CENG 222 Statistical Methods for Computer Engineering

Week 11

Chapter 10 10.1 Chi-square Tests

- Introduced in Section 9.5.1 (not covered)
- Used to model sample variance.
- Recall that sample variance is:

$$-s^{2} = \frac{1}{n-1} \sum_{i=1}^{n} (X_{i} - \bar{X})^{2}$$

- s^2 is not Normal because the summands $(X_i \overline{X})^2$ are not independent, they all depend on \overline{X} .
- s² is also not symmetric (left tail of its distribution ends at 0 because it is always non-negative)

• When X_i s are independent and Normal with $Var(X_i) = \sigma^2$, the distribution of $\frac{(n-1)s^2}{\sigma^2} = \sum_{i=1}^n \left(\frac{X_i - \bar{X}}{\sigma}\right)^2$

is Chi-square with (n-1) degrees of freedom.

• Chi-square (X²) with *v* degrees of freedom is a continuous distribution with density:

$$f(x) = \frac{1}{\frac{v}{2^{\frac{v}{2}}\Gamma(\frac{v}{2})}} x^{\frac{v}{2}-1} e^{-x/2}, \qquad x > 0$$

- Chi-square is a special case of Gamma
 Chi-square(v) = Gamma(v/2,1/2)
 - For example, Chi-square with 2 degrees of freedom is Exponential(1/2)
- Chi-square (X²) expectation and variance: E(X) = vVar(X) = 2v
- Chi-square (X²) is introduced by Karl Pearson (1857-1936) who was the teacher of the Student (William Gosset).

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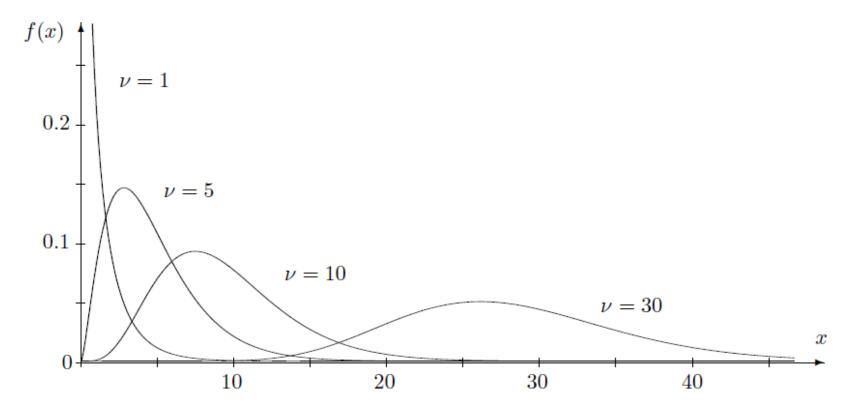


FIGURE 9.12: Chi-square densities with $\nu = 1, 5, 10$, and 30 degrees of freedom. Each distribution is right-skewed. For large ν , it is approximately Normal.

Chi-Square Tests

- Tests of *counts* by comparison of *observed* counts with *expected* counts
 - Use bins for continuous distributions
- Chi-square statistic

$$X^{2} = \sum_{k=1}^{N} \frac{\{Obs(k) - Exp(k)\}^{2}}{Exp(k)}$$

N: number of categories or bins

Obs(k) is the observed counts of sampling units in category k. Exp(k) = expected number of sampling units is the null hypothesis H_0 is true.

Chi-square tests

- The Chi-square test is always a one-sided right-tail test.
- Level alpha rejection region is:
 - $-R = [X_{\alpha}^2, +\infty)$
- P-value is

 $-P = \mathbf{P}(\mathbf{X}^2 > \mathbf{X}_{obs}^2)$

• In order to apply Chi-square test, each category should have an expected count of at least 5. If not, merge categories to increase count.

Testing a distribution

• To test whether a sample $(X_1, X_2, ..., X_n)$ of size *n* is from a distribution F_0 .

 $-H_0$: $F=F_0$ vs H_A : $F\neq F_0$

- 1. Divide the support of F_0 into bins $B_1 \dots B_N$ (5-8 bins are sufficient).
- 2. Count number of sampling units falling into each bin B_k
- 3. $Exp(k)=nF_0(B_k)$. Check if all expected counts are > 5. If so, compute test statistic and conduct the test; if not, merge bins and restart from Step 1.

Example 10.1: Fair Die?

• 90 tosses of a die are observed

1	2	3	4	5	6
20	15	12	17	9	17

- F_0 = discrete uniform distribution 1..6
- Bins are already defined for this discrete distribution

-Exp(k) = 90*1/6=15 (no need to merge bins)

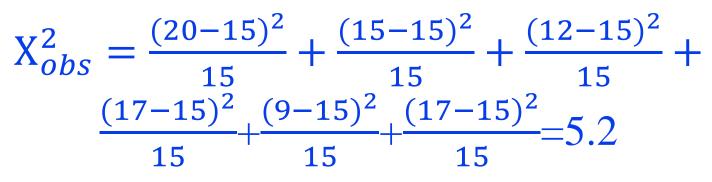
• Compute X²_{obs}

Example 10.1: Fair Die?

• 90 tosses of a die are observed

1	2	3	4	5	6
20	15	12	17	9	17

• Compute X²_{obs}



• v = N - 1 = 5

- From Table A6, $P = P(X^2 > 5.2) = 0.2 ... 0.8$
- Cannot reject H_0 . Evidence for unfairness is not sufficient.

Testing a family of distributions

- First, estimate the distribution parameters (may use MLE)
 - Degrees of freedom of X² is reduced by the number of distribution parameters estimated
 - (N d 1) where d is the number of estimated parameters.
- Then, conduct the X² test as before.

Example 10.2: Transmission errors

- Transmission errors in communication channels are usually Poisson. Let's test this.
- 170 channels are randomly selected

0	1	2	3	4	5	7
44	52	36	20	12	5	1

- Estimate lambda
- $\hat{\lambda} = \bar{X} = \frac{44(0) + 52(1) + 36(2) + 20(3) + 12(4) + 5(5) + 1(7)}{170} = 1.55$

Example 10.2: Transmission errors

• 170 channels are randomly selected

0	1	2	3	4	5	7
44	52	36	20	12	5	1

- $\hat{\lambda} = 1.55$
- If we select 6 bins (last bin: # errors ≥5) the last bins expected count becomes 3.6. So, reduce to 5 bins (last bin: # errors ≥4)

k	0	1	2	3	4
Exp(k)	36	55.9	43.4	22.5	12.3
Obs(k)	44	52	36	20	18

Example 10.2: Transmission errors

k	0	1	2	3	4
Exp(k)	36	55.9	43.4	22.5	12.3
Obs(k)	44	52	36	20	18

• $X_{obs}^2 = 6.2$

- v = N 1 1 = 3
- From Table A6, $P = P(X^2 > 6.2) = 0.1 ... 0.2$
- Conclusion: There is no evidence against a Poisson distribution of the number of transmission errors.

Testing independence

- Testing independence of two factors A and B.
- A and B partition the population into k and m categories, respectively.

	B_1	B_2		B_m	row total
A_1	n_{11}	n_{12}	• • •	n_{1m}	n_1 .
A_2	n_{21}	n_{22}	• • •	n_{2m}	n_2 .
•••				•••	
A_k	n_{k1}	n_{k2}	•••	n_{km}	n_k .
$\operatorname{column}_{\operatorname{total}}$	n1	n2		$n \cdot m$	n=n

• Use ratios to estimate probabilities $x \in A_i$, $x \in B_j$, and $x \in A_i \cap B_j$

Testing independence

• If the null hypothesis was true, the expected count n_{ij} would be $n \frac{n_{i.}}{n} \frac{n_{.j}}{n}$

	B_1	B_2		B_m	row total
A_1	n_{11}	n_{12}	•••	n_{1m}	n_1 .
A_2	n_{21}	n_{22}	•••	n_{2m}	n_2 .
• • •					
A_k	n_{k1}	n_{k2}	•••	n_{km}	n_k .
$\operatorname{column}_{\operatorname{total}}$	n1	n2		$n \cdot m$	n=n

• $X_{obs}^2 = \sum_{i=1}^k \sum_{j=1}^m \frac{\{Obs(i,j) - \widehat{Exp}(i,j)\}^2}{\widehat{Exp}(i,j)}$ • v = (k-1)(m-1)

Example 10.4: Spam vs Image Attachments

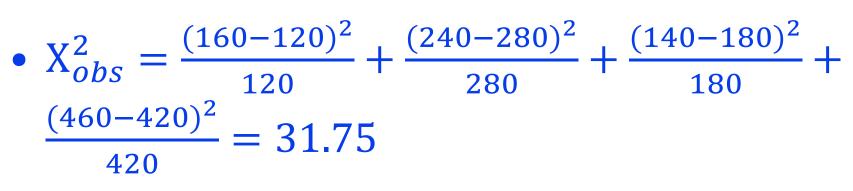
• A sample of 1000 emails is observed:

$Obs(i, j) = n_{ij}$	With images	No images	n_i .
Spam	160	240	400
No spam	140	460	600
$n_{\cdot j}$	300	700	1000

• Expected counts are estimated as:

$\widehat{Exp}(i,j) = \frac{(n_i.)(n_j)}{n}$	With images	No images	n_i .
Spam	120	280	400
No spam	180	420	600
$n_{\cdot j}$	300	700	1000

Example 10.4: Spam vs Image Attachments



•
$$v = (2 - 1)(2 - 1) = 1$$

- From Table A6, *P* < 0.001.
- We have significant evidence that image attachments are related to being spam.