



Geometric Image Processing in Remote Sensing

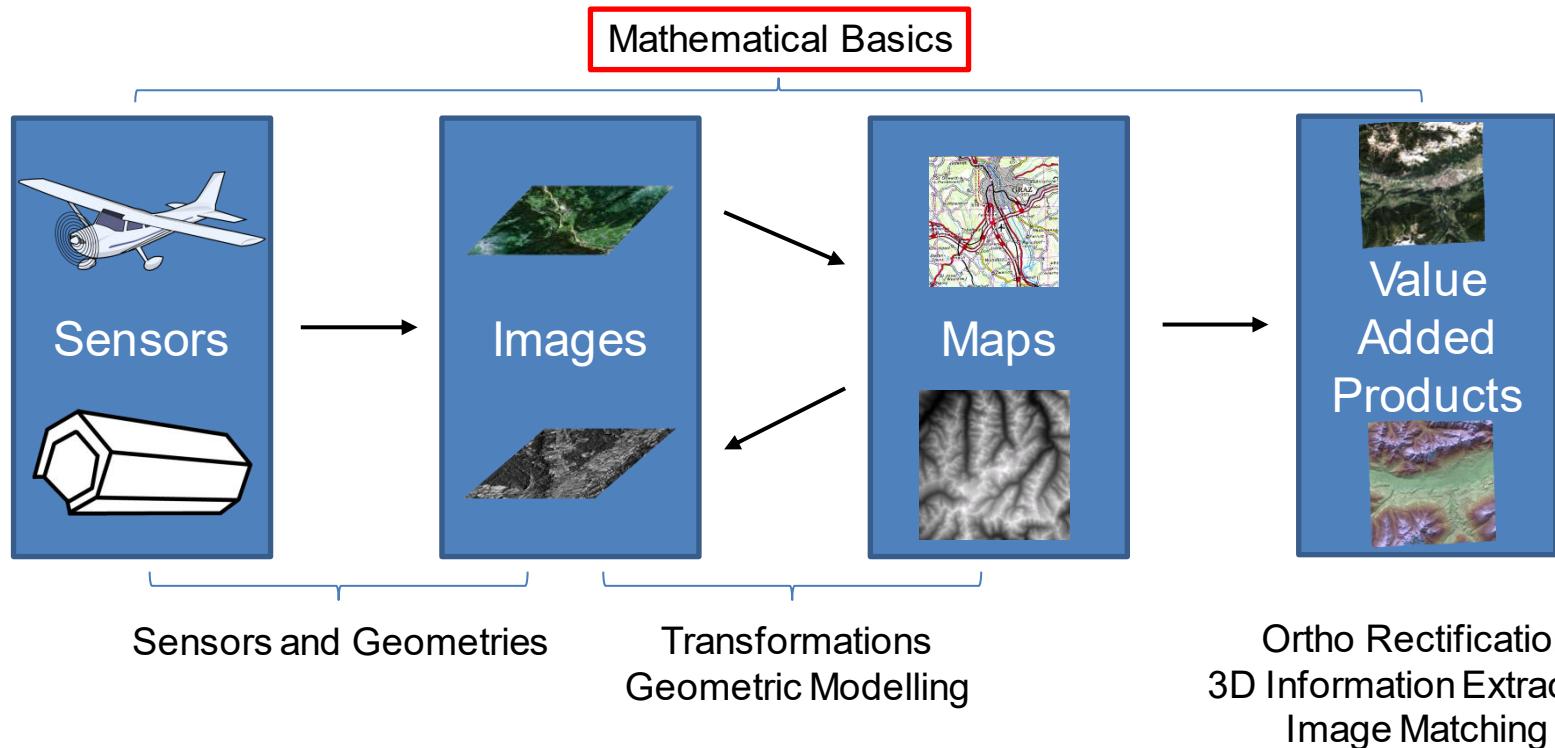
Lecture 2 – Mathematical Basics

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WS 2020/2021



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Lecture Overview



Learning Goals

- ☒ Ability to describe Newton's method and its applications
- ☒ [Newton Methode und deren Anwendung beschreiben können]

Mathematical Notations

- ❖ Domains $\mathbb{N}, \mathbb{Z}, \mathbb{R}, \mathbb{C}, \mathbb{H}$
- ❖ Numbers $x \in \mathbb{R}; x = \pi \approx 3.14159$

$$i \in \mathbb{N}_0; i = 42$$

- ❖ Vectors $\boldsymbol{v} \in \mathbb{R}^n; \boldsymbol{v} \in \mathbb{R}^2 = \begin{bmatrix} a \\ b \end{bmatrix} = [a, b]^T$
- ❖ Matrices $\boldsymbol{M} \in \mathbb{R}^{m \times n}; \boldsymbol{M} \in \mathbb{R}^{2 \times 3} = \begin{bmatrix} a & b & c \\ d & e & f \end{bmatrix}$

Mathematical Notations

❖ Functions

$$f(\boldsymbol{x}) : \mathbb{R}^n \rightarrow \mathbb{R}$$

$$f : \mathbb{R}^2 \rightarrow \mathbb{R} \quad \text{with} \quad f(x, y) = xy^2 + x - 1$$

❖ Equation systems

$$F(\boldsymbol{x}) : \mathbb{R}^{m \times n} \rightarrow \mathbb{R}^n$$

$$F : \mathbb{R}^{2 \times 3} \rightarrow \mathbb{R}^3 \quad \text{with}$$

$$F_1(x, y) = xy^2 + 1$$

$$F_2(x, y) = x + y - 3$$

$$F_3(x, y) = x^2 + y - 2$$

Matrix Notation

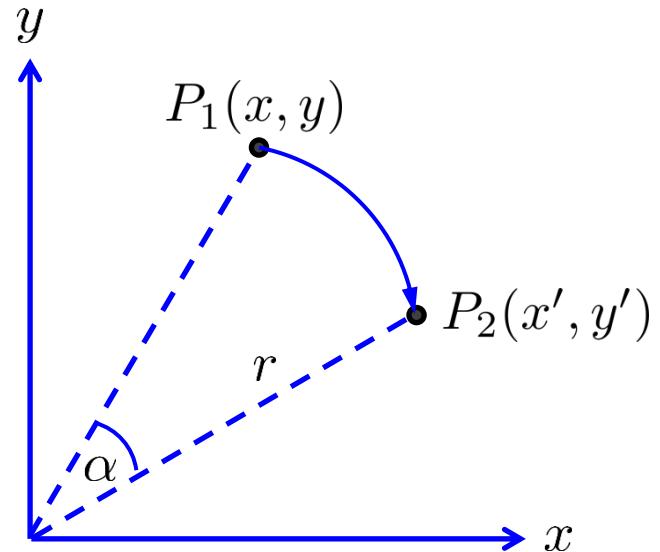
❖ Example – Rotation in 2D

$$x' = x \cos \alpha + y \sin \alpha$$

$$y' = -x \sin \alpha + y \cos \alpha$$

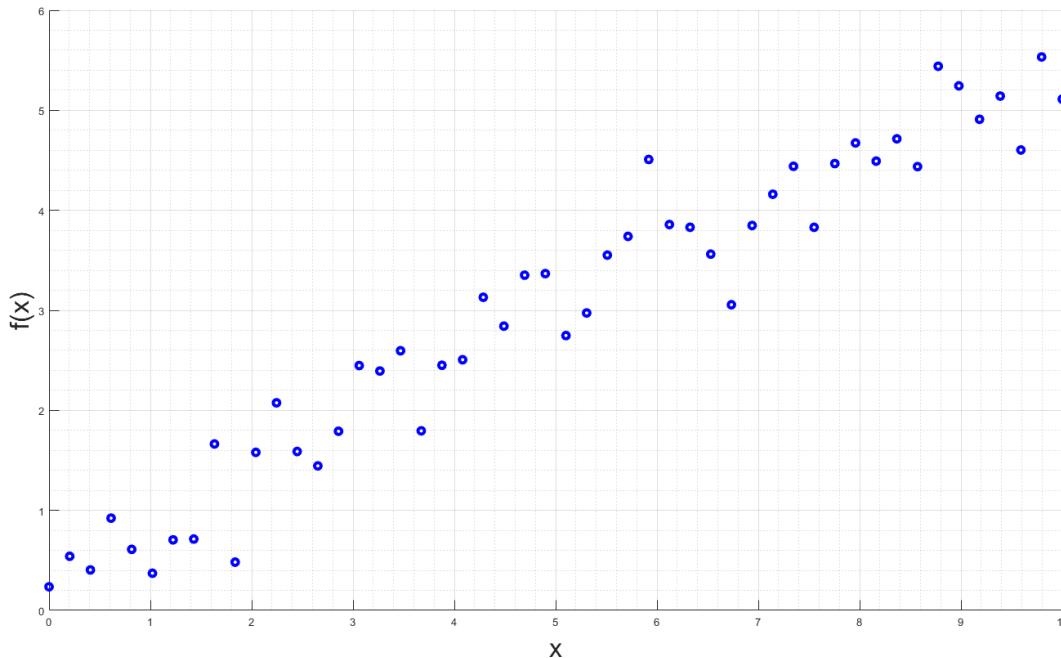
$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos \alpha & \sin \alpha \\ -\sin \alpha & \cos \alpha \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

$$\mathbf{x}' = \mathbf{R}(\alpha) \mathbf{x}$$



Parameter Adjustment – Example

- ❖ Find a line that optimally fits the measured points



One equation per point

$$y_1 = a + b x_1 + r_1$$

$$y_2 = a + b x_2 + r_2$$

⋮

$$y_n = a + b x_n + r_n$$

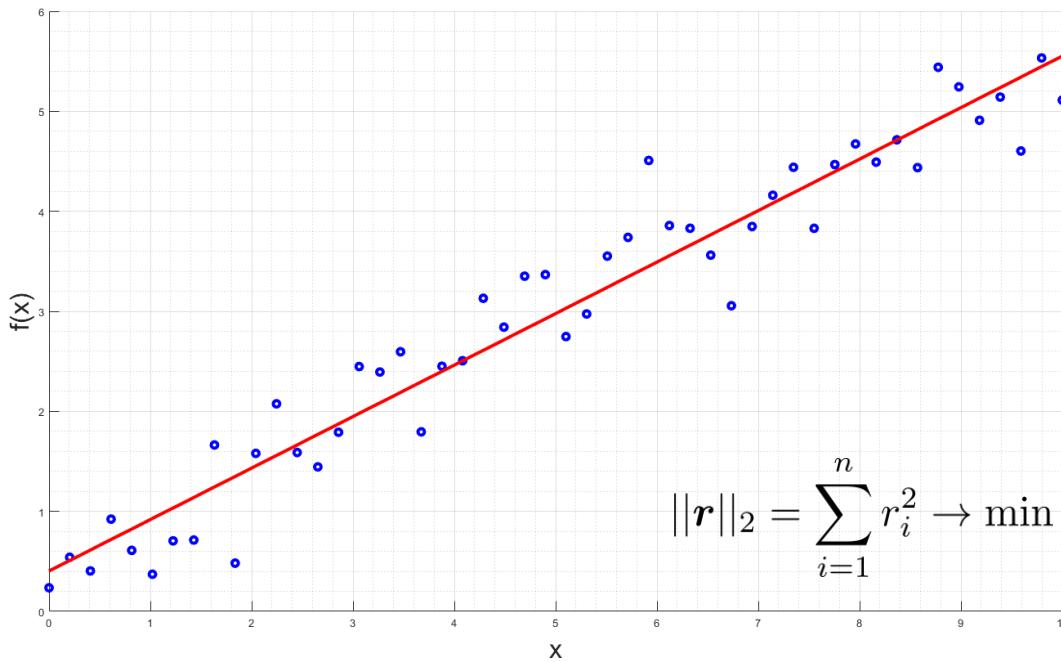


$$\mathbf{l} = \mathbf{A}\mathbf{x} + \mathbf{r}$$

$$\mathbf{x} = \begin{bmatrix} a \\ b \end{bmatrix}$$

Parameter Adjustment – Example

- ❖ Find a line that optimally fits the measured points



One equation per point

$$y_1 = a + b x_1 + r_1$$

$$y_2 = a + b x_2 + r_2$$

⋮

$$y_n = a + b x_n + r_n$$



$$l = Ax + r$$

$$x = \begin{bmatrix} a \\ b \end{bmatrix}$$

Least Squares Adjustment

- Least squares adjustment (over-determined system)

$$Ax = b$$

equation system does
not have a solution

$$Ax - b = 0$$

reformulate

$$r = \min_x ||Ax - b||_2$$

find best „solution“
via least squares with
residuals r

$$\tilde{x} = A^+ b$$

$$A^+ = (A^T A)^{-1} A^T$$

pseudo inverse of A

$$\tilde{x} = (A^T A)^{-1} A^T b$$

- Could also be solved via Singular Value Decomposition (SVD)

Least Squares – Example

- Find an affine transformation between two 2D point sets

$$x' = ax + by + e$$

$$y' = cx + dy + f$$

affine transformation

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} a & b & e \\ c & d & f \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

matrix notation

How to convert to form $\mathbf{A}\mathbf{x} = \mathbf{b}$

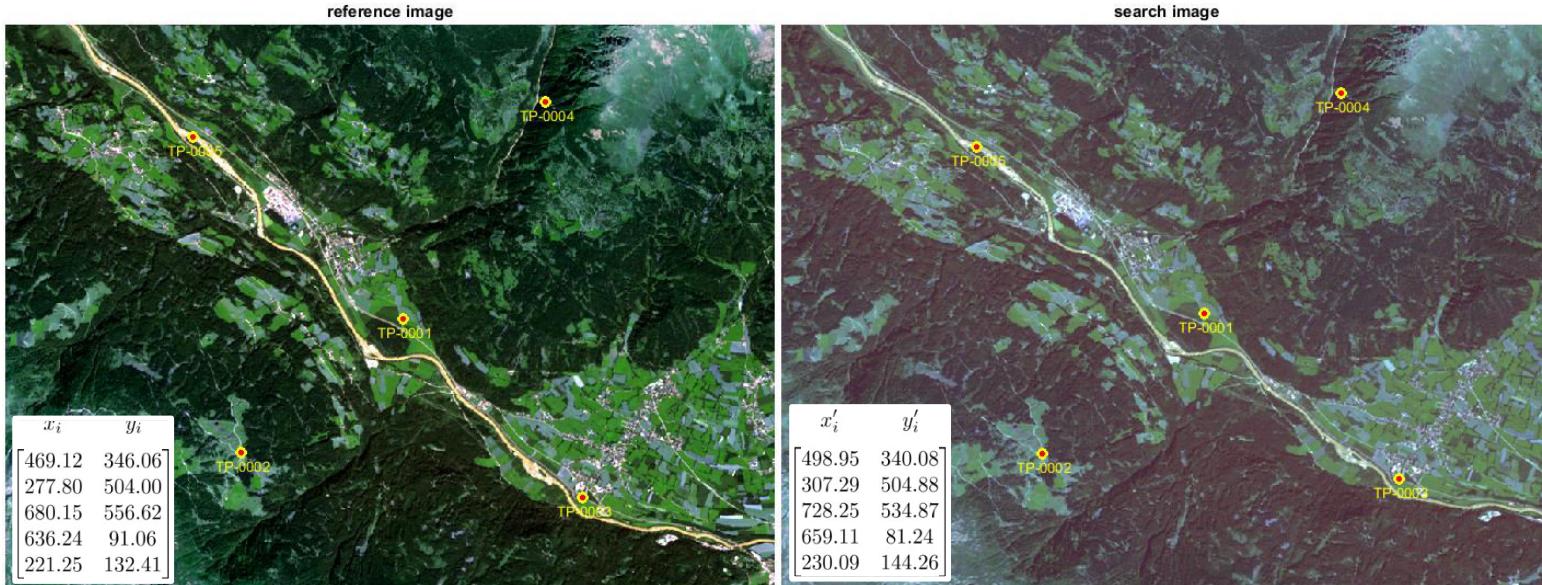
Two rows for each points
(two equations)

$$\begin{bmatrix} x & y & 0 & 0 & 1 & 0 \\ 0 & 0 & x & y & 0 & 1 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \\ d \\ e \\ f \end{bmatrix} = \begin{bmatrix} x' \\ y' \end{bmatrix}$$

$$\tilde{\mathbf{x}} = (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \mathbf{b}$$

least squares solution

Least Squares – Example



$$Ax - b = 0$$

$$A\tilde{x} - b = r$$

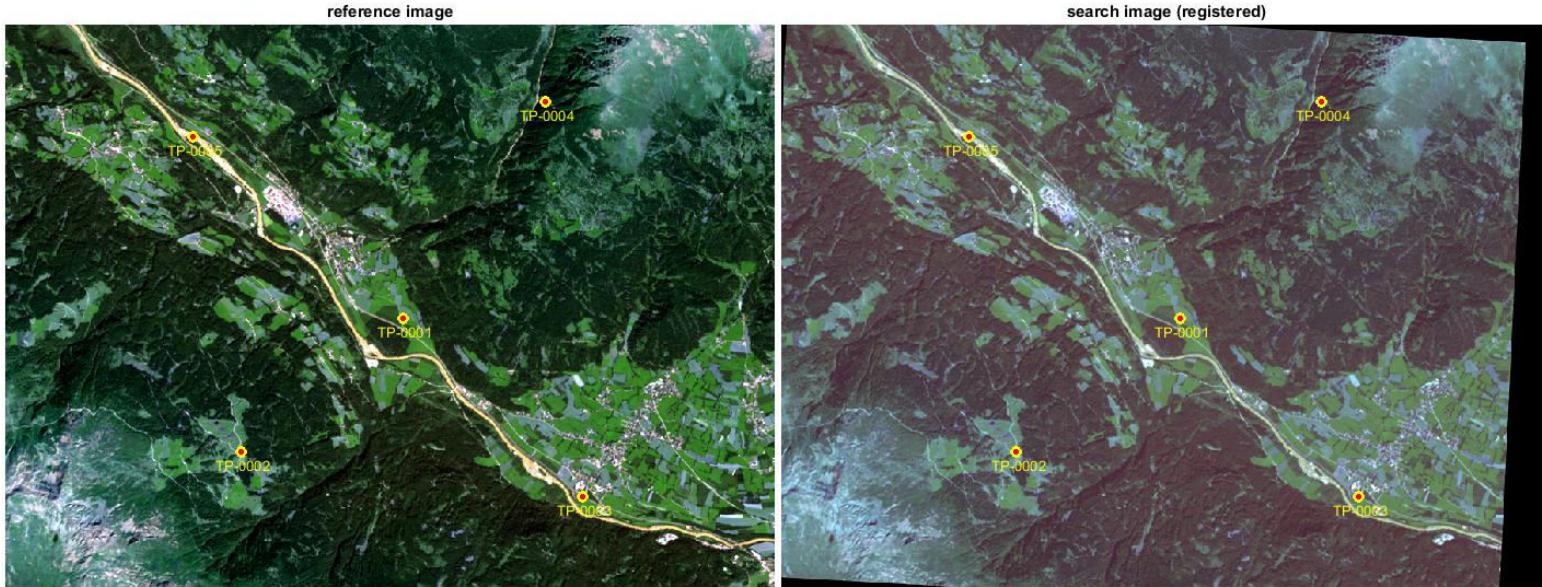
$$A = \begin{bmatrix} 469.12 & 346.06 & 0.00 & 0.00 & 1.00 & 0.00 \\ 0.00 & 0.00 & 469.12 & 346.06 & 0.00 & 1.00 \\ 277.80 & 504.00 & 0.00 & 0.00 & 1.00 & 0.00 \\ 0.00 & 0.00 & 277.80 & 504.00 & 0.00 & 1.00 \\ 680.15 & 556.62 & 0.00 & 0.00 & 1.00 & 0.00 \\ 0.00 & 0.00 & 680.15 & 556.62 & 0.00 & 1.00 \\ 636.24 & 91.06 & 0.00 & 0.00 & 1.00 & 0.00 \\ 0.00 & 0.00 & 636.24 & 91.06 & 0.00 & 1.00 \\ 221.25 & 132.41 & 0.00 & 0.00 & 1.00 & 0.00 \\ 0.00 & 0.00 & 221.25 & 132.41 & 0.00 & 1.00 \end{bmatrix}$$

$$\tilde{x} = \begin{bmatrix} 1.04 \\ 0.05 \\ -0.05 \\ 0.98 \\ -6.49 \\ 26.46 \end{bmatrix}$$

$$b = \begin{bmatrix} 498.95 \\ 340.08 \\ 307.29 \\ 504.88 \\ 728.25 \\ 534.87 \\ 659.11 \\ 81.24 \\ 230.09 \\ 144.26 \end{bmatrix} \quad r = \begin{bmatrix} -0.52 \\ -0.06 \\ 0.24 \\ 0.11 \\ 0.07 \\ -0.05 \\ 0.20 \\ 0.08 \\ 0.01 \\ -0.07 \end{bmatrix}$$

affine transformation
parameters

Least Squares – Example



Least Squares – Example



search image

Least Squares – Example



reference image

Least Squares – Example



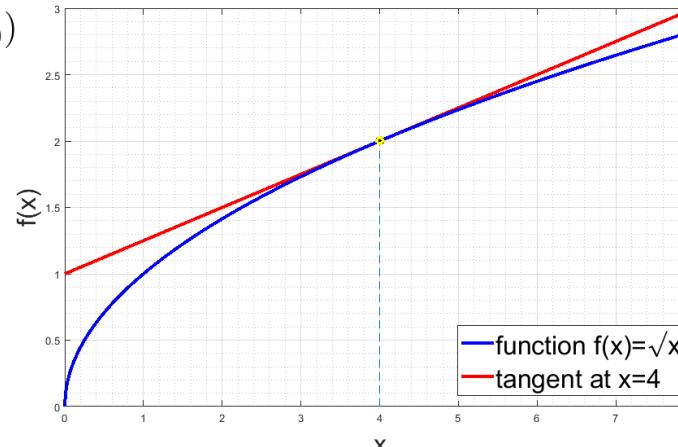
registered search image

Linearization

- ❖ Linearization of a function $f(x)$ is the linear approximation of $f(x)$ at a given point x_0
 - ❖ Taylor expansion at x_0

$$T_n(x) = \sum_{k=0}^n \frac{f^{(k)}(x_0)}{k!} (x - x_0)^k = f(x_0) + \frac{f'(x_0)}{1!}(x - x_0) + \frac{f''(x_0)}{2!}(x - x_0)^2 + \frac{f'''(x_0)}{3!}(x - x_0)^3 + \dots$$

$$f(x) \approx f(x_0) + f'(x_0)(x - x_0)$$

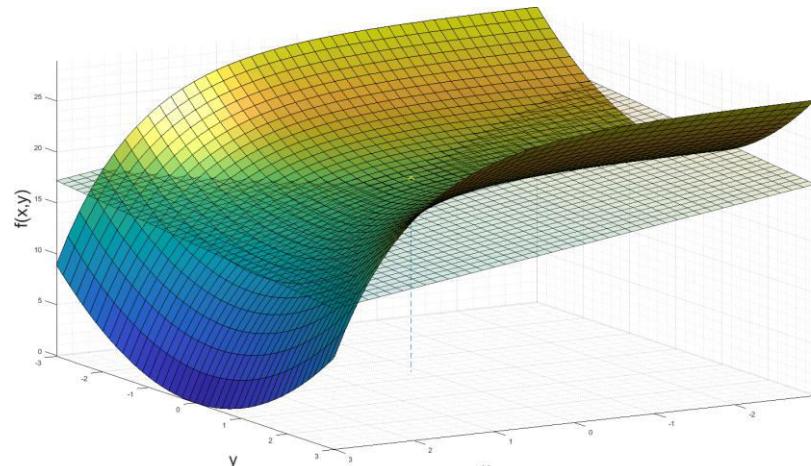


Linearization

- ❖ Linearization of a multivariable function $f(x, y) = f(\mathbf{x})$

$$f(x, y) \approx f(x_0, y_0) + \frac{\partial f(x, y)}{\partial x} \Big|_{x_0, y_0} (x - x_0) + \frac{\partial f(x, y)}{\partial y} \Big|_{x_0, y_0} (y - y_0)$$

$$f(\mathbf{x}) \approx f(\mathbf{x}_0) + \nabla f|_{\mathbf{x}_0} (\mathbf{x} - \mathbf{x}_0) \quad \text{with} \quad \nabla \dots \text{nabla operator} \quad \nabla = \left(\frac{\partial}{\partial x_1}, \dots, \frac{\partial}{\partial x_n} \right)$$



$$f(x, y) = 20 - e^x + y^2$$

Linearization – Example

- ❖ Approximation near $x = x_0$

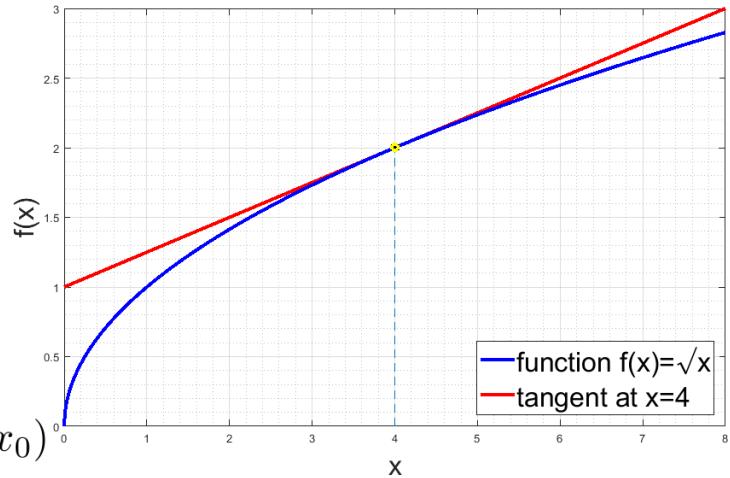
$$f(x) = \sqrt{x} \quad \text{and} \quad \sqrt{4} = 2 \\ \sqrt{4.001} = ?$$

linearization of $f(x)$ at $x = x_0$ yields

$$y(x) = f(x_0) + f'(x_0)(x - x_0) = \sqrt{x_0} + \frac{1}{2\sqrt{x_0}}(x - x_0)$$

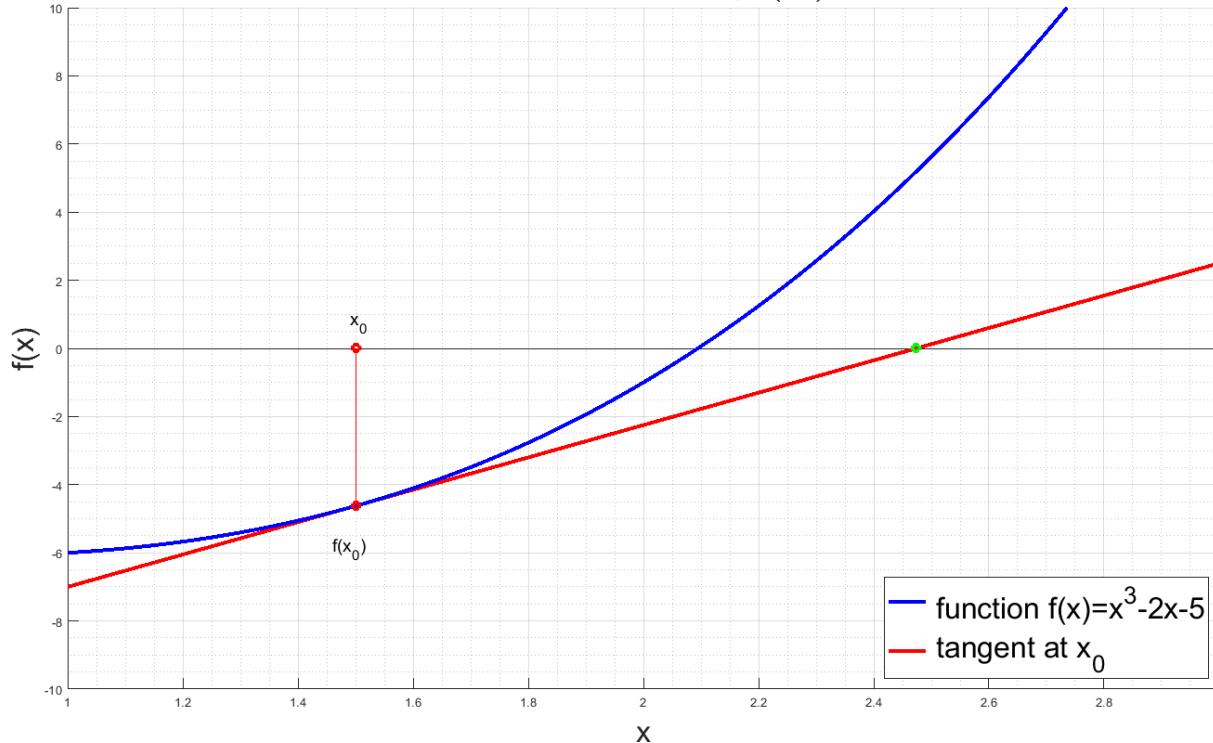
$$x_0 = 4 \quad \text{and} \quad y(x) = 2 + \frac{x - 4}{4} \quad \text{and} \quad y(4.001) = 2.00025$$

is very close to the real value $\sqrt{4.001} \approx 2.000249984$



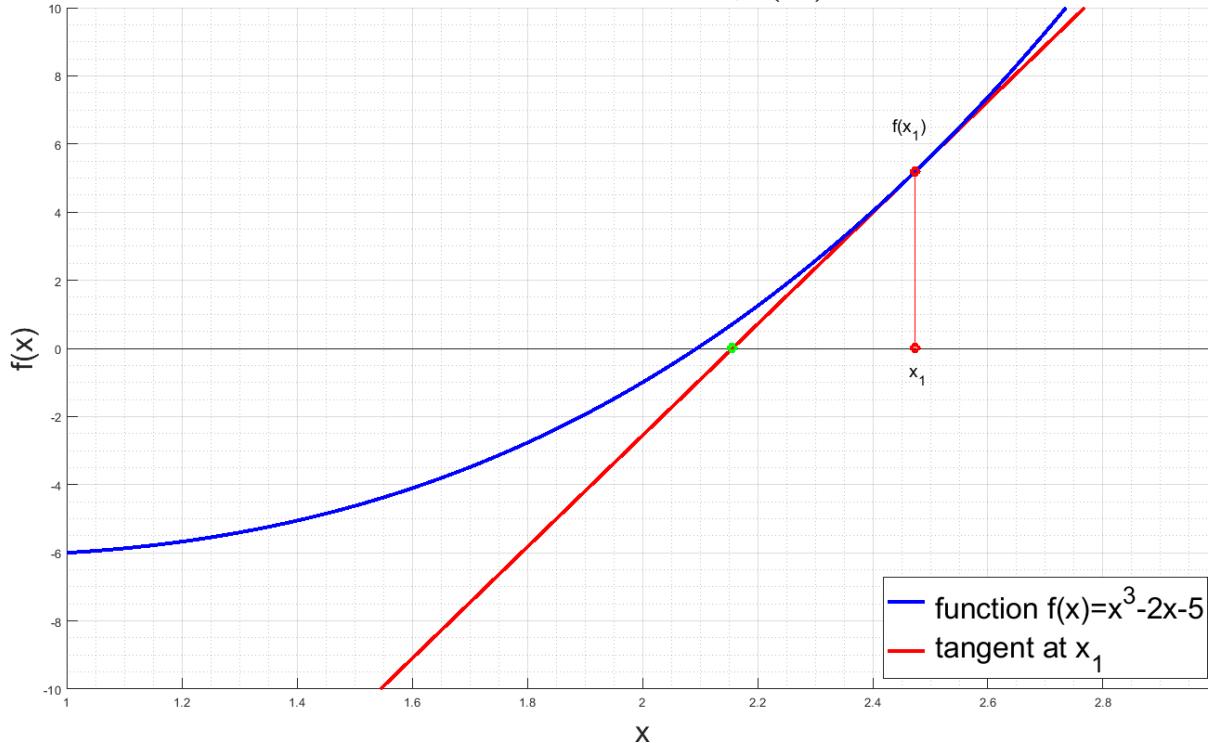
Newton's Method (from 1669)

find a solution for $f(x) = 0$



Newton's Method (from 1669)

find a solution for $f(x) = 0$

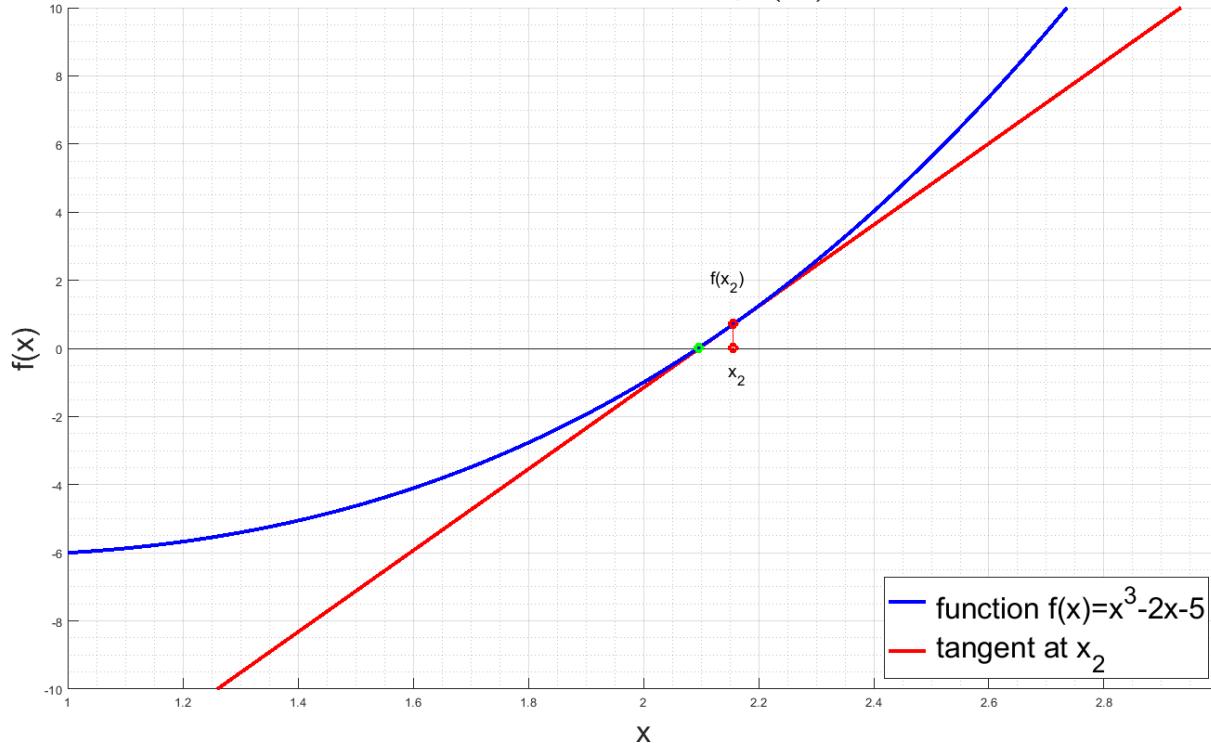


$$x_0 = 1.500000$$

$$x_1 = 2.473684$$

Newton's Method (from 1669)

find a solution for $f(x) = 0$



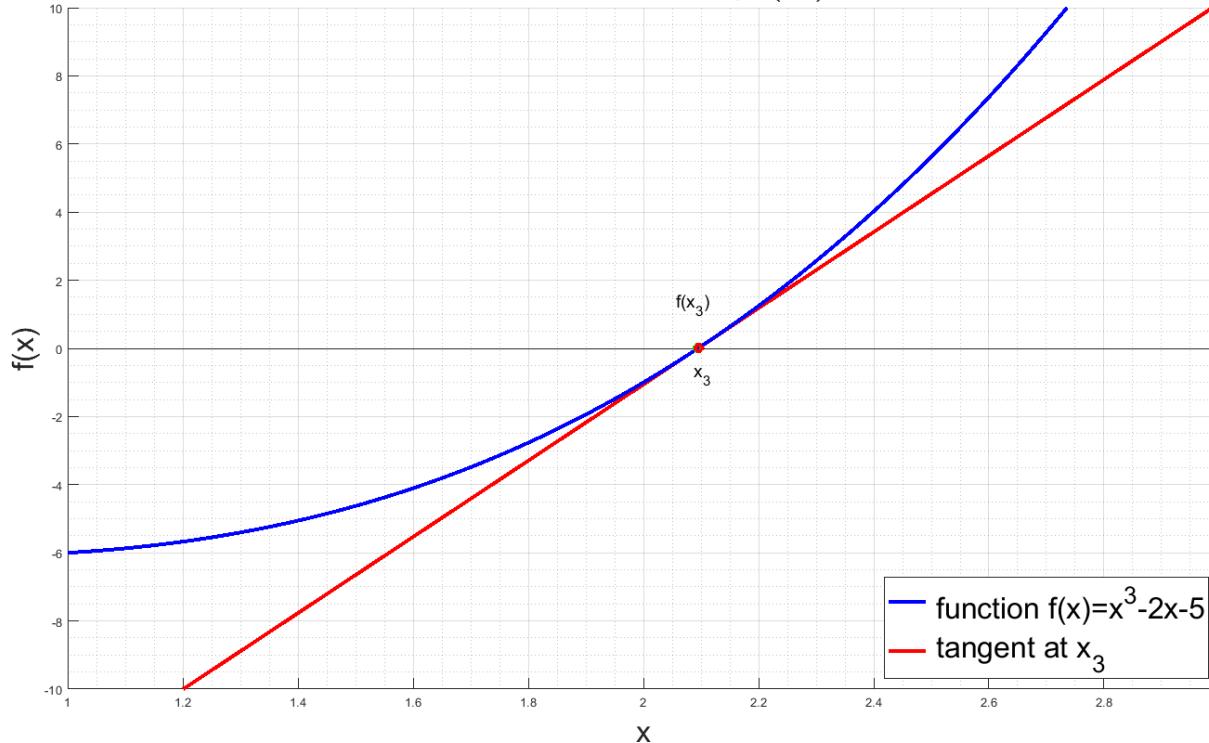
$$x_0 = 1.500000$$

$$x_1 = 2.473684$$

$$x_2 = 2.156433$$

Newton's Method (from 1669)

find a solution for $f(x) = 0$



$$x_0 = 1.500000$$

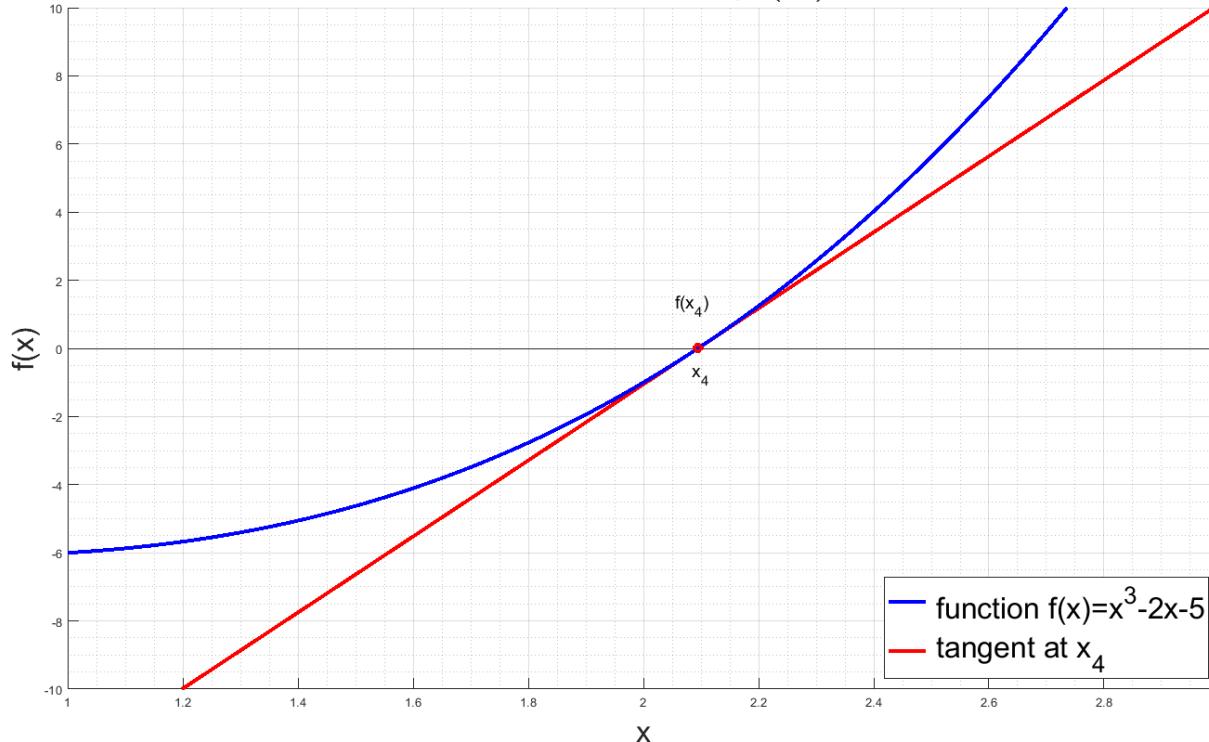
$$x_1 = 2.473684$$

$$x_2 = 2.156433$$

$$x_3 = 2.096605$$

Newton's Method (from 1669)

find a solution for $f(x) = 0$



$$x_0 = 1.500000$$

$$x_1 = 2.473684$$

$$x_2 = 2.156433$$

$$x_3 = 2.096605$$

$$x_4 = 2.094554$$

$$x \approx 2.094551$$

Newton's Method

❖ Linearization and Least Squares Adjustment

❖ Allows to solve non-linear equation systems

$F(\boldsymbol{x}) = \mathbf{0}$... non linear multivariable equation system

\boldsymbol{x}_0 ... starting point

Jacobian matrix

$$\mathbf{J}_F(\boldsymbol{a}) := \frac{\partial F}{\partial \boldsymbol{x}}(\boldsymbol{a}) = \left(\frac{\partial F_i}{\partial x_j}(\boldsymbol{a}) \right)_{i,j} =$$

$$\begin{bmatrix} \frac{\partial F_1}{\partial x_1}(\boldsymbol{a}) & \frac{\partial F_1}{\partial x_2}(\boldsymbol{a}) & \cdots & \frac{\partial F_1}{\partial x_n}(\boldsymbol{a}) \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial F_m}{\partial x_1}(\boldsymbol{a}) & \frac{\partial F_m}{\partial x_2}(\boldsymbol{a}) & \cdots & \frac{\partial F_m}{\partial x_n}(\boldsymbol{a}) \end{bmatrix}$$

❖ Linearization

$$F(\boldsymbol{x} + \Delta \boldsymbol{x}) \approx F(\boldsymbol{x}) + \mathbf{J}_F(\boldsymbol{x}) \Delta \boldsymbol{x}$$

❖ Iterate

$$\mathbf{J}_F(\boldsymbol{x}_n) \Delta \boldsymbol{x}_n + F(\boldsymbol{x}_n) = \mathbf{0} \rightarrow \text{least squares solution for } \Delta \boldsymbol{x}_n$$

$$\boldsymbol{x}_{n+1} = \boldsymbol{x}_n + \Delta \boldsymbol{x}_n$$

Newton's Method – Algorithm

Algorithm 4.1: Solving non-linear equation systems with Newton's method.

Input:

```

1      non-linear equation system of form  $F(\mathbf{x}) = \mathbf{0}$ 
2      and its Jacobian matrix  $J_F$ 
3      starting vector  $\mathbf{x}_0$ 
4      maximal iterations           // E.g., set to 20.
5      tolerance                   // E.g., set to  $1e-7$ .

```

Output:

```

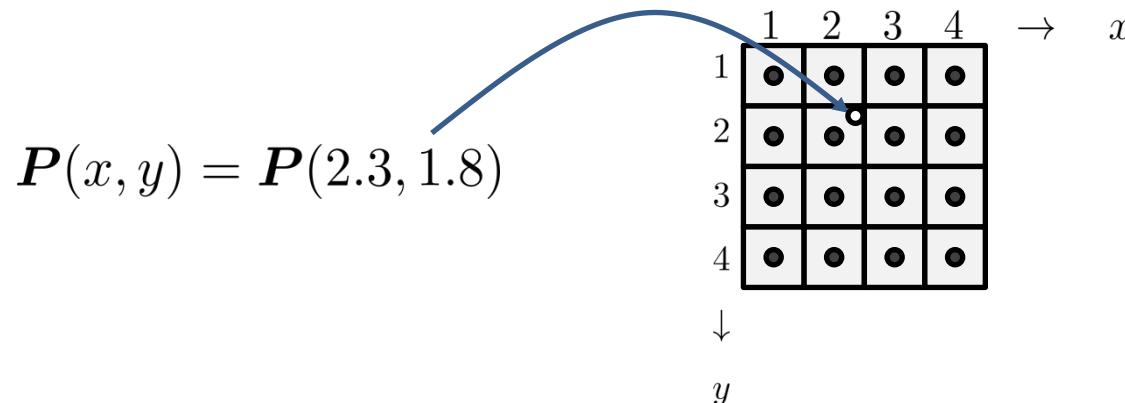
6      solution vector  $\mathbf{x}_{n+1}$ 
```

```

7 Function NewtonsMethod( $F, J_F, \mathbf{x}_0, \text{iterations}, \text{tolerance}$ ):
8   for  $n = 0 : \text{iterations}$  do
9      $J_F(\mathbf{x}_n)\Delta\mathbf{x}_n + F(\mathbf{x}_n) = \mathbf{0}$     // Solve for  $\Delta\mathbf{x}_n$  via least squares.
10     $\mathbf{x}_{n+1} = \mathbf{x}_n + \Delta\mathbf{x}_n$                   // Get next approximation.
11    if ( $|\Delta\mathbf{x}_n| \leq \text{tolerance} \cdot |\mathbf{x}_n|$ ) then
12      break                                     // Solution found within given tolerance.
13    end
14  end
15  return  $\mathbf{x}_{n+1}$                                 // Return solution vector.
```

Interpolation of Pixel Values

- ❖ Get the pixel value at a subpixel location
 - ❖ Get value from given image at location with subpixel coordinate
 - ❖ Pixel  with center •

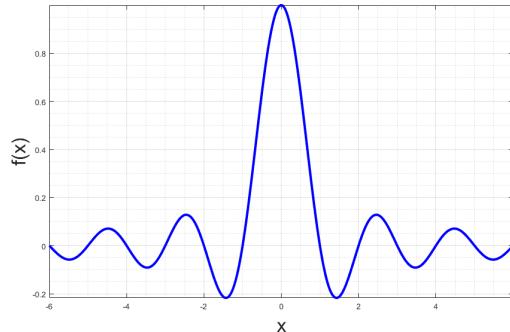


- ❖ Also called resampling

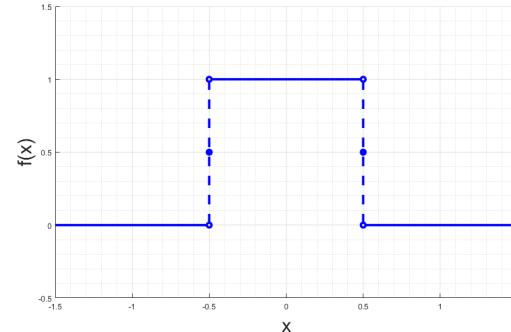
Interpolation of Pixel Values

❖ Interpolation of different order

- ❖ Use neighboring pixel values to interpolate the new value
- ❖ Nearest, Linear, Cubic, Quintic, Windowed Sinc
- ❖ The sinc function is the Fourier transform of the rectangular function



$$\text{sinc}(x) = \frac{\sin(\pi x)}{\pi x}$$



$$\text{rect}(x) = \begin{cases} 0 & \text{if } |x| > \frac{1}{2} \\ \frac{1}{2} & \text{if } |x| = \frac{1}{2} \\ 1 & \text{if } |x| < \frac{1}{2} \end{cases}$$

Interpolation of Pixel Values – Example



input



nearest



linear



reduced by
factor 4



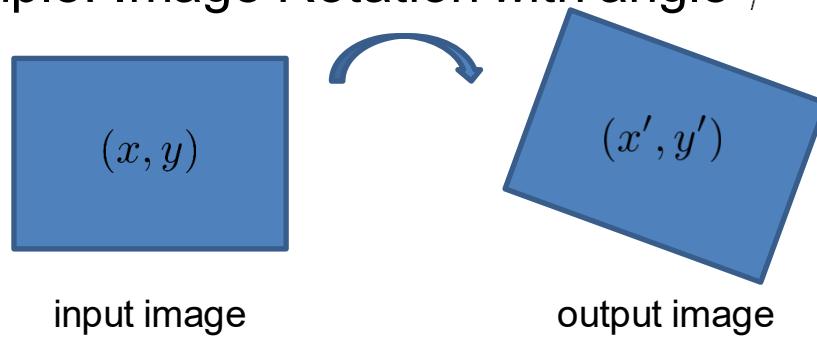
cubic



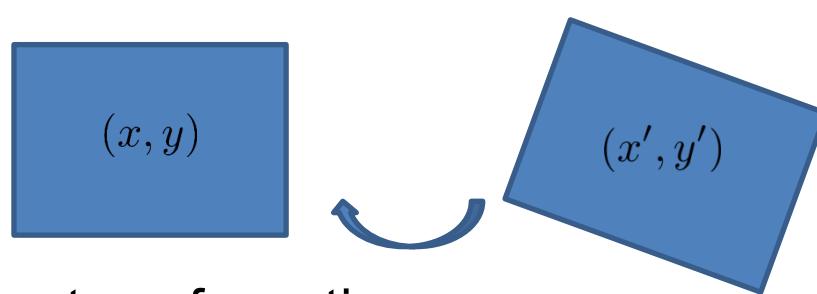
sinc 16

Interpolation of Pixel Values

- ❖ Example: Image Rotation with angle ϕ



$$\mathbf{x}' = \mathbf{R}(\phi)\mathbf{x}$$

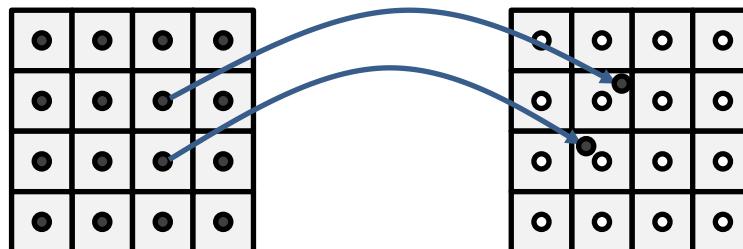


$$\mathbf{x} = \mathbf{R}^{-1}(\phi)\mathbf{x}'$$

- ❖ Inverse transformation

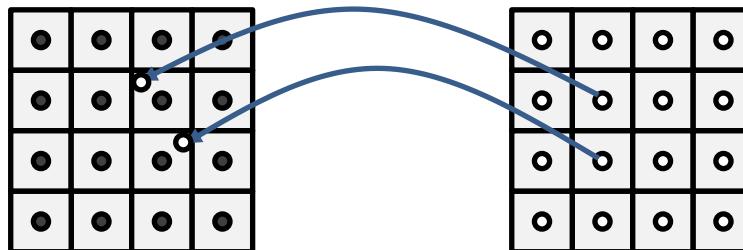
Interpolation of Pixel Values

- ❖ Example: Image Rotation with angle ϕ



input image

output image



$$\mathbf{x}' = \mathbf{R}(\phi)\mathbf{x}$$

direct mapping

$$\mathbf{x} = \mathbf{R}^{-1}(\phi)\mathbf{x}'$$

indirect mapping

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