

$$\lim_{n \rightarrow a} f(n) = f(a) +$$

$$\frac{f'(a)(n-a)}{1!} +$$

$$\frac{f''(a)(n-a)^2}{2!} +$$

$$\frac{f'''(a)(n-a)^3}{3!} + \dots$$

e.g.  $n-a = 0.1$   
 $(n-a)^2 = 0.01$

if  $n$  is close to  $a$   
 $0.001$

$$f(n) \approx f(a) + f'(a)(n-a)$$

$$\begin{cases} n-a = y \\ a = Sy \end{cases}$$

$$\Rightarrow f(y+Sy) \approx f(y) + f'(y)Sy$$

 $f(n)$  $f(n, y)$ 

$$\frac{d^2f}{dn dy} \quad \text{Leibniz notation}$$

$$\frac{df(n,y)}{dn} \quad \frac{d\left(\frac{df}{dn}\right)}{dn} = \frac{d^2f}{dn^2}$$

Lagrange's Notation

$$f' = \frac{df}{dx} \quad f'(n) = \frac{df(n)}{dn}$$

Newton's Notation

$$y(t) \rightarrow \dot{y}(t) = \frac{dy}{dt}$$

$$\ddot{y} = \frac{d^2y}{dt^2}$$

 $I(n, y)$ 

$$I(n+u, y+v) \approx I(n, y) + u \cdot \frac{\partial I(n, y)}{\partial n} + v \cdot \frac{\partial I(n, y)}{\partial y}$$

if  $u, v$  small

$$= I + u \cdot I_n + v \cdot I_y$$

 $f(n)$  continuous  $\lambda_x = 0.01$ 

a couple of things didn't get the time  
to talk about during the lecture

1) Matrix  $A$  (e.g.  $2 \times 2$ ) is "positive definite"

if all its eigenvalues are positive

(e.g.  $\lambda_1 > 0$  &  $\lambda_2 > 0$  if  $A$  is  $2 \times 2$ )

Equivalently,  $\vec{v}^T A \vec{v} > 0$  for any  
vector  $\vec{v}$  that is not  $\vec{0}$  (i.e.  $\begin{bmatrix} 0 \\ 0 \end{bmatrix}$ )

Similarly, matrix  $A$  is "positive semi-definite"  
if its eigenvalues are non-negative  $\geq 0$

or  $\vec{v}^T A \vec{v} \geq 0$

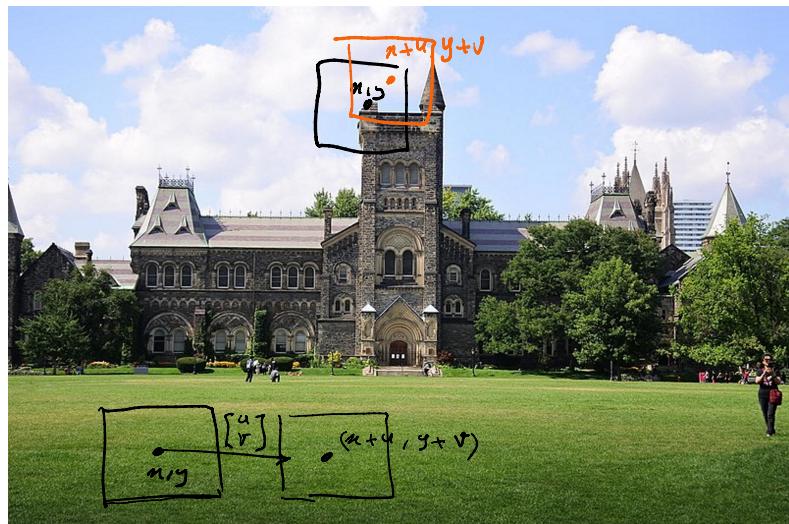
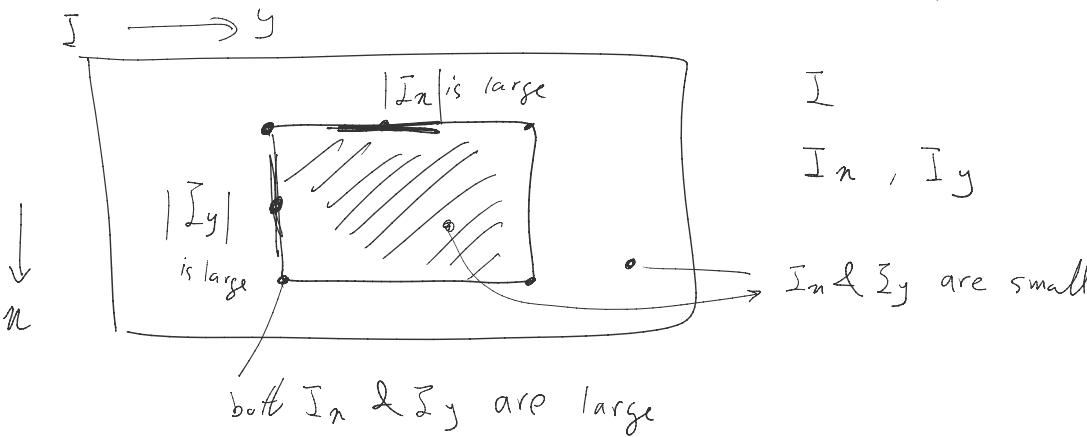
2) if  $A$  is symmetric and if  $A$  can be written

as  $A = B^T B$  (Cholesky Decomposition)

then  $A$  is positive definite.

$$\vec{v}^T A \vec{v} = \vec{v}^T (B^T B) \vec{v} = (\vec{v}^T B^T) (B \vec{v})$$

$f(n)$  continuous  $\Delta x = 0.01$   
 image smallest  $u \otimes v = 1$



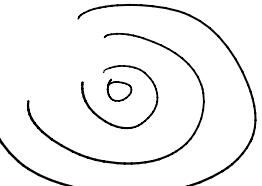
$w$ : window function  
 (weight)

We want  $E_{WSSD}(u, v)$  to be large for any  $u \otimes v$

$$\sum_n \sum_y w(n, y) \left( \overline{I(n, y)} - \overline{I(n+u, y+v)} \right)^2$$

$$E_{WSSD}(u, v) = \sum_n \sum_y w(n, y) \left( \frac{\overline{I(n, y)}}{\text{intensity}} - \frac{\overline{I(n+u, y+v)}}{\text{shifted intensity}} \right)^2$$

$$G(n, y)$$



$$\sum w = 1$$

small

$V^T A V = V^T (B^T B) V = (V \text{ is } 1 \times 1 \times 1)$   
 $= (\vec{B} \vec{V})^T (\vec{B} \vec{V}) = \vec{U}^T \vec{U} > 0$   
 define  $\vec{U} = \vec{B} \vec{V}$  if  $\vec{U} \neq \vec{0}$

### 3) Re: Corner Detection

$$[u \ v] M \begin{bmatrix} u \\ v \end{bmatrix} = [u \ v] V \Sigma V^T \begin{bmatrix} u \\ v \end{bmatrix}$$

$$\vec{e} = \begin{bmatrix} u \\ v \end{bmatrix}, \quad V^{-1} = V^T$$

$$= (\vec{e}^T V) \sum (V^T \vec{e})$$

$$= (V^T \vec{e})^T \sum (V \vec{e})$$

$$(\vec{e}' = V^T \vec{e})$$

$$= \vec{e}'^T \sum \vec{e}' \quad \vec{e}' = \begin{bmatrix} a \\ b \end{bmatrix}$$

$$= \lambda_1 a^2 + \lambda_2 b^2$$

to make this large

$$= \sum_n \sum_y W(n,y) \left( I(n,y) - I(n,y) - u \frac{\partial I(n,y)}{\partial n} + v \frac{\partial I(n,y)}{\partial y} \right)^2$$

$\lambda_1$  &  $\lambda_2$  should be large

$$= \sum_n \sum_y w(n,y) (-u^T_{\perp n} - v^T_{\perp y})^2$$

$$= \sum_n \sum_y w(n,y) \left( u^2 I_n^2 + 2uv I_n I_y + v^2 I_y^2 \right)$$

$$= \sum_n \sum_y w(n, y) \left( [u \ v] \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} \right)$$

$$= \begin{bmatrix} u & v \end{bmatrix}_{1 \times 2} \left( \sum_n \sum_y w(n,y) \begin{bmatrix} I_n^2 & I_n I_y \\ I_n I_y & I_y^2 \end{bmatrix} \right) \begin{bmatrix} u \\ v \end{bmatrix}_{2 \times 1}$$

M

$$\begin{bmatrix} u & v \end{bmatrix} M_{2 \times 2} \begin{bmatrix} u \\ v \end{bmatrix}$$

$$\vec{e} = \begin{bmatrix} u \\ v \end{bmatrix}$$

$$E_{\text{MSE}}(\vec{e}) = \vec{e}^T M \vec{e}$$

for any small  $u \& v$   
 $\hookrightarrow$  we want large  $E(u, v)$

$\rightarrow$  WSSD  
 ↳ we want large  $E(u, v)$

$$\text{S.V.D} \quad A_{m \times n} = U \Sigma V^T$$

$$\left[ \begin{array}{c} \\ \end{array} \right] = \left[ \begin{array}{c} \\ \end{array} \right] \left[ \begin{array}{c} \\ \end{array} \right] \left[ \begin{array}{c} \\ \end{array} \right] \left[ \begin{array}{c} \\ \end{array} \right]$$

if  $A$  is square : E.V.D.

$$A \vec{v} = \lambda \vec{v} \rightarrow \underbrace{(A - \lambda I)}_x \vec{v} = 0$$

$$A_{m \times m} = V \Sigma^{-1} V^T = V \Sigma V^T \quad \sigma_i = |\lambda_i|$$

if  $A$ : real & symmetric  $\rightarrow \lambda$  real

$$V^T = V^{-1} \quad V V^T = V^T V = I$$

$$M = \sum_{n \in \mathbb{Z}^2} \sum_{y \in \mathbb{Z}^2} w(n, y) \begin{bmatrix} I_n^2 & I_n I_y \\ I_n I_y & I_y^2 \end{bmatrix}$$

$M$ : 2<sup>nd</sup> moment matrix (structure tensor)

$$\sum_{n \in \mathbb{Z}^2} \sum_{y \in \mathbb{Z}^2} w(n, y) \begin{bmatrix} I_n^2 & I_n I_y \\ I_n I_y & I_y^2 \end{bmatrix}$$

$M$ : symmetric & real valued  $\rightarrow$  eigenvalues are real

$$\det \left( \begin{bmatrix} I_n^2 & I_n I_y \\ I_n I_y & I_y^2 \end{bmatrix} \right) = 0 \quad J_n(n, y)$$

$$I_n^2 I_y^2 - I_n I_y I_n I_y = 0$$

$$\det = 0 \rightarrow \lambda_1 = 0$$

$$\lambda_2 \geq 0$$

sum of positive semi-definite matrices  $\rightarrow$  tive semi-definite

$$M: \lambda_1, \lambda_2 \geq 0$$

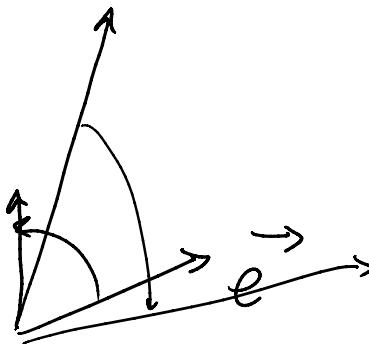
$$\therefore \vec{v} \rightarrow (V T S V^{-1}) \vec{e} = V \sum (V^{-1} \vec{e})$$

$$M \vec{e} = (V \sum V^\top) \vec{e} = V \sum (V^\top e)$$

$V$ : orthonormal

$$VV^\top = I$$

$$R^\top = R^{-1}$$



$$\begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix}$$

$$E_{WSSD}(u, v) = [u, v] M \begin{bmatrix} u \\ v \end{bmatrix}$$

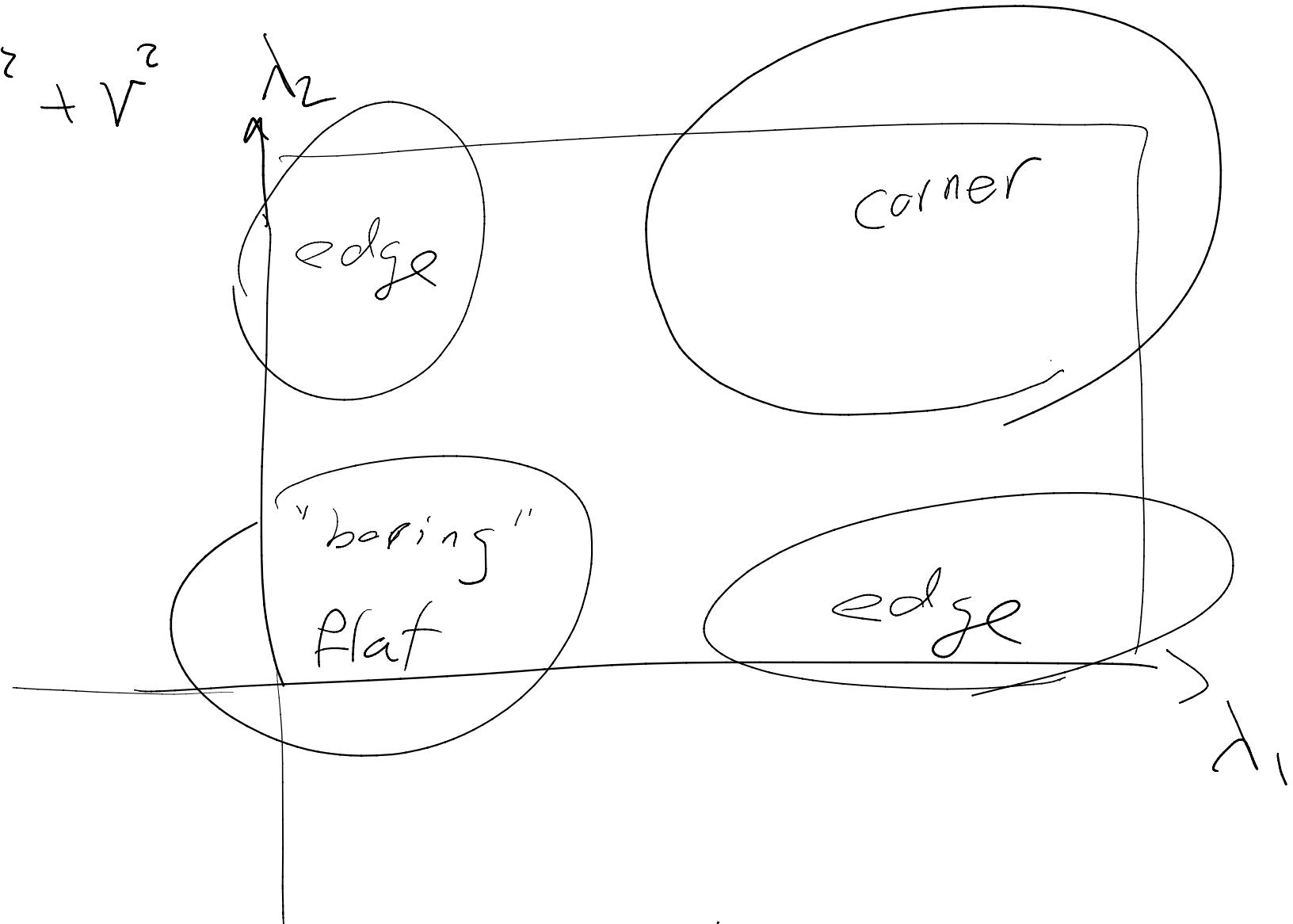
$$= [u \ v] \underbrace{\check{V}}_{\check{U}} \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} \underbrace{\check{V}^{-1}}_{\check{M}} \begin{bmatrix} u \\ v \end{bmatrix} \quad \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$e^T e = [u \ v] \begin{bmatrix} u \\ v \end{bmatrix} = \vec{e} \cdot \vec{e} = u^2 + v^2$$

$\lambda_1$ : large

$\lambda_2$ : large

$$[u \ v] M \begin{bmatrix} u \\ v \end{bmatrix}$$



We want  $M$  to have large eigenvalues

$M$ : real & symmetric

$$\text{and } M \leftarrow M^{-1}$$

$$\det(AB) = \det(A)\det(B)$$

$$M = V \sum \Sigma$$

$$\det(A\Sigma) = \det(V) \det(\Sigma) \det(V^{-1})$$

$$\det(M) = \underline{\det(V)} \det(\Sigma) \underline{\det(V^{-1})}$$

$$V: \text{orthonormal} \quad VV^T = I \quad V: \text{rotation}$$

$$\det \begin{pmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{pmatrix} = \cos^2 \theta + \sin^2 \theta = 1$$

$$\det(V) = 1 \quad \det(V^{-1}) = 1$$

$$\det(M) = \det \begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{pmatrix} = \lambda_1 \lambda_2 - 0 = \underline{\lambda_1 \lambda_2}$$

$$\text{trace}(M) = \lambda_1 + \lambda_2$$