# Summarizing Variation Matrix Algebra

Benjamin Neale Analytic and Translational Genetics Unit, Massachusetts General Hospital Program in Medical and Population Genetics, Broad Institute of Harvard and MIT

#### Goals of the session

- Introduce summary statistics
- Learn basics of matrix algebra
- Reinforce basic OpenMx syntax
- Introduction to likelihood







Each individual score (the i refers to the i<sup>th</sup> individual)

# • Formula $\sum_{i=1}^{\infty} (x_i)/N$

#### Sum Sample size

Each individual score (the i refers to the i<sup>th</sup> individual)

Formula ∑(x<sub>i</sub>)/N
Can compute with

- Formula  $\sum(x_i)/N$
- Can compute with
  - Pencil
  - Calculator
  - SAS
  - SPSS
  - Mx
  - R, others....

#### Means and matrices

- For all continuous traits we will have a mean
  - Let's say we have 100 traits (a lot!)
  - If we had to specify each mean separately we would have something like this:
    - M1 M2 M3 ... M99 M100 (without "..."!)
  - This is where matrices are useful: they are boxes to hold numbers

## Means and matrices cont' d

 So rather than specify all 100 means in OpenMx we can define a matrix to hold all of our means:

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mxMatrix(type="Full", nrow=1, ncol=100, free=TRUE, values=5, name="M")

## Means and matrices cont' d

 So rather than specify all 100 means in OpenMx we can define a matrix to hold all of our means:

mxMatrix(type="Full", nrow=1, ncol=100, free=TRUE, values=5, name="M")

Quick note on specification of matrices in text: Matrix M has dimension 1,100 meaning 1 row And 100 columns – two mnemonics – like a procession rows first then columns, or RC = Roman Catholic

# To the Variance!

We'll start with coin tossing...

#### **One Coin toss**

2 outcomes



#### **Two Coin toss**

#### 3 outcomes



#### **Four Coin toss**

5 outcomes



#### **Ten Coin toss**

11 outcomes



Outcome

#### Fort Knox Toss Infinite outcomes



#### Variance

Measure of Spread

- Easily calculated
- Individual differences

# Average squared deviation

Normal distribution



#### **Measuring Variation**

Weighs & Means

- Absolute differences?
- Squared differences?
- Absolute cubed?
- Squared squared?

#### **Measuring Variation**

Ways & Means



Squared differences

Fisher (1922) Squared has minimum variance under normal distribution

#### 1. Calculate mean

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- 2. Calculate each squared deviation:

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  - 1. Subtract the mean from each observations and square individually:  $(x_i-\mu)^2$

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  - 2. Sum up all the squared deviations
- 3. Divide sum of squared deviations by (N-1)

#### Your turn to calculate

#### Data Subject Weight in kg

1	80	1.	Calculate mean
2	70	2.	Calculate each deviation from the mean
3	75	3.	Square each deviation
4	85		individually
·		4.	Sum the squared deviations
5	90	5.	Divide by number of subjects - 7

#### Your turn to calculate

#### Data Subject Weight in kg

1	80	1.	Calculate mean (80)
2	70	2.	Calculate each deviation from the mean (0,-10,-5,5,10)
3	75	3.	Square each deviation individually
4	85		(0,100,25,25,100)
	4. 90 5.	4.	Sum the squared deviations (250)
5		5.	Divide by number of subjects $-1$ (250/(5-1))=(250/4)=62.5



 Measure of association between two variables

#### Covariance

 Measure of association between two variables

Closely related to variance

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 Measure of association between two variables

- Closely related to variance
- Useful to partition variance









Covariance .3

Covariance .5

Covariance .7

 Calculate mean for each variables: (μ<sub>x</sub>,μ<sub>y</sub>)
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- 2. Calculate each deviation:
  - Subtract the mean for variable 1 from each observations of variable 1 (x<sub>i</sub> - µ<sub>x</sub>)
  - Likewise for variable 2, making certain to keep the variables paired within subject (y<sub>i</sub> - μ<sub>y</sub>)

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  - Likewise for variable 2, making certain to keep the variables paired within subject (y<sub>i</sub> - μ<sub>y</sub>)

Multiply the deviation for variable 1 and variable 2:
 (x<sub>i</sub> - μ<sub>x</sub>) \* (y<sub>i</sub> - μ<sub>y</sub>)

- Calculate mean for each variables: (μ<sub>x</sub>,μ<sub>y</sub>)
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    1 (x<sub>i</sub> µ<sub>x</sub>)
  - 2.Likewise for variable 2, making certain to keep the variables paired within subject (y<sub>i</sub> - μ<sub>v</sub>)

Multiply the deviation for variable 1 and variable 2:

 (x<sub>i</sub> - μ<sub>x</sub>) \* (y<sub>i</sub> - μ<sub>y</sub>)

 Sum up all the multiplied deviations: Σ(x<sub>i</sub> - μ<sub>x</sub>) \* (y<sub>i</sub> - μ<sub>y</sub>)

- Calculate mean for each variables: (μ<sub>x</sub>,μ<sub>y</sub>)
- 2. Calculate each deviation:
  - 1.Subtract the mean for 4.
    variable 1 from each
    observations of variable 5.
    1 (x<sub>i</sub> µ<sub>x</sub>)
  - 2.Likewise for variable 2, making certain to keep the variables paired within subject  $(y_i - \mu_v)$

 Multiply the deviation for variable 1 and variable 2: (x<sub>i</sub> - μ<sub>x</sub>) \* (y<sub>i</sub> - μ<sub>y</sub>)

> Sum up all the multiplied deviations:  $\Sigma(x_i - \mu_x) * (y_i - \mu_y)$

Divide sum of the multiplied deviations by (N-1):  $\Sigma((x_i - \mu_x) * (y_i - \mu_y))/(N-1)$ 

### Your turn to calculate

Data: Subject	Х	Y	1. 2.	Calculate means Calculate each deviation:
1	80	180		1. Subtract the mean X from each observations of X
2	70	175	3.	<ol> <li>Likewise for Y</li> <li>Multiply the deviation for X</li> </ol>
3	75	170	Л	and Y pair-wise
4	85	190	4.	deviation
5	90	185	5.	Divide sum of the multiplied deviations by (N-1)

• *J* 

### Your turn to calculate

Data: Subject	Х	Y	1. Calculate means: (80,180)
1	80	180	2. Calculate each deviation:
2	70	175	1.Subtract the mean for variable 1 from each observations of variable 1
3	75	170	(0,-10,-5,5,10)
4	85	190	2.Likewise for variable 2, making certain to keep the variables paired within
5	90	185	subject (0,-5,-10,10,5)

### Your turn to calculate

Data:			3.	Mu
Subject	Х	Y		var
1	80	180		(0,- 10,
2	70	175	4.	Sur
3	75	170		dev 0+5
4	85	190	5.	Div dev
5	90	185		200

Multiply the deviation for variable 1 and variable 2: (0,-10,-5,5,10)\*(0,-5,-10,10,5) (0,50,50,50,50)

. Sum up all the multiplied deviation 0+50+50+50+50=200

Divide sum of the multiplied deviations by (N-1):
 200/4=50

Covariance Formula

$$\sigma_{xy} = \sum (x_i - \mu_x) * (y_i - \mu_y)$$
(N-1)

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(N-1)
Sum

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(N-1)

Each individual score on trait x (the i refers to the i<sup>th</sup> pair)

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(N-1)
Mean
of x

Covariance Formula

$$\sigma_{xy} = \sum (x_i - \mu_x) * (y_i - \mu_y)$$
(N-1)
Number of
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(N-1)

Each individual score on trait y (the i refers to the i<sup>th</sup> pair)

Covariance Formula

$$\sigma_{xy} = \frac{\sum(x_i - \mu_x) * (y_i - \mu_y)}{(N-1)}$$
Mean
of y

Covariance Formula



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If we have 5 traits we have: 5 variances (V1, V2, ... V5) 10 covariances (CV1-2, CV1-3,...CV4-5

- Just like means, we can put variances and covariances in a box
  - In fact this is rather convenient, because:
  - Cov(X,X) = Var(x) so the organization is natural

Trait 1Trait 2Trait 3Trait 4Trait 1Var(T1)Var(T1)Trait 2Trait 3Trait 3Trait 4

	Variances, covariances, and matrices cont' d						
Trait 1	<b>Trait 1</b> Var(T1)	Trait 2	Trait 3	Trait 4			
Trait 2		Var(T2)					
Trait 3			Var(T3)				
Trait 4				Var(T4)			

### Trait 1Trait 2Trait 3Trait 4Trait 1Cov(T1,T2)

Trait 2

Trait 3

Trait 4

Trait 1Trait 2Trait 3Trait 4Trait 1Cov(T1,T2)Cov(T1,T3)Cov(T1,T4)

**Trait 2** Cov(T2,T1) Cov(T2,T3) Cov(T2,T4)

**Trait 3** Cov(T3,T1) Cov(T3,T2) Cov(T3,T4)

**Trait 4** Cov(T4,T1) Cov(T4,T2) Cov(T4,T3)

Trait 1Trait 2Trait 3Trait 4Trait 1Cov(T1,T2)Cov(T1,T3)Cov(T1,T4)

**Trait 2** Cov(T2,T1) Cov(T2,T3) Cov(T2,T4)

**Trait 3** Cov(T3,T1) Cov(T3,T2) Cov(T3,T4)

**Trait 4** Cov(T4,T1) Cov(T4,T2) Cov(T4,T3)

Note Cov(T3,T1)=Cov(T1,T3)

 Trait 1
 Trait 2
 Trait 3
 Trait 4

 Trait 1
 Var(T1)
 Cov(T1,T2)
 Cov(T1,T3)
 Cov(T1,T4)

 Trait 2
 Cov(T2,T1)
 Var(T2)
 Cov(T2,T3)
 Cov(T2,T4)

 Trait 3
 Cov(T3,T1)
 Cov(T3,T2)
 Var(T3)
 Cov(T3,T4)

 Trait 4
 Cov(T4,T1)
 Cov(T4,T2)
 Cov(T4,T3)
 Var(T4)









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Considered another way, a symmetric matrix's transpose is equal to itself.

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Transpose is exchanging rows and columns
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Considered another way, a symmetric matrix's **transpose** is equal to itself.

$$A = \begin{pmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{pmatrix}$$

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Considered another way, a symmetric matrix's **transpose** is equal to itself.

$$A = \begin{pmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{pmatrix} \qquad A' = \begin{pmatrix} A' = \\ Or \\ A^{T} \end{pmatrix}$$

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OpenMx uses mxFIMLObjective to calculate the variance-covariance matrix for the data (let's stick with matrix V)

mxMatrix(type="Sym", nrow=2, ncol=2, free=TRUE, values=.5, name="V")

type specifies what kind of matrix – symmetric nrow specifies the number of rows ncol specifies the number of columns free means that OpenMx will estimate

# How else can we get a symmetric matrix?

We can use matrix algebra and another matrix type.

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Let's begin with matrix multiplication

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Let's extend this to a simple case: Two 2x2 matrices

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Let's extend this to a simple case: Two 2x2 matrices

$$\begin{pmatrix}
 A & B \\
 C & D
 \end{pmatrix}
 \%^*\%
 \begin{pmatrix}
 E & F \\
 G & H
 \end{pmatrix}$$

 $\begin{pmatrix}
 A & B \\
 C & D
 \end{pmatrix}
 \%*\%
 \begin{pmatrix}
 E & F \\
 G & H
 \end{pmatrix}$ 



RULE: The number of columns in the 1<sup>st</sup> matrix must equal the number of rows in the 2<sup>nd</sup> matrix.

$$\left(\begin{array}{ccc}
A & B \\
C & D
\end{array}\right)\%*\%\left(\begin{array}{ccc}
E & F \\
G & H
\end{array}\right)$$

Step 1: Determine the size of the box (matrix) needed for the answer

$$\left(\begin{array}{ccc}
A & B \\
C & D
\end{array}\right)\%*\%\left(\begin{array}{ccc}
E & F \\
G & H
\end{array}\right)$$

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•The resulting matrix will have dimension: the number of rows of the 1<sup>st</sup> matrix by the number of columns of the 2<sup>nd</sup> matrix



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RULE: The number of columns in the 1<sup>st</sup> matrix must equal the number of rows in the 2<sup>nd</sup> matrix.



Step 2: Calculate each element of the resulting matrix.



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Step 2: Calculate each element of the resulting matrix.There are 4 elements in our new matrix: 1,1; 1,2; 2,1;2,2



Step 2: Calculate each element of the resulting matrix. Each element is the cross-product of the corresponding row of the 1<sup>st</sup> matrix and the corresponding column of the 2<sup>nd</sup> matrix (e.g. element 2,1 will be the cross product of the 2<sup>nd</sup> row of matrix 1 and the 1<sup>st</sup> column of matrix 2)

### What's a cross-product?

•Used in the context of vector multiplication:

•We have 2 vectors of the same length (same number of elements)

•The cross-product (x) is the sum of the products of the elements, e.g.:

•Vector  $1 = \{a b c\}$  Vector  $2 = \{d e f\}$ 

•V1 x V2 = a\*d +b\*e +c\*f

$$\begin{pmatrix} A & B \\ C & D \end{pmatrix} \% * \% \begin{pmatrix} E & F \\ G & H \end{pmatrix} = \begin{pmatrix} O \\ 2 \times 2 \end{pmatrix}$$

$$2 \times 2 \qquad 2 \times 2 \qquad 2 \times 2$$

Step 2, element 1,1: cross-product row1 matrix1 with column1 matrix2

 $\{AB\} \times \{EG\} = (A^*E + B^*G)$ 

$$\begin{pmatrix} A & B \\ C & D \end{pmatrix} \% * \% \begin{pmatrix} E & F \\ G & H \end{pmatrix} = \begin{pmatrix} AE + BG & O \\ 2 \times 2 & 2 \times 2 & 2 \times 2 \end{pmatrix}$$

Step 2, element 1,2: cross-product row1 matrix1 with column2 matrix2

 $\{AB\} \times \{FH\} = (A^*F + B^*H)$ 

$$\begin{pmatrix} A & B \\ C & D \end{pmatrix} \% * \% \begin{pmatrix} E & F \\ G & H \end{pmatrix} = \begin{pmatrix} AE + BG & AF + BH \\ O & \end{pmatrix}$$
  
$$2 \times 2 \qquad 2 \times 2 \qquad 2 \times 2$$

Step 2, element 2,1: cross-product row2 matrix1 with column1 matrix2

 $\{CD\} \times \{EG\} = (C^*E + D^*G)$ 

$$\begin{pmatrix} A & B \\ C & D \end{pmatrix} \% \% \begin{pmatrix} E & F \\ G & H \end{pmatrix} = \begin{pmatrix} AE + BG & AF + BH \\ CE + DG & O \end{pmatrix}$$

$$2 \times 2 \qquad 2 \times 2 \qquad 2 \times 2$$

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$$\begin{pmatrix} A & B \\ C & D \end{pmatrix} \% * \% \begin{pmatrix} E & F \\ G & H \end{pmatrix} = \begin{pmatrix} AE + BG & AF + BH \\ CE + DG & CF + DH \end{pmatrix}$$

$$2 \times 2 \qquad 2 \times 2 \qquad 2 \times 2$$

Step 2, element 2,2: cross-product row2 matrix1 with column2 matrix2

 $\{CD\} \times \{FH\} = (C^*F + D^*H)$ 

#### **Matrix multiplication exercises**

$$\begin{array}{cccc} L & \begin{pmatrix} 2 & 0 \\ 1 & 4 \end{pmatrix} & A \begin{pmatrix} 1 \\ 2 \\ 5 \end{pmatrix} & B & C \\ \begin{pmatrix} 4 & 7 & -4 \end{pmatrix} & \begin{pmatrix} -4 & 2 \\ -3 & 2 \\ 2 & -2 \end{pmatrix}$$

Calculate:

- 1. L<sup>%\*%</sup> t(L) (L times L transpose)
- 2. B<sup>%\*%</sup>A
- 3. A<sup>%\*%</sup>B

#### 4. C<sup>%\*%</sup>A

 $\begin{array}{ccc}
1 & 4 & 2 \\
2 & 17
\end{array}$ 

 $\begin{array}{cccc}
1 & \left( \begin{array}{ccc}
4 & 2\\
2 & 17 \end{array} \right) & 2 & \left( \begin{array}{c}
-2\\
\end{array} \right)
\end{array}$ 

Incomputable
# What have we learned?

•Matrix multiplication is not commutative:

•E.g. A\*B ≠ B\*A

•The product of a lower matrix and its transpose is symmetric

•Not all matrices were made to multiply with one another

### Correlation

- Standardized covariance
- Calculate by taking the covariance and dividing by the square root of the product of the variances
- Lies between -1 and 1



## **Calculating Correlation from data**

Data:			. 1	Calculate mean for X and Y
Subject	Χ	Y	2.	Calculate variance for X and Y
1	80	180	3.	Calculate covariance for X and Y
2	70	175	4.	Correlation formula is $cov_{yy}/(\sqrt{(var_y * var_y)})$
3	75	170	5.	Variance of X is 62.5, and Variance
4	85	190		of Y is 62.5, covariance(X,Y) is 50
5	90	185		

## **Calculating Correlation from data**

Data:			1	Correlation formula is $cov_{xy}/(\sqrt{(var_x * var_y)})$
Subject	Х	Y	1.	
1	80	180	2.	Variance of X is 62.5, and Variance of Y is 62.5, covariance(X,Y) is 50
2	70	175	3.	Answer: $50/(\sqrt{(62.5*62.5)})=.8$
3	75	170		
4	85	190		
5	90	185		

• We can standardize an entire variance covariance matrix and turn it into a correlation matrix

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- What will we need?

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- What will we need?

Covariance(X,Y)

 $\mathbf{r}_{\mathbf{x}\mathbf{y}} = \underbrace{\boldsymbol{\sigma}_{\mathbf{x}\mathbf{y}}}_{\text{Variance}(X)} \underbrace{\boldsymbol{\sigma}_{\mathbf{x}}^2 \mathbf{\sigma}_{\mathbf{y}}^2}_{\text{Variance}(Y)}$ 

#### **Standardization back to boxes**

• We'll start with our Variance Covariance matrix:

$$V = \begin{pmatrix} V_{1} & CV_{12} & CV_{13} \\ CV_{21} & V_{2} & CV_{23} \\ CV_{31} & CV_{32} & V_{3} \end{pmatrix}$$

#### **Standardization back to boxes**

• We'll start with our Variance Covariance matrix:

$$V = \begin{pmatrix} V_{1} & CV_{12} & CV_{13} \\ CV_{21} & V_{2} & CV_{23} \\ CV_{31} & CV_{32} & V_{3} \end{pmatrix}$$

- •We'll use 4 operators:
- •Dot product (\*)
- Inverse (solve)
- •Square root (\sqrt)

•Pre-multiply and post-multiply by the transpose (%&%)

# Formula to standardize V: solve (sqrt (I\*V) ) %&% V

Extracts the variances

The dot product does element by element multiplication, so the dimensions of the two matrices must be equal, resulting in a matrix of the same size







# Formula to standardize V: solve (sqrt (I\*V) ) %&% V

Inverts the matrix

The inverse of matrix B is the matrix that when multiplied by B yields the identity matrix:

B %\*% B<sup>-1</sup> = B<sup>-1</sup> %\*%B = I

Warning: not all matrices have an inverse. A matrix with no inverse is a **singular** matrix. A zero matrix is a good example.

# Formula to standardize V: solve (sqrt (I\*V)) %&% V

Inverts the matrix

Let's call this K:

$$\begin{pmatrix} \sqrt{V_1} & 0 & 0 \\ 0 & \sqrt{V_2} & 0 \\ 0 & 0 & \sqrt{V_3} \end{pmatrix}^{-1} = \begin{pmatrix} 1/\sqrt{V_1} & 0 & 0 \\ 0 & 1/\sqrt{V_2} & 0 \\ 0 & 0 & 1/\sqrt{V_3} \end{pmatrix}$$

#### **Operator roundup**

Operator %\*% \* / solve

+

%&%

Function Matrix multiplication Dot product Element-byelement division Inverse Element-byelement addition Element-byelement subtraction Pre- and postmultiplication

Rule  $C_1 = R_2$   $R_1 = R_2 \& C_1 = C_2$  $R_1 = R_2 \& C_1 = C_2$ 

non-singular  $R_1 = R_2 \& C_1 = C_2$ 

 $R_1 = R_2 \& C_1 = C_2$ 

 $C_1 = R_2 = C_2$ 

Full list can be found:

http://openmx.psyc.virginia.edu/wiki/matrix-operators-and-functions