) \left( \frac{nM}{N} \right) \left( 1 - \frac{M}{N} \right)}{\frac{N^2}{n^2} n \left( \frac{M}{N} \right) \left( 1 - \frac{M}{N} \right)} = \frac{N-n}{N-1}$$

which shows that the variance is lower by a factor of  $(N-n)/(N-1)$  when sampling is conducted with replacement.

– Note that the relative variance does not depend on  $M$ . It only depends on  $N$  and  $n$ . It's always above 1, but gets closer and closer to 1 as  $N$  gets bigger.

- In our example, the ratio of the variances would be

$$\frac{140-20}{140-1} = 0.8633094.$$

Once again, this suggests that the estimate will be slightly more precise when sampling without replacement.

## Sampling without Replacement

The following table presents the values required for each possible value of  $X$  – the number of “diseased” candies sampled. The columns are:

- $x$  – the possible values (from 0 to  $n$ )

x	P	Estimate	Variance	Phat	Lower	Upper	Precision
0	0.0006480	0	0.0000000	1.0000000	0	18	18
1	0.0063998	7	0.8201439	0.4067804	1	27	26
2	0.0289161	14	1.5539568	0.3077208	3	36	33
3	0.0794321	21	2.2014388	0.2621072	7	43	36
4	0.1486987	28	2.7625899	0.2355596	12	51	39
5	0.2015305	35	3.2374101	0.2184487	17	58	41
6	0.2050456	42	3.6258993	0.2069165	23	66	43
7	0.1602655	49	3.9280576	0.1991090	29	72	43
8	0.0976618	56	4.1438849	0.1940435	35	79	44
9	0.0468191	63	4.2733813	0.1911835	41	86	45
10	0.0177393	70	4.3165468	0.1902579	47	93	46
11	0.0053165	77	4.2733813	0.1911835	54	99	45
12	0.0012569	84	4.1438849	0.1940435	61	105	44
13	0.0002329	91	3.9280576	0.1991090	68	111	43
14	0.0000334	98	3.6258993	0.2069165	74	117	43
15	0.0000037	105	3.2374101	0.2184487	82	123	41
16	0.0000003	112	2.7625899	0.2355596	89	128	39
17	0.0000000	119	2.2014388	0.2621072	97	133	36
18	0.0000000	126	1.5539568	0.3077208	104	137	33
19	0.0000000	133	0.8201439	0.4067804	113	139	26
20	0.0000000	140	0.0000000	1.0000000	122	140	18

## Sampling with Replacement

y	P	Estimate	Variance	Phat	Lower	Upper	Precision	Rel_Precision	Rel_Variance
0	0.0011952	0	0.00	1.0000000	0	19	19	1.0555556	NaN
1	0.0095616	7	0.95	0.3773536	1	29	28	1.0769231	1.158333
2	0.0363340	14	1.80	0.2851798	3	37	34	1.0303030	1.158333
3	0.0872015	21	2.55	0.2428289	7	45	38	1.0555556	1.158333
4	0.1482426	28	3.20	0.2181994	12	52	40	1.0256410	1.158333
5	0.1897505	35	3.75	0.2023312	17	60	43	1.0487805	1.158333
6	0.1897505	42	4.20	0.1916390	22	67	45	1.0465116	1.158333
7	0.1518004	49	4.55	0.1844012	28	74	46	1.0697674	1.158333
8	0.0986703	56	4.80	0.1797058	34	80	46	1.0454545	1.158333
9	0.0526241	63	4.95	0.1770550	40	87	47	1.0444444	1.158333
10	0.0231546	70	5.00	0.1761971	46	94	48	1.0434783	1.158333
11	0.0084199	77	4.95	0.1770550	53	100	47	1.0444444	1.158333
12	0.0025260	84	4.80	0.1797058	60	106	46	1.0454545	1.158333
13	0.0006218	91	4.55	0.1844012	66	112	46	1.0697674	1.158333
14	0.0001244	98	4.20	0.1916390	73	118	45	1.0465116	1.158333
15	0.0000199	105	3.75	0.2023312	80	123	43	1.0487805	1.158333
16	0.0000025	112	3.20	0.2181994	88	125	37	0.9487179	1.158333
17	0.0000002	119	2.55	0.2428289	95	125	30	0.8333333	1.158333
18	0.0000000	126	1.80	0.2851798	103	125	22	0.6666667	1.158333
19	0.0000000	133	0.95	0.3773536	111	125	14	0.5384615	1.158333
20	0.0000000	140	0.00	1.0000000	121	125	4	0.2222222	NaN