170S Week 8 Discussion Notes

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This week we will discuss chi-squared and t-distributions, which we have been using in our study of confidence intervals. The hope is that this will fill in any gaps in the lectures or in your previous knowledge.

Warmup. Let $n > 0$ be an integer, and consider

$$\mathbf{I} - \frac{1}{n}\mathbf{1}\mathbf{1}^T,$$

the difference between the $n \times n$ identity matrix and the matrix where every entry is $\frac{1}{n}$. For example, for $n = 3$ we have

$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} - \frac{1}{3}\begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}\begin{pmatrix} 1 & 1 & 1 \end{pmatrix} = \begin{pmatrix} \frac{2}{3} & -\frac{1}{3} & -\frac{1}{3} \\ -\frac{1}{3} & \frac{2}{3} & -\frac{1}{3} \\ -\frac{1}{3} & -\frac{1}{3} & \frac{2}{3} \end{pmatrix}.$$

Describe the eigenvalues and eigenvectors.

Solution. This is a projection matrix because

$$\left(\mathbf{I} - \frac{1}{n}\mathbf{1}\mathbf{1}^T\right)\left(\mathbf{I} - \frac{1}{n}\mathbf{1}\mathbf{1}^T\right) = \left(\mathbf{I} - \frac{2}{n}\mathbf{1}\mathbf{1}^T + \frac{1}{n^2}\mathbf{1}\mathbf{1}^T\mathbf{1}\mathbf{1}^T\right) = \mathbf{I} - \frac{1}{n}\mathbf{1}\mathbf{1}^T,$$

so by the spectral theorem (this is real and symmetric) it is orthogonal projection onto a subspace. To determine which subspace, observe that $\mathbf{1}$ is in the kernel and that the first $n - 1$ vectors in the matrix are linearly independent. To summarize, there exists an orthonormal basis of eigenvectors, one with eigenvalue 0 and the others with eigenvalue 1. $\square$

Chi-squared distributions

Definition. The *chi-squared distribution with n degrees of freedom* is the distribution of the sum of squares of n independent standard normals:

$$\chi^2(n) \sim Z_1^2 + \ldots + Z_n^2 \quad \text{where} \quad Z_1, \ldots, Z_n \sim \mathrm{Norm}(0, 1)$$

are independent.

This is a great starter definition (different from the one in the book) because we can easily deduce some basic properties. For example $\chi^2(1) = \text{Norm}(0,1)$, and if $\chi^2(n)$ and $\chi^2(m)$ are independent, then $\chi^2(n) + \chi^2(m) = \chi^2(n+m)$. These are both theorems in the textbook. Furthermore, we can deduce that the mean is

$$\mathbb{E}(\chi^2(n)) = \mathbb{E}(Z_1^2 + \ldots + Z_n^2) = \mathbb{E}(Z_1^2) + \ldots + \mathbb{E}(Z_n^2) = n$$

since $1 = \text{Var}(Z_i) = \mathbb{E}(Z_i^2) - \mathbb{E}(Z_i)^2 = \mathbb{E}(Z_i^2)$, and the variance is

$$\text{Var}(\chi^2(n)) = \text{Var}(Z_1^2 + \ldots + Z_n^2) = \text{Var}(Z_1^2) + \ldots + \text{Var}(Z_n^2) = 2n$$

since $\text{Var}(Z_i^2) = \mathbb{E}(Z_i^4) - \mathbb{E}(Z_i^2)^2 = 3 - 1 = 2$ using this MSE answer.

The key property of chi-squared distributions for statistics is the following:

Key Property.

$$\sum_{i=1}^{n} (Z_i - \bar{Z})^2 \sim \chi^2(n-1),$$

where $Z_1, \ldots, Z_n \sim \text{Norm}(0,1)$ are i.i.d. standard normals.

In other words, subtracting off the mean from each Z_i before squaring amounts to removing one of the degrees of freedom. Interestingly, we can read off that the LHS has mean $n-1$, which would be quite difficult to determine without this knowledge.

Proof of Key Property. We begin by vectorizing. Let $\mathbf{z} \in \mathbb{R}^n$ denote the column vector consisting of the $Z_1, \ldots, Z_n$ so that $\bar{Z} = \frac{1}{n}\mathbf{1}^T\mathbf{z}$. Then

$$\begin{aligned}
\sum_{i=1}^{n} (Z_i - \bar{Z})^2 &= \sum_{i=1}^{n} \left(Z_i - \frac{1}{n}\mathbf{1}^T\mathbf{z} \right)^2 \\
&= \left(\mathbf{z} - \frac{1}{n}\mathbf{1}\mathbf{1}^T\mathbf{z} \right)^T \left(\mathbf{z} - \frac{1}{n}\mathbf{1}\mathbf{1}^T\mathbf{z} \right) \\
&= \mathbf{z}^T \left(\mathbf{I} - \frac{1}{n}\mathbf{1}\mathbf{1}^T \right)^T \left(\mathbf{I} - \frac{1}{n}\mathbf{1}\mathbf{1}^T \right) \mathbf{z} \\
&= \mathbf{z}^T \left(\mathbf{I} - \frac{1}{n}\mathbf{1}\mathbf{1}^T \right) \mathbf{z},
\end{aligned}$$

where we are using our observation from the warmup that the matrix in the middle is a projection matrix. Moreover, in our warmup we found that the dimension of the 0-eigenspace is 1 and the dimension of the 1-eigenspace is $k-1$. Thus, by the spectral theorem we can find an orthonormal basis of eigenvectors $\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_n$ where $\mathbf{v}_1$ has eigenvalue 0 and the others $\mathbf{v}_2, \ldots, \mathbf{v}_n$ have eigenvalue 1.

Consider

$$\mathbf{Q} = \begin{pmatrix} \mathbf{v}_1 & \mathbf{v}_2 & \cdots & \mathbf{v}_n \end{pmatrix}$$

which is orthogonal in the sense that $\mathbf{Q}^T\mathbf{Q} = \mathbf{I}$. Recall that changing bases preserves normality (*e.g.* we discussed that $a \cdot \mathrm{Norm}(\mu, \sigma^2) = \mathrm{Norm}(a\mu, a^2\sigma^2)$), and here we in fact have

$$\mathbf{x} = \mathbf{Q}^T\mathbf{z} \sim \mathrm{Norm}(\mathbf{0}, \mathbf{Q}^T\mathbf{I}\mathbf{Q}) = \mathrm{Norm}(\mathbf{0}, \mathbf{I}).$$

Thus

$$\begin{aligned}
\mathbf{z}^T\left(\mathbf{I} - \frac{1}{n}\mathbf{1}\mathbf{1}^T\right)\mathbf{z} &= \mathbf{x}^T\mathbf{Q}^T\left(\mathbf{I} - \frac{1}{n}\mathbf{1}\mathbf{1}^T\right)\mathbf{Q}\mathbf{x} \\
&= \mathbf{x}^T\mathbf{Q}^T\begin{pmatrix}\mathbf{0} & \mathbf{v}_2 & \cdots & \mathbf{v}_n\end{pmatrix}\mathbf{x} \\
&= \mathbf{x}^T\begin{pmatrix}\mathbf{0} & \mathbf{e}_2 & \cdots & \mathbf{e}_k\end{pmatrix}\mathbf{x} \\
&= \mathbf{x}_2^2 + \cdots + \mathbf{x}_n^2 \\
&\sim \chi^2(n-1).
\end{aligned}$$

□

Student's t-distributions

In short, t-distributions are generalizations of the standard normal distribution, and we use them in statistics when the true variance is known.

Let $X_1, \ldots, X_n \sim \mathrm{Norm}(\mu, \sigma^2)$ be independent samples from a normal random variable. Assume that μ is known.

Motivation. When σ^2 is also known, then by 170A/170E we have

$$\frac{\bar{X} - \mu}{\sqrt{\sigma^2/n}} \sim \mathrm{Norm}(0, 1),$$

and even if X is arbitrary, we can use the central limit theorem

$$\frac{\bar{X} - \mu}{\sqrt{\sigma^2/n}} \to \mathrm{Norm}(0, 1) \qquad \text{as } n \to \infty$$

to approximate this quantity.

What do we do if σ^2 is unknown? Of course we can estimate σ^2 using the unbiased estimator s^2, the sample variance, so now we are looking at

$$\frac{\bar{X} - \mu}{\sqrt{s^2/n}}.$$

Unfortunately, this is not normal because the s^2 is itself a random variable and not just a constant like σ^2 was. But it is a tractable thing.

Definition. The *Student's t-distribution with $n-1$ degrees of freedom* is the distribution of the quantity

$$\frac{\bar{X} - \mu}{\sqrt{s^2/n}} \sim t_{n-1}.$$

Let us explain how this can be defined in terms of a chi-squared distribution. The important point is as follows:

Proposition.

$$(n-1)\frac{s^2}{\sigma^2} \sim \chi^2(n-1).$$

Note that the mean of the LHS is $n-1$ because s^2 is an unbiased estimator for σ^2, and the mean of the RHS is $n-1$ by above.

Proof of Proposition. We will use the Key Property of chi-squared distributions that we discussed above for the random variables

$$Z_i = \frac{X_i - \mu}{\sigma} \sim \mathrm{Norm}(0,1).$$

Note that these are still independent random variables, and observe that

$$\bar{Z} = \frac{1}{n}\sum_{i=1}^{n} Z_i = \frac{1}{n}\sum_{i=1}^{n} \frac{X_i - \mu}{\sigma} = \frac{\bar{X} - \mu}{\sigma}.$$

By the aforementioned Key Property, we have

$$\begin{aligned}
(n-1)\frac{s^2}{\sigma^2} &= \frac{1}{\sigma^2}\sum_{i=1}^{n}(X_i - \bar{X})^2 \\
&= \sum_{i=1}^{n}\left(\frac{X_i - \bar{X}}{\sigma}\right)^2 \\
&= \sum_{i=1}^{n}\left(Z_i - \bar{Z}\right)^2 \\
&\sim \chi^2(n-1),
\end{aligned}$$

as desired. □

Now observe that the quantity we used to define the Student t-distribution is simply

$$t_{n-1} \sim \frac{\bar{X} - \mu}{\sqrt{s^2/n}} = \frac{\bar{X} - \mu}{\sqrt{\sigma^2/n}} \cdot \frac{1}{\sqrt{s^2/\sigma^2}} \sim \frac{\mathrm{Norm}(0,1)}{\sqrt{\chi^2(n-1)/(n-1)}}.$$