Eigenvalues and Eigenvectors

- Suppose A is an $n \times n$ symmetric matrix with real entries.
- The function from R^n to R defined by

$$x \mapsto x^t A x$$

  is called a quadratic form.
- We can maximize $x^T A x$ subject to $x^T x = ||x||^2 = 1$ by Lagrange multipliers:

$$x^T A x - \lambda(x^T x - 1)$$

- Take derivatives and get

$$x^T x = 1$$

  and

$$2Ax - 2\lambda x = 0$$

- We say that v is an eigenvector of A with eigenvalue λ if $v \neq 0$ and
$$Av = \lambda v$$
- For such a v and λ with $v^T v = 1$ we find
$$v^T A v = \lambda v^T v = \lambda.$$
- So the quadratic form is maximized over vectors of length one by the eigenvector with the largest eigenvalue.
- Call that eigenvector v_1, eigenvalue λ_1.
- Maximize $x^T A x$ subject to $x^T x = 1$ and $v_1^T x = 0$.
- Get new eigenvector and eigenvalue.

Summary of Linear Algebra Results

Theorem

Suppose A is a real symmetric $n \times n$ matrix.

1. *There are n orthonormal eigenvectors $v_1, \ldots, v_n$ with corresponding eigenvalues $\lambda_1 \geq \cdots \geq \lambda_n$.*
2. *If P is the $n \times n$ matrix whose columns are $v_1, \ldots, v_n$ and Λ is the diagonal matrix with $\lambda_1, \ldots, \lambda_n$ on the diagonal then*

$$AP = P\Lambda \quad or \quad P^T \Lambda P = A \quad and \quad P^T AP = \Lambda \quad and \quad P^T P = I \quad a$$

3. *If A is non-negative definite (that is, A is a variance covariance matrix) then each $\lambda_i \geq 0$.*
4. *A is singular if and only if at least one eigenvalue is 0.*
5. *The determinant of A is $\prod \lambda_i$.*

The trace of a matrix

Definition: If A is square then the trace of A is the sum of its diagonal elements:

$$\mathrm{tr}(A) = \sum_i A_{ii}$$

Theorem

If A and B are any two matrices such that AB is square then

$$\mathrm{tr}(AB) = \mathrm{tr}(BA)$$

If $A_1, \ldots, A_r$ are matrices such that $\prod_{j=1}^r A_j$ is square then

$$\mathrm{tr}(A_1 \cdots A_r) = \mathrm{tr}(A_2 \cdots A_r A_1) = \cdots = \mathrm{tr}(A_s \cdots A_r A_1 \cdots A_{s-1})$$

If A is symmetric then

$$\mathrm{tr}(A) = \sum_i \lambda_i$$

Idempotent Matrices

Definition: A symmetric matrix A is idempotent if $A^2 = AA = A$.

Theorem

A matrix A is idempotent if and only if all its eigenvalues are either 0 or 1. The number of eigenvalues equal to 1 is then $\mathrm{tr}(A)$.

Proof: If A is idempotent, λ is an eigenvalue and v a corresponding eigenvector then

$$\lambda v = Av = AAv = \lambda Av = \lambda^2 v$$

Since $v \neq 0$ we find $\lambda - \lambda^2 = \lambda(1-\lambda) = 0$ so either $\lambda = 0$ or $\lambda = 1$.

Conversely

- Write
$$A = P\Lambda P^T$$
so
$$A^2 = P\Lambda P^T P\Lambda P^T = P\Lambda^2 P^T$$
- Have used the fact that P is orthogonal.
- Each entry in the diagonal of Λ is either 0 or 1
- So $\Lambda^2 = \Lambda$
- So
$$A^2 = A.$$

Finally

$$\begin{aligned}\mathrm{tr}(A) &= \mathrm{tr}(P\Lambda P^T) \\ &= \mathrm{tr}(\Lambda P^T P) \\ &= \mathrm{tr}(\Lambda)\end{aligned}$$

Since all the diagonal entries in Λ are 0 or 1 we are done the proof.

Independence

Definition: If $U_1, U_2, \ldots U_k$ are random variables then we call $U_1, \ldots, U_k$ independent if

$$P(U_1 \in A_1, \ldots, U_k \in A_k) = P(U_1 \in A_1) \times \cdots \times P(U_k \in A_k)$$

for any sets $A_1, \ldots, A_k$.
We usually either:

- Assume independence because there is no physical way for the value of any of the random variables to influence any of the others.
  OR
- We prove independence.

Joint Densities

- How do we prove independence?
- We use the notion of a **joint density**.
- $U_1, \ldots, U_k$ have joint density function $f = f(u_1, \ldots, u_k)$ if

$$P((U_1, \ldots, U_k) \in A) = \underset{A}{\int \cdots \int} f(u_1, \ldots, u_k) du_1 \cdots du_k$$

- Independence of $U_1, \ldots, U_k$ is equivalent to

$$f(u_1, \ldots, u_k) = f_1(u_1) \times \cdots \times f_k(u_k)$$

  for some densities $f_1, \ldots, f_k$.
- In this case f_i is the density of U_i.
- ASIDE: notice that for an independent sample the joint density is the likelihood function!

Application to Normals: Standard Case

If

$$Z = \begin{bmatrix} Z_1 \\ \vdots \\ Z_n \end{bmatrix} \sim MVN(0, I_{n\times n})$$

then the joint density of Z, denoted $f_Z(z_1, \ldots, z_n)$ is

$$f_Z(z_1, \ldots, z_n) = \phi(z_1) \times \cdots \times \phi(z_n)$$

where

$$\phi(z_i) = \frac{1}{\sqrt{2\pi}} e^{-z_i^2/2}$$

So

$$f_Z = (2\pi)^{-n/2} \exp\left\{-\frac{1}{2}\sum_{i=1}^n z_i^2\right\}$$
$$= (2\pi)^{-n/2} \exp\left\{-\frac{1}{2} z^T z\right\}$$

where

$$z = \begin{bmatrix} z_1 \\ \vdots \\ z_n \end{bmatrix}$$

Application to Normals: General Case

If $X = AZ + \mu$ **and** A is invertible then for any set $B \in R^n$ we have

$$\begin{aligned}
P(X \in B) &= P(AZ + \mu \in B) \\
&= P(Z \in A^{-1}(B - \mu)) \\
&= \int \cdots \int_{A^{-1}(B-\mu)} (2\pi)^{-n/2} \exp\left\{-\frac{1}{2} z^T z\right\} dz_1 \cdots dz_n
\end{aligned}$$

Make the change of variables $x = Az + \mu$ in this integral to get

$$\begin{aligned}
P(X \in B) = \int \cdots \int_B & (2\pi)^{-n/2} \\
& \times \exp\left\{-\frac{1}{2}\left(A^{-1}(x-\mu)\right)^T \left(A^{-1}(x-\mu)\right)\right\} J(x) dx_1 \cdots dx_n
\end{aligned}$$

Here $J(x)$ denotes the Jacobian of the transformation

$$J(x) = J(x_1, \ldots, x_n) = \left|\det\left(\frac{\partial z_i}{\partial x_j}\right)\right| = \left|\det\left(A^{-1}\right)\right|$$

Algebraic manipulation of the integral then gives

$$P(X \in B) = \int_B \cdots \int (2\pi)^{-n/2}$$
$$\times \exp\left\{-\frac{1}{2}(x-\mu)^T\Sigma^{-1}(x-\mu)\right\} |\det A^{-1}| dx_1 \cdots dx_n$$

where

$$\begin{aligned}
\Sigma &= AA^T \\
\Sigma^{-1} &= \left(A^{-1}\right)^T\left(A^{-1}\right) \\
\det\Sigma^{-1} &= \left(\det A^{-1}\right)^2 \\
&= \frac{1}{\det\Sigma}
\end{aligned}$$

Multivariate Normal Density

- Conclusion: the $MVN(\mu, \Sigma)$ density is

$$(2\pi)^{-n/2} \exp\left\{ -\frac{1}{2}(x-\mu)^T \Sigma^{-1} (x-\mu) \right\} (\det \Sigma)^{-1/2}$$

- What if A is not invertible? Ans: there is no density.
- How do we apply this density?
- Suppose

$$X = \left[\begin{array}{c} X_1 \\ \hline X_2 \end{array} \right]$$

and

$$\Sigma = \left[\begin{array}{c|c} \Sigma_{11} & \Sigma_{12} \\ \hline \Sigma_{21} & \Sigma_{22} \end{array} \right]$$

- Now suppose $\Sigma_{12} = 0$

Assuming $\Sigma_{12} = 0$

1. $\Sigma_{21} = 0$
2. In homework you checked that

$$\Sigma^{-1} = \left[\begin{array}{c|c} \Sigma_{11}^{-1} & 0 \\ \hline 0 & \Sigma_{22}^{-1} \end{array}\right]$$

3. Writing

$$x = \left[\begin{array}{c} x_1 \\ \hline x_2 \end{array}\right]$$

and

$$\mu = \left[\begin{array}{c} \mu_1 \\ \hline \mu_2 \end{array}\right]$$

we find

$$(x-\mu)^T\Sigma^{-1}(x-\mu) = (x_1-\mu_1)^T\Sigma_{11}^{-1}(x_1-\mu_1) + (x_2-\mu_2)^T\Sigma_{22}^{-1}(x_2-\mu_2)$$

4. So, if $n_1 = \dim(X_1)$ and $n_2 = \dim(X_2)$ we see that

$$f_X(x_1, x_2) = (2\pi)^{-n_1/2} \exp\left\{-\frac{1}{2}(x_1 - \mu_1)^T \Sigma_{11}^{-1}(x_1 - \mu_1)\right\}$$
$$\times (2\pi)^{-n_2/2} \exp\left\{-\frac{1}{2}(x_2 - \mu_2)^T \Sigma_{22}^{-1}(x_2 - \mu_2)\right\}$$

5. So X_1 and X_2 are independent.

Summary

- If $\text{Cov}(X_1, X_2) = \text{E}[(X_1 - \mu_1)(X_2 - \mu_2)^T] = 0$ then X_1 is independent of X_2.
- **Warning**: This only works provided

$$X = \left[\frac{X_1}{X_2}\right] \sim MVN(\mu, \Sigma)$$

- **Fact**: However, it works even if Σ is singular, but you can't prove it as easily using densities.

Application: independence in linear models

$$\begin{aligned}\hat{\mu} &= X\hat{\beta} = X(X^TX)^{-1}X^TY \\ &= X\beta + H\epsilon \\ \hat{\epsilon} &= Y - X\hat{\beta} \\ &= \epsilon - H\epsilon \\ &= (I-H)\epsilon\end{aligned}$$

So

$$\left[\frac{\hat{\mu}}{\hat{\epsilon}}\right] = \sigma \underbrace{\left[\frac{H}{I-H}\right]}_{A} \frac{\epsilon}{\sigma} + \underbrace{\left[\frac{\mu}{0}\right]}_{b}$$

Hence

$$\left[\frac{\hat{\mu}}{\hat{\epsilon}}\right] \sim MVN\left(\left[\frac{\mu}{0}\right]; AA^T\right)$$

Now

$$A = \sigma \left[\frac{H}{I - H} \right]$$

so

$$\begin{aligned} AA^T &= \sigma^2 \left[\frac{H}{I - H} \right] \left[H^T \quad (I-H)^T \right] \\ &= \sigma^2 \begin{bmatrix} HH & H(I-H) \\ (I-H)H & (I-H)(I-H) \end{bmatrix} \\ &= \sigma^2 \begin{bmatrix} H & H-H \\ H-H & I-H-H+HH \end{bmatrix} \\ &= \sigma^2 \begin{bmatrix} H & 0 \\ 0 & I-H \end{bmatrix} \end{aligned}$$

The 0s **prove** that $\hat{\epsilon}$ and $\hat{\mu}$ are independent.
It follows that $\hat{\mu}^T\hat{\mu}$, the regression sum of squares (not adjusted) is independent of $\hat{\epsilon}^T\hat{\epsilon}$, the Error sum of squares.

Joint Densities: some manipulations

- Suppose Z_1 and Z_2 are independent standard normals.
- Their joint density is

$$f(z_1, z_2) = \frac{1}{2\pi} \exp(-(z_1^2 + z_2^2)/2) \,.$$

- Show meaning of joint density by computing density of a χ_2^2 random variable.
- Let $U = Z_1^2 + Z_2^2$.
- By definition U has a χ^2 distribution with 2 degrees of freedom.

Computing χ^2_2 density

- Cumulative distribution function of U is

$$F(u) = P(U \le u).$$

- For $u \le 0$ this is 0 so take $u \ge 0$.
- Event $U \le u$ is same as event that point (Z_1, Z_2) is in the circle centered at the origin and having radius $u^{1/2}$.
- That is, if A is the circle of this radius then

$$F(u) = P((Z_1, Z_2) \in A)\,.$$

- By definition of density this is a double integral

$$\int\int_A f(z_1, z_2)\, dz_1\, dz_2\,.$$

- You do this integral in polar co-ordinates.

Integral in Polar co-ordinates

- Let $z_1 = r\cos\theta$ and $z_2 = r\sin\theta$.
- we see that

$$f(r\cos\theta, r\sin\theta) = \frac{1}{2\pi}\exp(-r^2/2)\,.$$

- The Jacobian of the transformation is r so that $dz_1\,dz_2$ becomes $r\,dr\,d\theta$.
- Finally the region of integration is simply $0 \le \theta \le 2\pi$ and $0 \le r \le u^{1/2}$ so that

$$\begin{aligned}
P(U \le u) &= \int_0^{u^{1/2}} \int_0^{2\pi} \frac{1}{2\pi}\exp(-r^2/2) r\,dr\,d\theta \\
&= \int_0^{u^{1/2}} r\exp(-r^2/2)dr \\
&= -\exp(-r^2/2)\Big|_0^{u^{1/2}} \\
&= 1 - \exp(-u/2)\,.
\end{aligned}$$

- Density of U found by differentiating to get

$$f(u) = \frac{1}{2}\exp(-u/2)$$

which is the exponential density with mean 2.
- This means that the χ^2_2 density is really an exponential density.

t tests

- We have shown that $\hat{\mu}$ and $\hat{\epsilon}$ are independent.
- So the Regression Sum of Squares (unadjusted) ($=\hat{\mu}^T\hat{\mu}$) and the Error Sum of Squares ($=\hat{\epsilon}^T\hat{\epsilon}$) are independent.
- Similarly

$$\left[\frac{\hat{\beta}}{\hat{\epsilon}}\right] \sim MVN\left(\left[\frac{\beta}{0}\right]; \sigma^2 \begin{bmatrix} (X^TX)^{-1} & 0 \\ 0 & I-H \end{bmatrix}\right)$$

so that $\hat{\beta}$ and $\hat{\epsilon}$ are independent.

Conclusions

- We see
$$a^T\hat\beta - a^T\beta \sim N\left(0, \sigma^2 a^t (X^TX)^{-1}a\right)$$
is independent of
$$\hat\sigma^2 = \frac{\hat\epsilon^T\hat\epsilon}{n-p}$$
- **If** we know that
$$\frac{\hat\epsilon^T\hat\epsilon}{\sigma^2} \sim \chi^2_{n-p}$$
then it would follow that
$$\frac{\frac{a^T\hat\beta - a^T\beta}{\sigma\sqrt{a^t(X^TX)^{-1}a}}}{\sqrt{\hat\epsilon^T\hat\epsilon/\{(n-p)\sigma^2\}}} = \frac{a^T(\hat\beta-\beta)}{\sqrt{\mathrm{MSE} a^t(X^TX)^{-1}a}} \sim t_{n-p}$$
- This leaves only the question: how do I know that
$$\hat\epsilon^T\hat\epsilon/\{\sigma^2\} \sim \chi^2_{n-p}$$

Distribution of the Error Sum of Squares

- **Recall**: if $Z_1, \ldots, Z_n$ are iid $N(0,1)$ then

$$U = Z_1^2 + \cdots + Z_n^2 \sim \chi_n^2$$

- So we rewrite $\hat{\epsilon}^T \hat{\epsilon} / \left\{\sigma^2\right\}$ as $Z_1^2 + \cdots + Z_{n-p}^2$ for some $Z_1, \ldots, Z_{n-p}$ which are iid $N(0,1)$.
- Put

$$Z^* = \frac{\epsilon}{\sigma} \sim MVN_n(0, I_{n\times n})$$

- Then

$$\frac{\hat{\epsilon}^T \hat{\epsilon}}{\sigma^2} = {Z^*}^T (I - H)(I - H) Z^* = {Z^*}^T (I - H) Z^*.$$

- Now define new vector Z from Z^* so that
  1. $Z \sim MVN(0, I)$
  2. ${Z^*}^T (I - H) Z^* = \sum_{i=1}^{n-p} Z_i^2$

Distribution of Quadratic Forms

Theorem

If Z has a standard n dimensional multivariate normal distribution and A is a symmetric $n \times n$ matrix then the distribution of $Z^T AZ$ is the same as that of

$$\sum \lambda_i Z_i^2$$

where the λ_i are the n eigenvalues of Q.

Theorem

The distribution in the last theorem is χ^2_ν if and only if all the λ_i are 0 or 1 and ν of them are 1.

Theorem

The distribution is chi-squared if and only if A is idempotent. In this case $\mathrm{tr}(A) = \nu$.

Rewriting a Quadratic Form as a Sum of Squares

- Consider $(Z^*)^T A Z^*$ where A is symmetric matrix and Z^* is standard multivariate normal.
- In earlier application $A = I - H$.
- Replace A by $\mathbf{P}\boldsymbol{\Lambda}\mathbf{P}^T$ in this formula
- Get

$$\begin{aligned}(Z^*)^T Q Z^* &= (Z^*)^T \mathbf{P}\boldsymbol{\Lambda}\mathbf{P}^T Z^* \\ &= (\mathbf{P}^T Z^*)^T \boldsymbol{\Lambda} (\mathbf{P}^T Z^*) \\ &= Z^T \boldsymbol{\Lambda} Z\end{aligned}$$

where $Z = \mathbf{P}^T Z^*$.

- Notice that Z has a multivariate normal distribution
- mean is 0 and variance is

$$\mathrm{Var}(Z) = \mathbf{P}^T\mathbf{P} = I_{n\times n}$$

- So Z is also standard multivariate normal!
- Now look at what happens when you multiply out

$$Z^T\mathbf{\Lambda}Z$$

- Multiplying a diagonal matrix by Z simply multiplies the ith entry in Z by the ith diagonal element
- So

$$\mathbf{\Lambda}Z = \begin{bmatrix} \lambda_1 Z_1 \\ \vdots \\ \lambda_n Z_n \end{bmatrix}$$

- Take dot product of this with Z:

$$Z^T \boldsymbol{\Lambda} Z = \sum \lambda_i Z_i^2 .$$

- Have rewritten our original quadratic form as a linear combination of squared independent standard normals,
- That is, as a linear combination of independent χ_1^2 variables.

Application to Error Sum of Squares

- Recall that
$$\frac{\mathrm{ESS}}{\sigma^2} = (Z^*)^T(I-H)Z^*$$
where $Z^* = \epsilon/\sigma$ is multivariate standard normal.
- The matrix $I - H$ is idempotent
- So ESS/σ^2 has a χ^2 distribution with degrees of freedom ν equal to $\mathrm{trace}(I-H)$:

$$\begin{aligned}
\nu &= \mathrm{trace}(I-H) \\
&= \mathrm{trace}(I) - \mathrm{trace}(H) \\
&= n - \mathrm{trace}(X(X^TX)^{-1}X^T) \\
&= n - \mathrm{trace}((X^TX)^{-1}X^TX) \\
&= n - \mathrm{trace}(I_{p\times p}) \\
&= n - p
\end{aligned}$$

Summary of Distribution theory conclusions

1. $\epsilon^T A\epsilon/\sigma^2$ has the same distribution as $\sum \lambda_1 Z_i^2$ where the Z_i are iid $N(0,1)$ random variables (so the Z_i^2 are iid χ_1^2) and the λ_i are the eigenvalues of A.
2. $A^2 = A$ (A is idempotent) implies that all the eigenvalues of A are either 0 or 1.
3. Points 1 and 2 prove that $A^2 = A$ implies that $\epsilon^T A\epsilon/\sigma^2 \sim \chi^2_{\mathrm{trace}(A)}$.
4. A special case is
$$\frac{\hat\epsilon^T\hat\epsilon}{\sigma^2} \sim \chi^2_{n-p}$$
5. t statistics have t distributions.
6. If $H_o : \beta = 0$ is true then
$$F = \frac{(\hat\mu^T\hat\mu)/p}{\hat\epsilon^T\hat\epsilon/(n-p)} \sim F_{p,n-p}$$

Many Extensions are Possible

The most important of these are:

1. If a "reduced" model is obtained from a "full" model by imposing k linearly independent linear restrictions on β (like $\beta_1 = \beta_2$, $\beta_1 + \beta_2 = 2\beta_3$) then

$$\text{Extra SS} = \frac{\mathrm{ESS}_R - \mathrm{ESS}_F}{\sigma^2} \sim \chi_k^2$$

   assuming that the null hypothesis (the restricted model) is true.

2. So the Extra Sum of Squares F test has an F-distribution.
3. In ANOVA tables which add up the various rows (not including the total) are independent.
4. When null H_o is **not true** distribution of Regression SS is **Non-central** χ^2.
5. Used in power and sample size calculations.