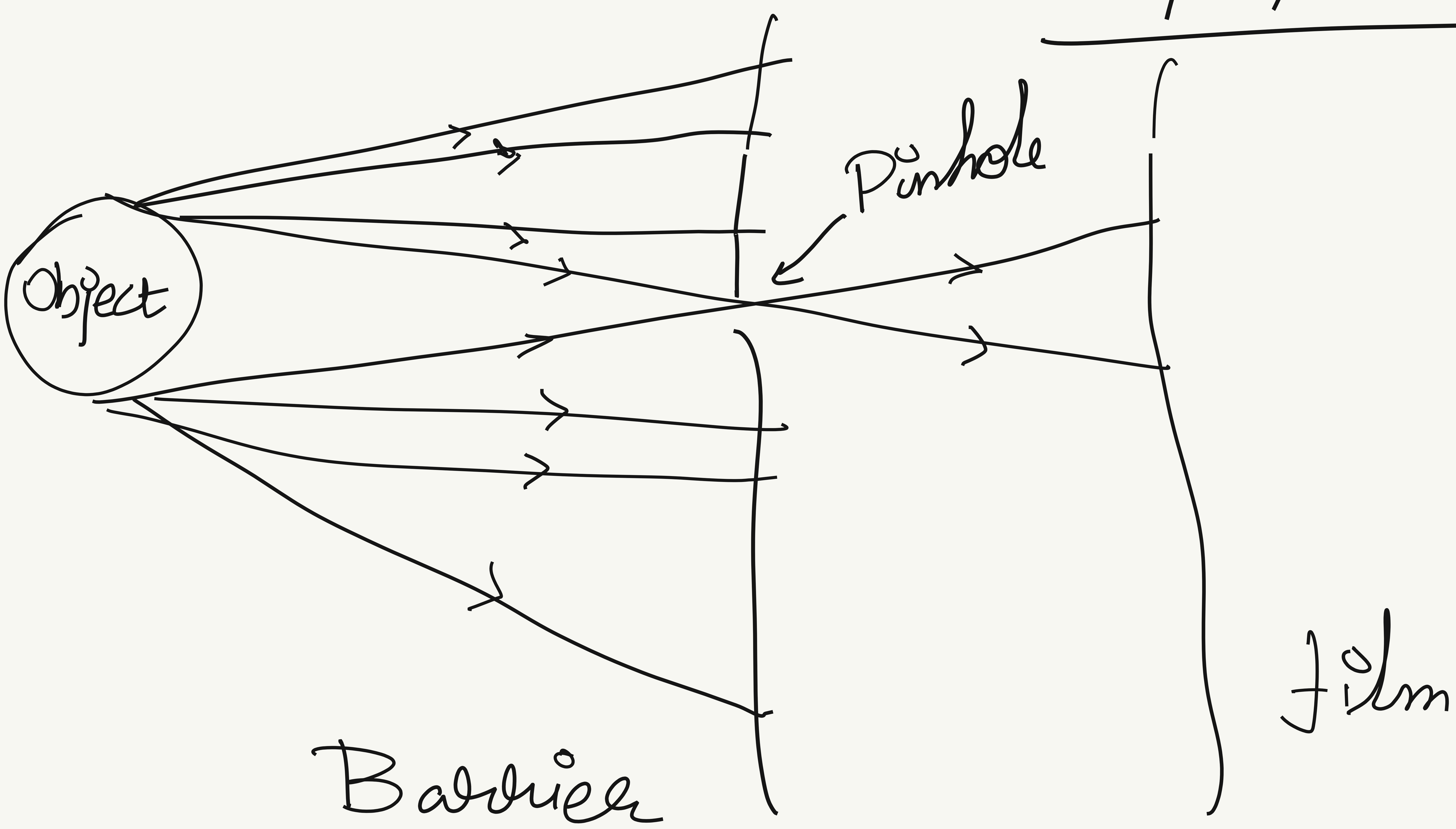
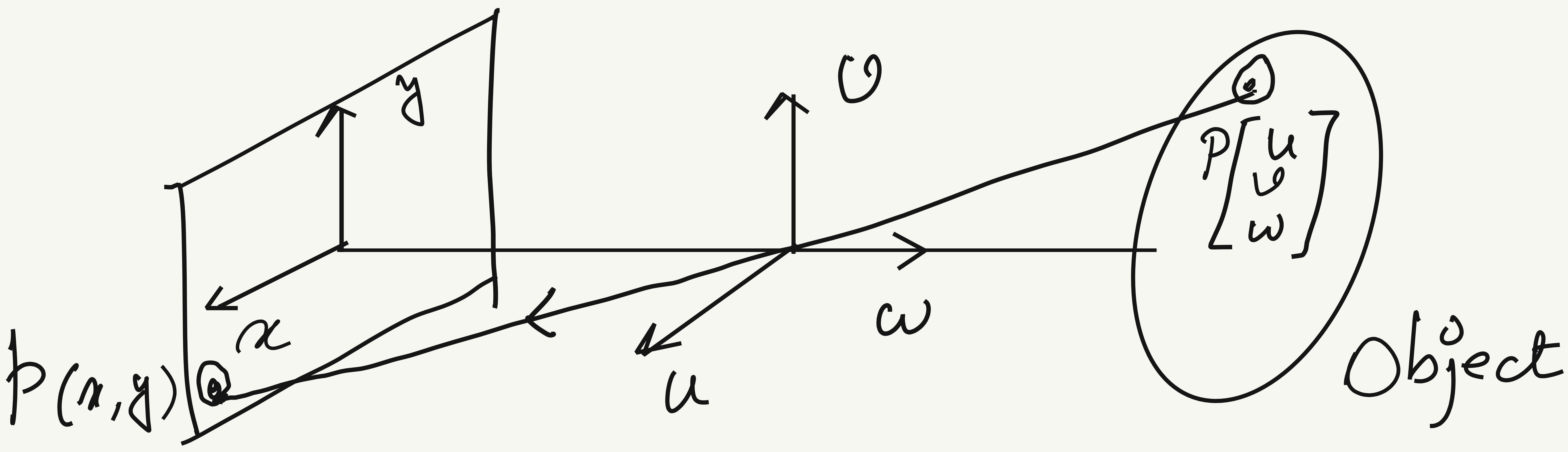
13/02/2023

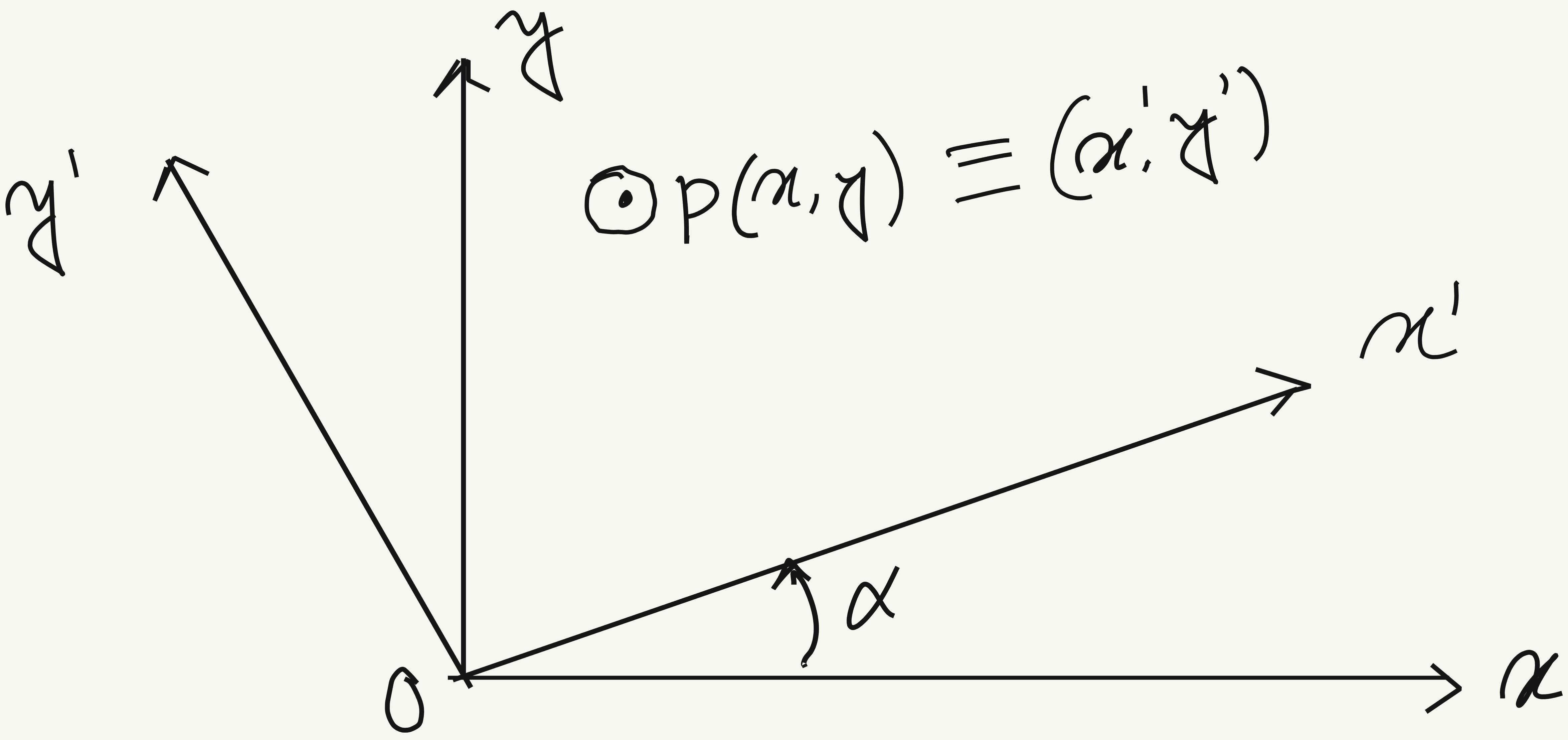


Pinhole → Optical center



From 3D to 2D.

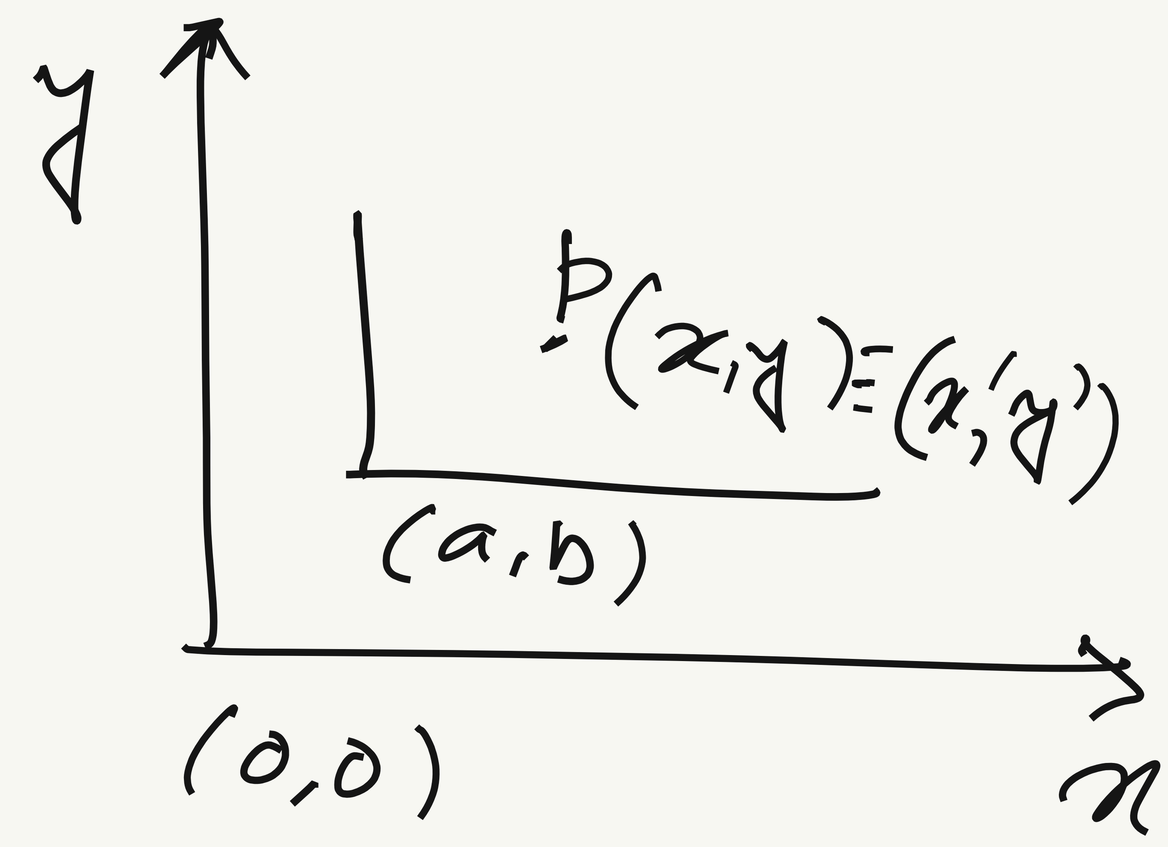
$$x = -f \cdot \frac{u}{w} \quad , \quad y = -f \cdot \frac{v}{w}$$



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

For Scale Changing,

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} S_x & 0 \\ 0 & S_y \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix}$$



For origin changing,

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} x \\ y \end{pmatrix} + \begin{pmatrix} -a \\ -b \end{pmatrix}$$ (Not-linear)

<u>Cartesian Co-ordinate</u>		<u>Homogeneous Co-ordinate</u>
(x, y, z)	$\longrightarrow$	(kx, ky, kz, k)
$\left(\frac{a}{d}, \frac{b}{d}, \frac{c}{d}\right)$	$\longleftarrow$	(a, b, c, d)

In this case,

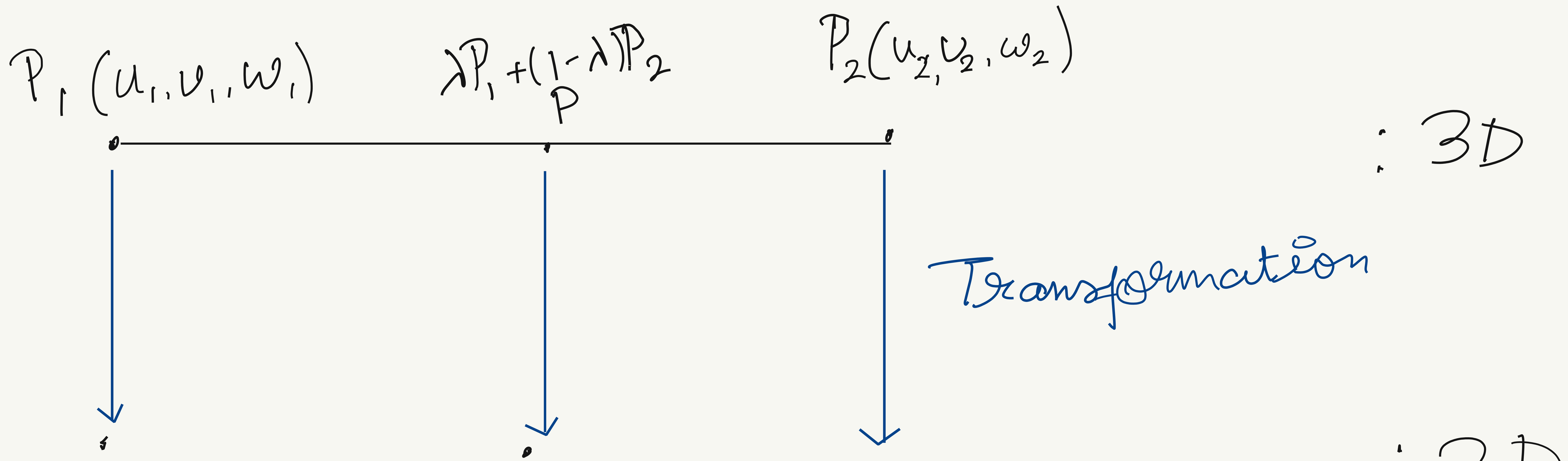
$$\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} x \\ y \end{pmatrix} + \begin{pmatrix} t_x \\ t_y \end{pmatrix}$$ (Translation) (Origin changing)

$$\begin{pmatrix} x' \\ y' \\ 1 \end{pmatrix} = \begin{pmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix}$$

Homogeneous co-ordinate when $K=1$ and we take 2D.

$$\begin{pmatrix} u \\ v \\ w/f \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1/f & 0 \end{pmatrix} \begin{pmatrix} u \\ v \\ w \\ 1 \end{pmatrix}$$

Image Co-ordinate in Homo. Co-ordinate system



$$p_1\left(f\cdot\frac{u_1}{w_1},\ f\cdot\frac{v_1}{w_1}\right) \qquad p \qquad p_2\left(f\cdot\frac{u_2}{w_2},\ f\cdot\frac{v_2}{w_2}\right)$$

Note that

$$p = \left(f\cdot\frac{\lambda u_1 + (1-\lambda)u_2}{\lambda w_1 + (1-\lambda)w_2},\ f\,\frac{\lambda v_1 + (1-\lambda)v_2}{\lambda w_1 + (1-\lambda)w_2}\right)$$

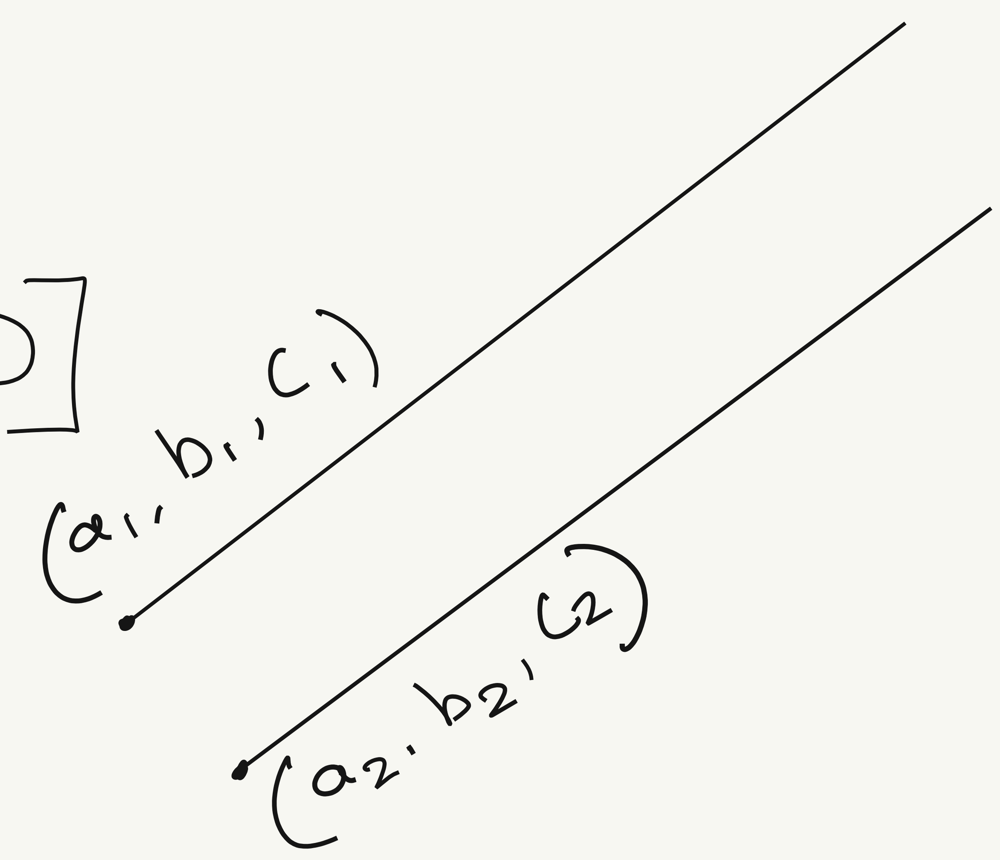
$$\begin{aligned}
x &= f\,\frac{\lambda u_1 + (1-\lambda)u_2}{\lambda w_1 + (1-\lambda)w_2} \\
&= f\cdot\frac{\lambda u_1}{\lambda w_1 + (1-\lambda)w_2} + f\cdot\frac{(1-\lambda)u_2}{\lambda w_1 + (1-\lambda)w_2} \\
&= \frac{\lambda w_1}{\lambda w_1 + (1-\lambda)w_2}\times f\cdot\frac{u_1}{w_1} + \frac{(1-\lambda)w_2}{\lambda w_1 + (1-\lambda)w_2}\times f\,\frac{u_2}{w_2} \\
&= \frac{\lambda w_1}{\lambda w_1 + (1-\lambda)w_2}\times f\,\frac{u_1}{w_1} + \left[1 - \frac{\lambda w_1}{\lambda w_1 + (1-\lambda)w_2}\right]\times f\,\frac{u_2}{w_2}
\end{aligned}$$

ie $x = \alpha\cdot f\frac{u_1}{w_1} + (1-\alpha)\cdot f\,\frac{u_2}{w_2}$, $\alpha = \frac{\lambda w_1}{\lambda w_1 + (1-\lambda)w_2}$

Similarly,

$$x = \alpha x_1 + (1-\alpha)x_2$$
$$y = \alpha y_1 + (1-\alpha)y_2$$

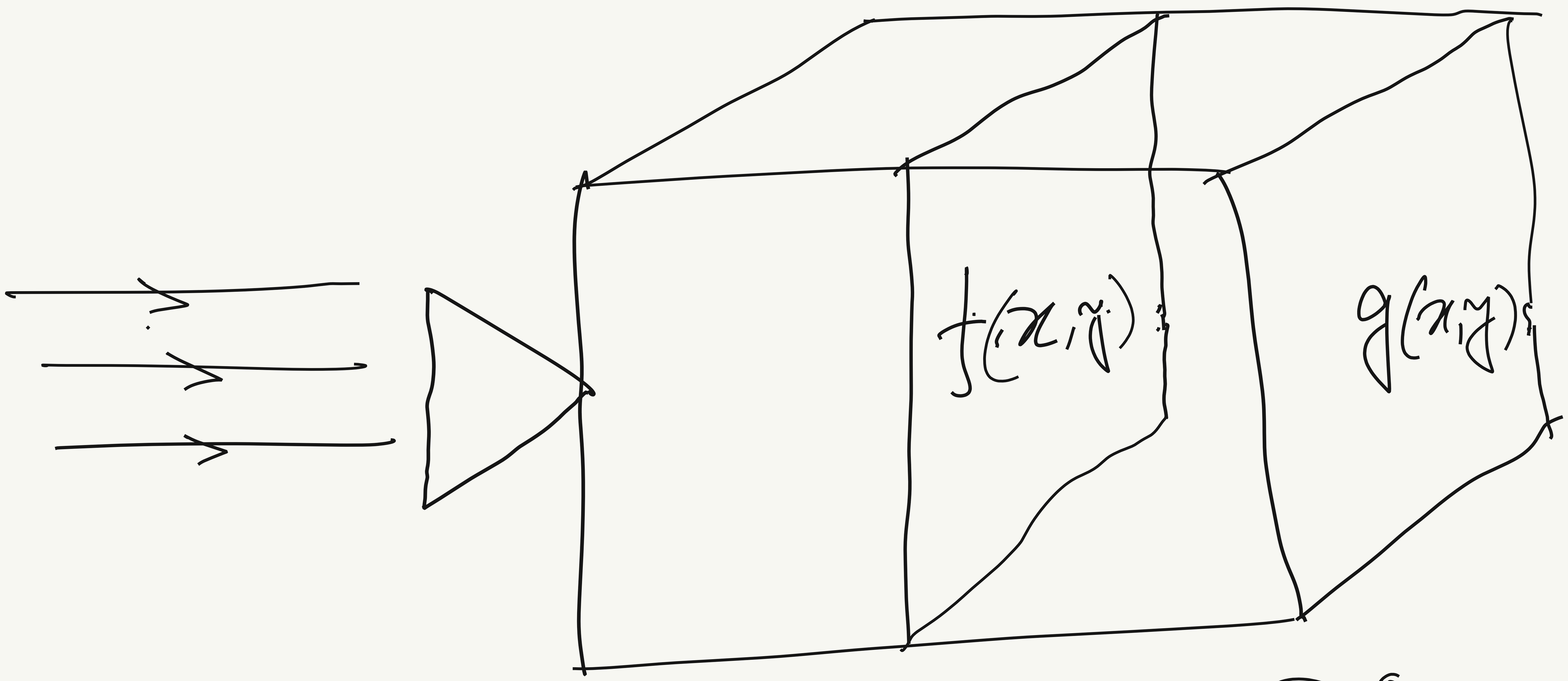
$$\begin{pmatrix}u\\v\\w\end{pmatrix} = \begin{pmatrix}a_i\\b_i\\c_i\end{pmatrix} + \lambda\begin{pmatrix}l\\m\\n\end{pmatrix}$$ [Eq of the St line in 3D]



f

$$x = \lim_{\lambda\to 0} f\,\frac{a_i + \lambda l}{c_i + \lambda n} = f\cdot\frac{l}{n}$$

$$y = \lim_{\lambda\to 0} f\cdot\frac{b_i + \lambda m}{c_i + \lambda n} = f\,\frac{m}{n}$$



Ideal Colour or Intensity Distribution $f(x,y)$

Recorded Image $g(x,y)$

The plane of $f(x,y)$ is totally hypothetical ie that may not be present in real life.

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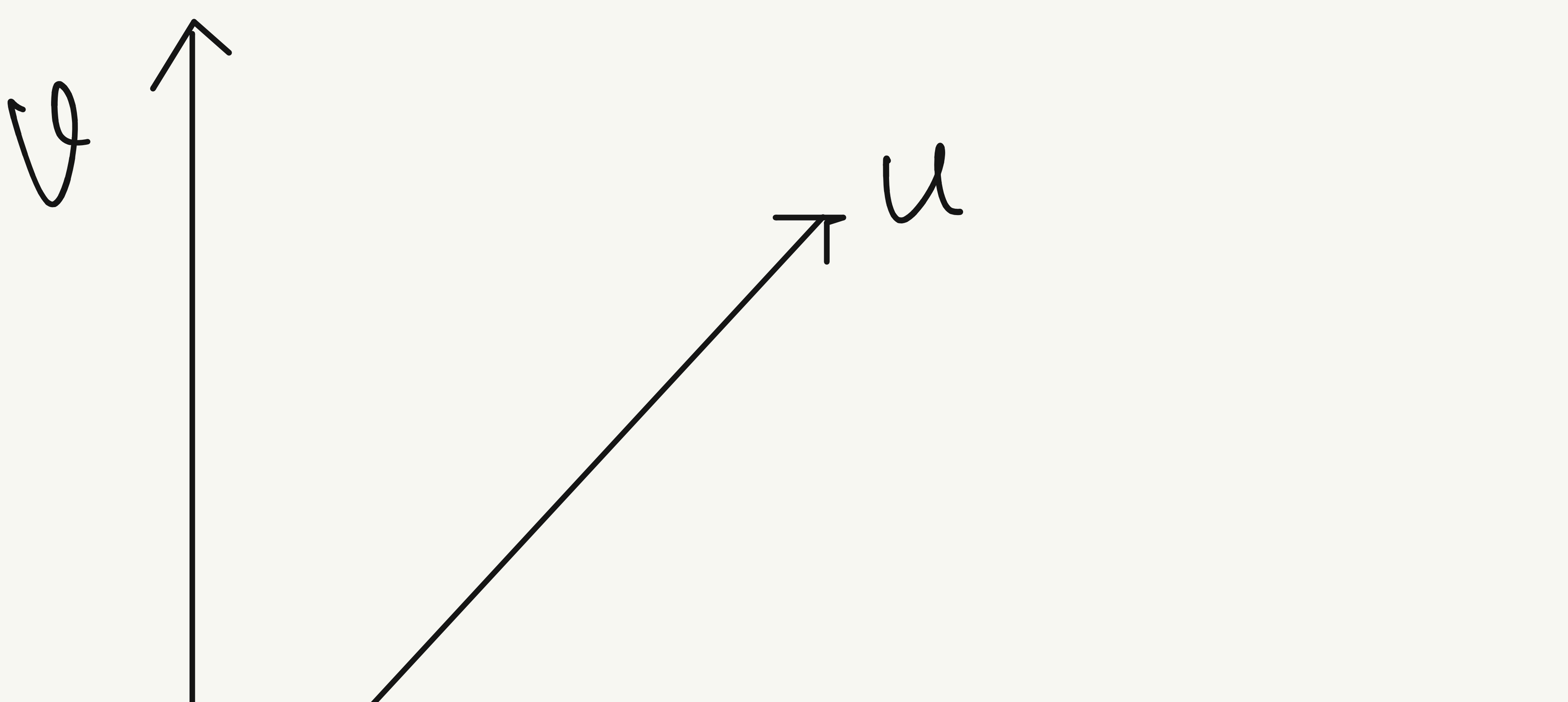
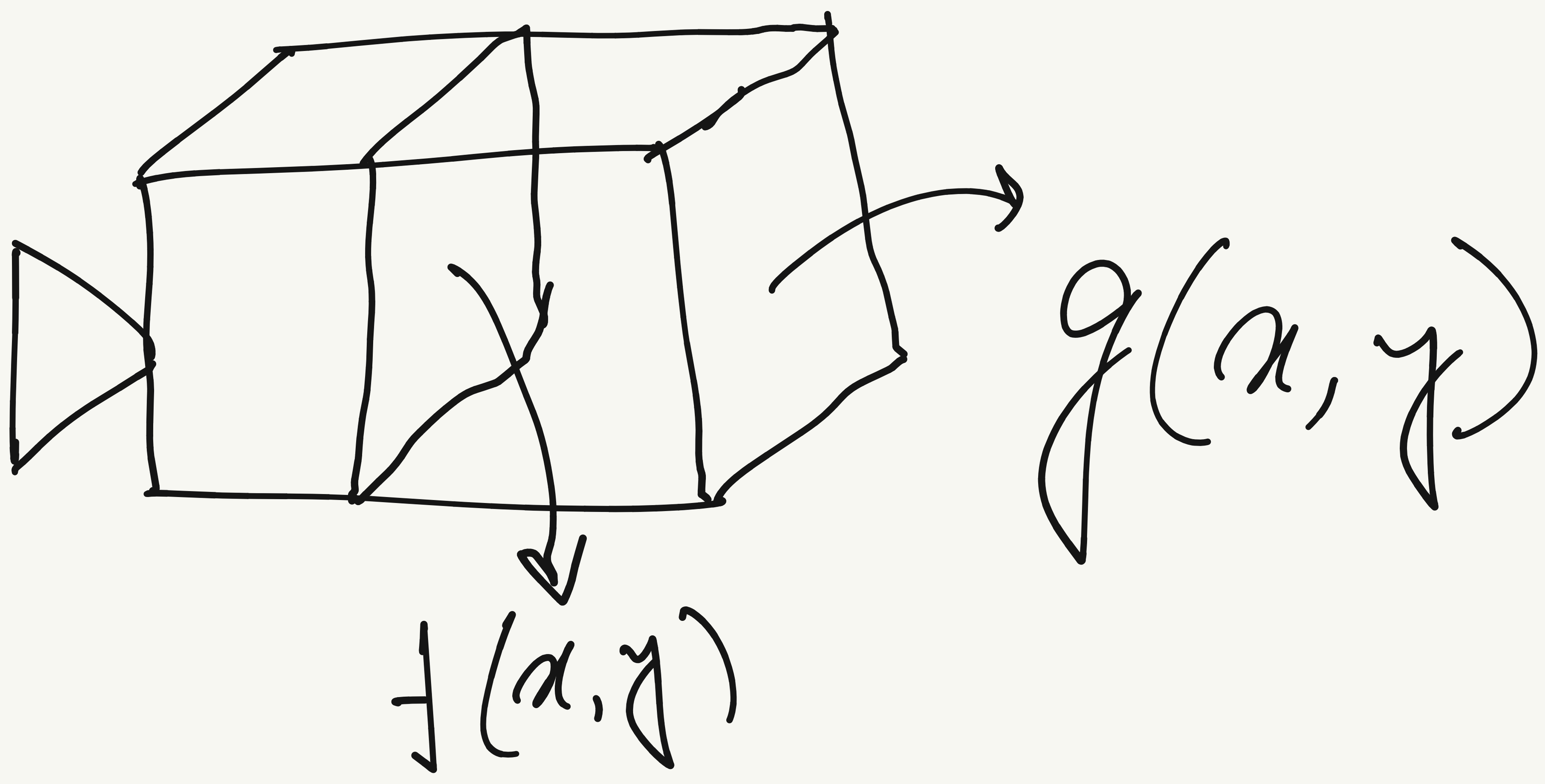
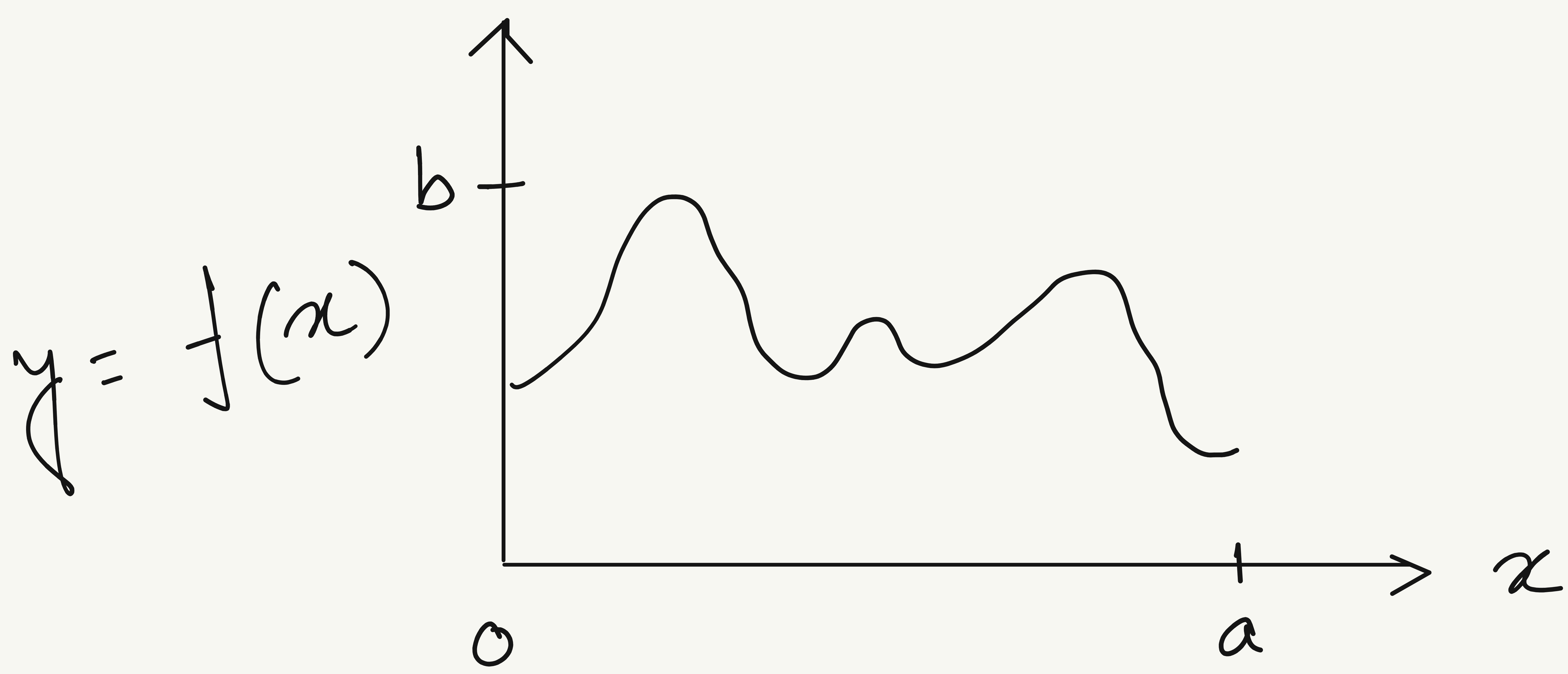


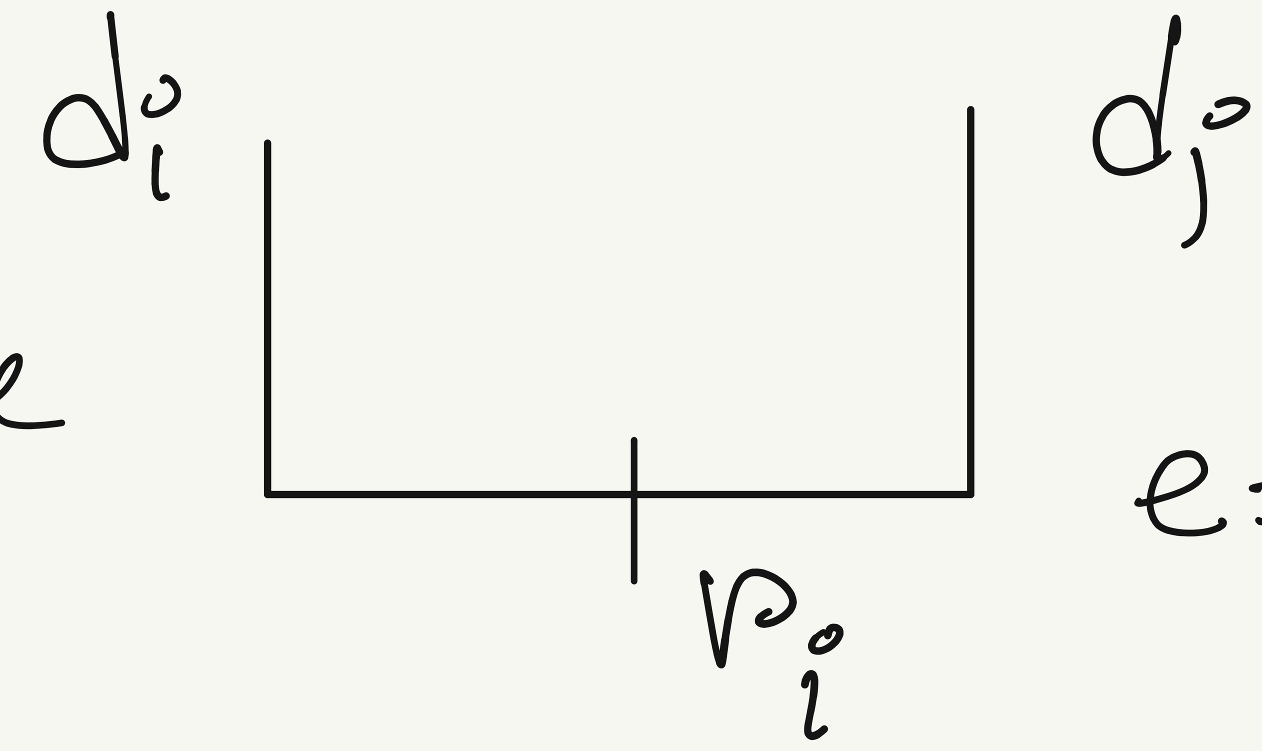




We divide the whole picture in many small blocks, called pixel.

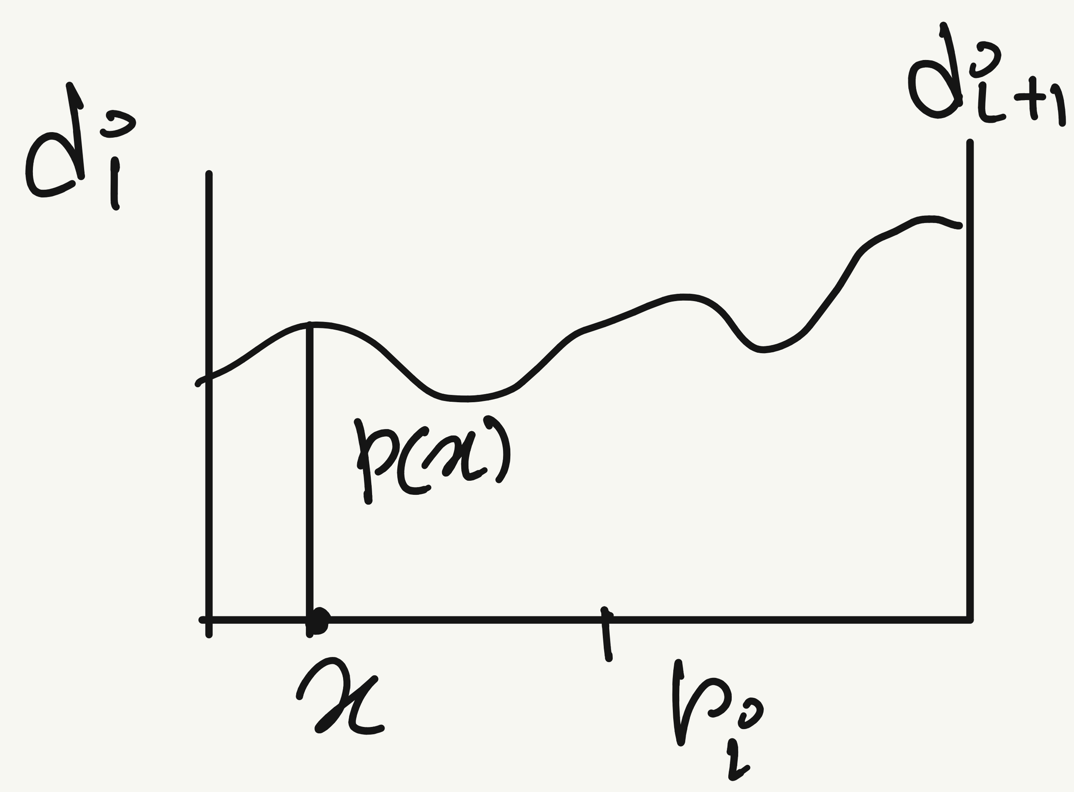
There is any possible value between lowest (black) to highest (white).

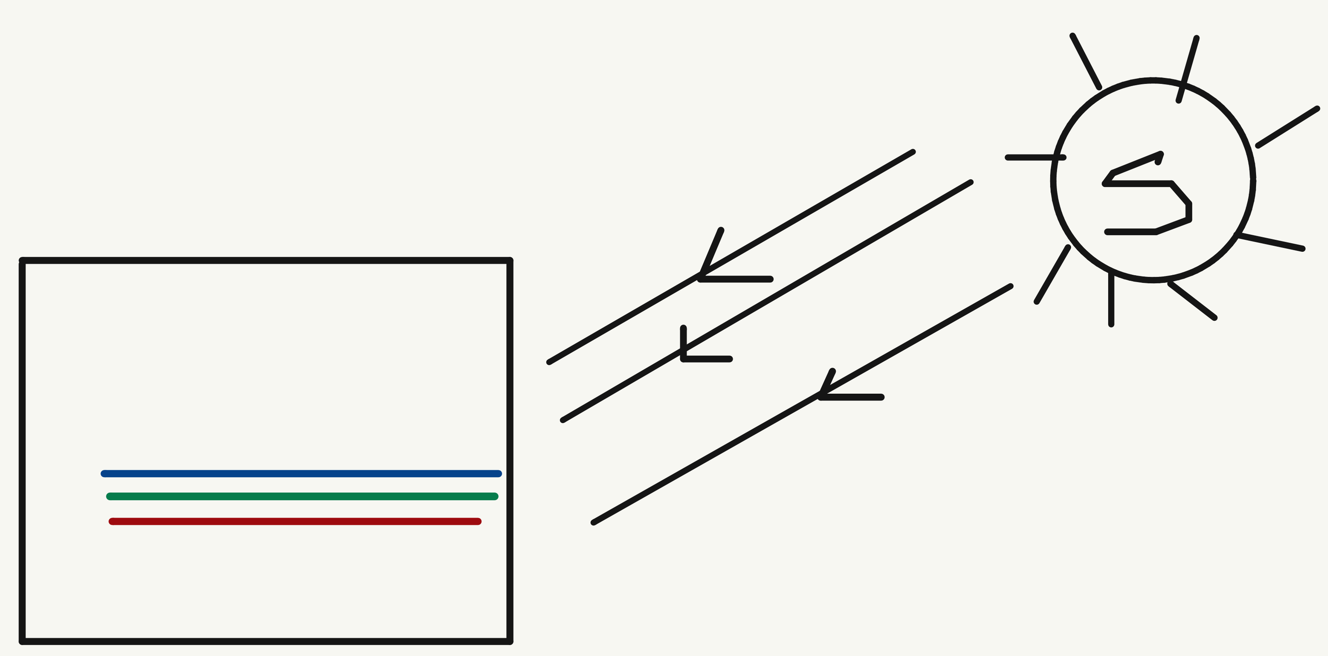
After getting the pixel value



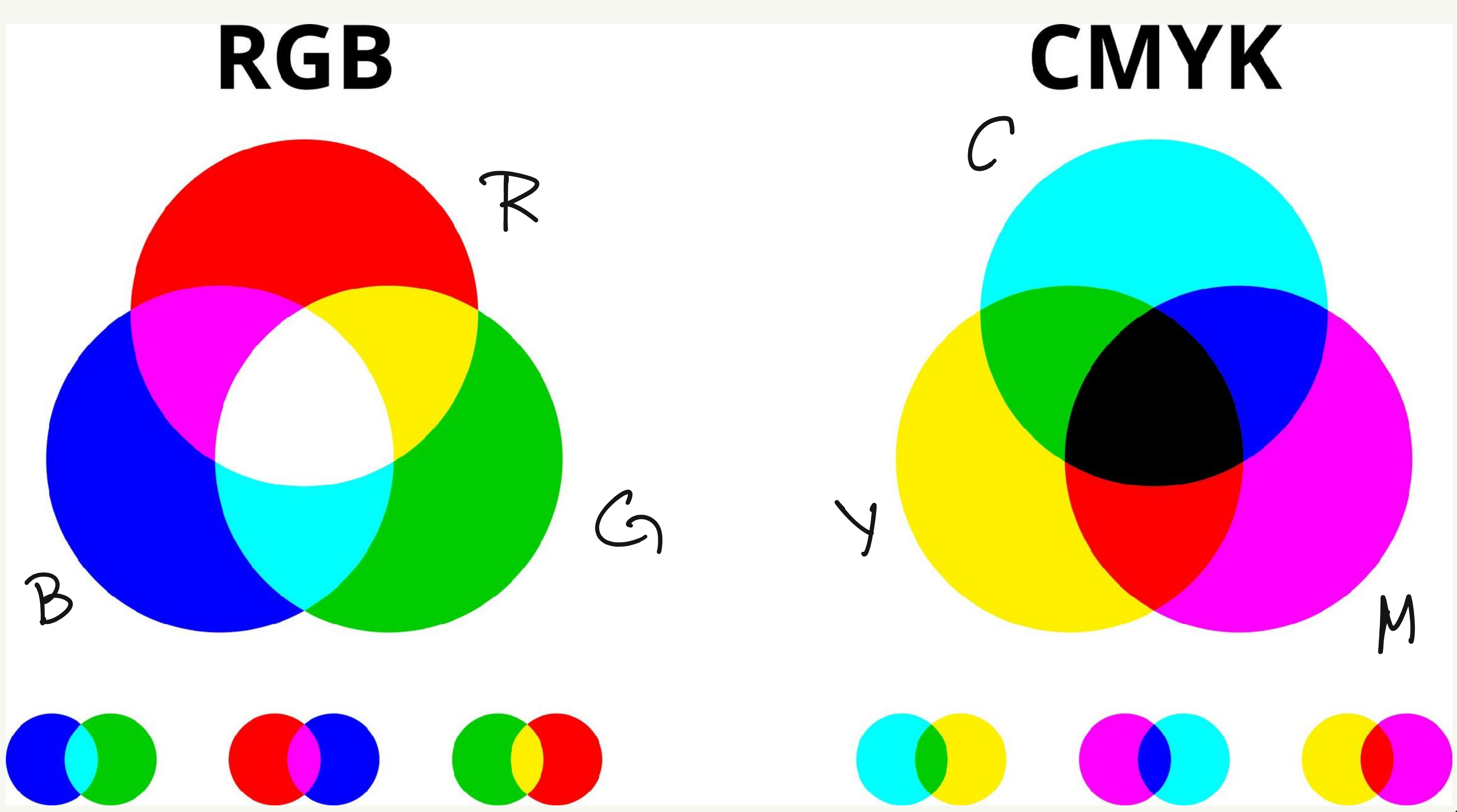
$e = |r_i - d_i|$

$$\text{Error} = \sum_i \int_{d_i}^{d_{i+1}} (r_i - x)^2 \, p(x) \, dx$$



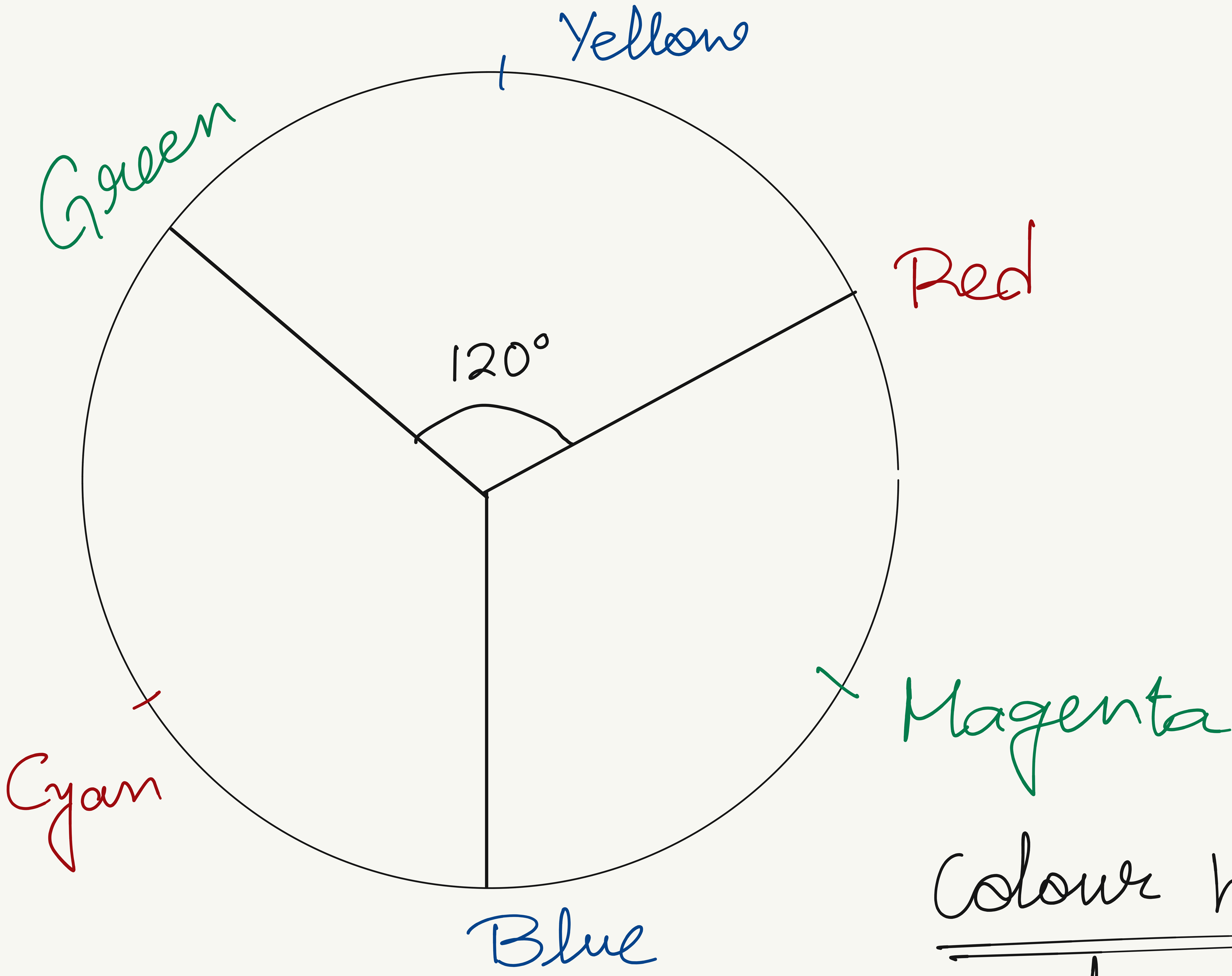


Everything just absorbed.



Normal Colours

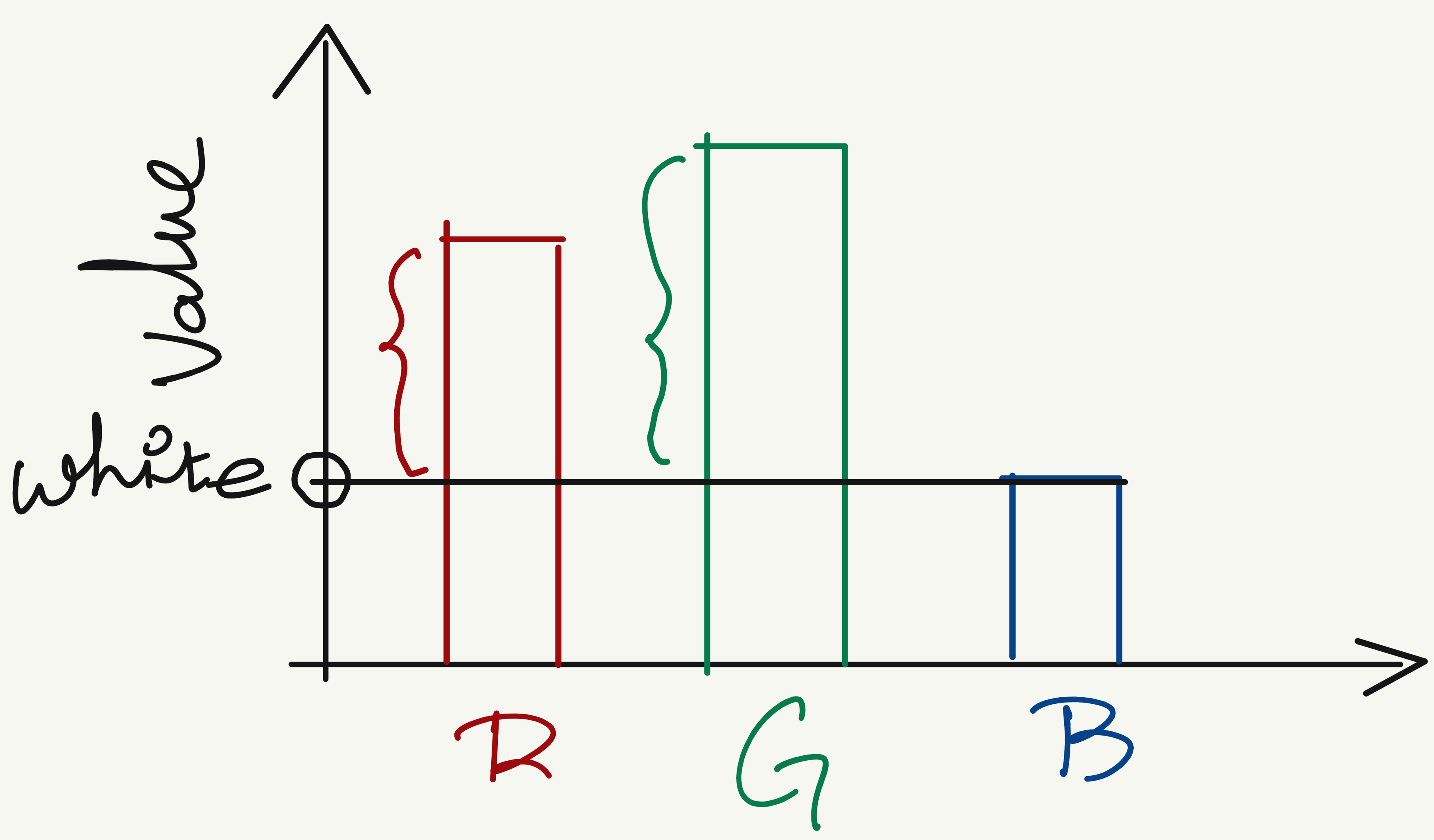
Complimentory Colours



Colour Wheel

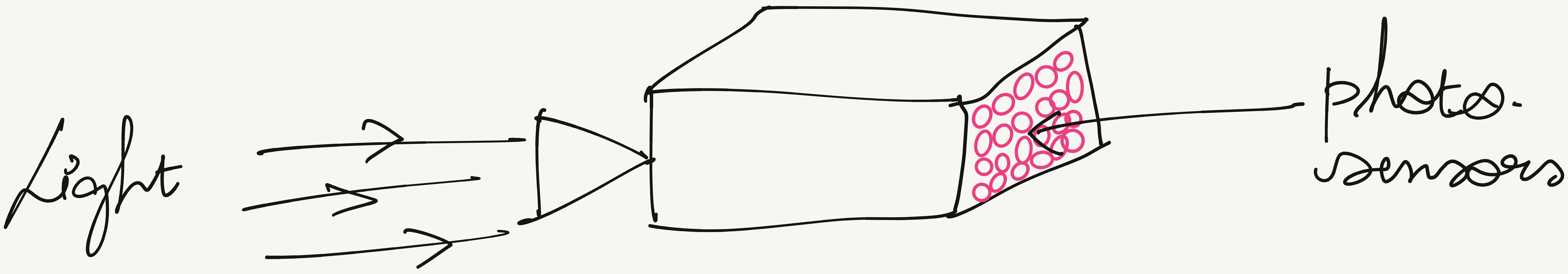
On the perijery all the colours are pure. At near the center (near white) colours are just mixtures of othere colours

$$g(x,y) = \begin{bmatrix} r \\ g \\ b \end{bmatrix}$$



$$\boxed{\text{White} = \text{Red} + \text{Green} + \text{Blue}}$$

Additive Model



- there are many photo-sensors in the image plane.

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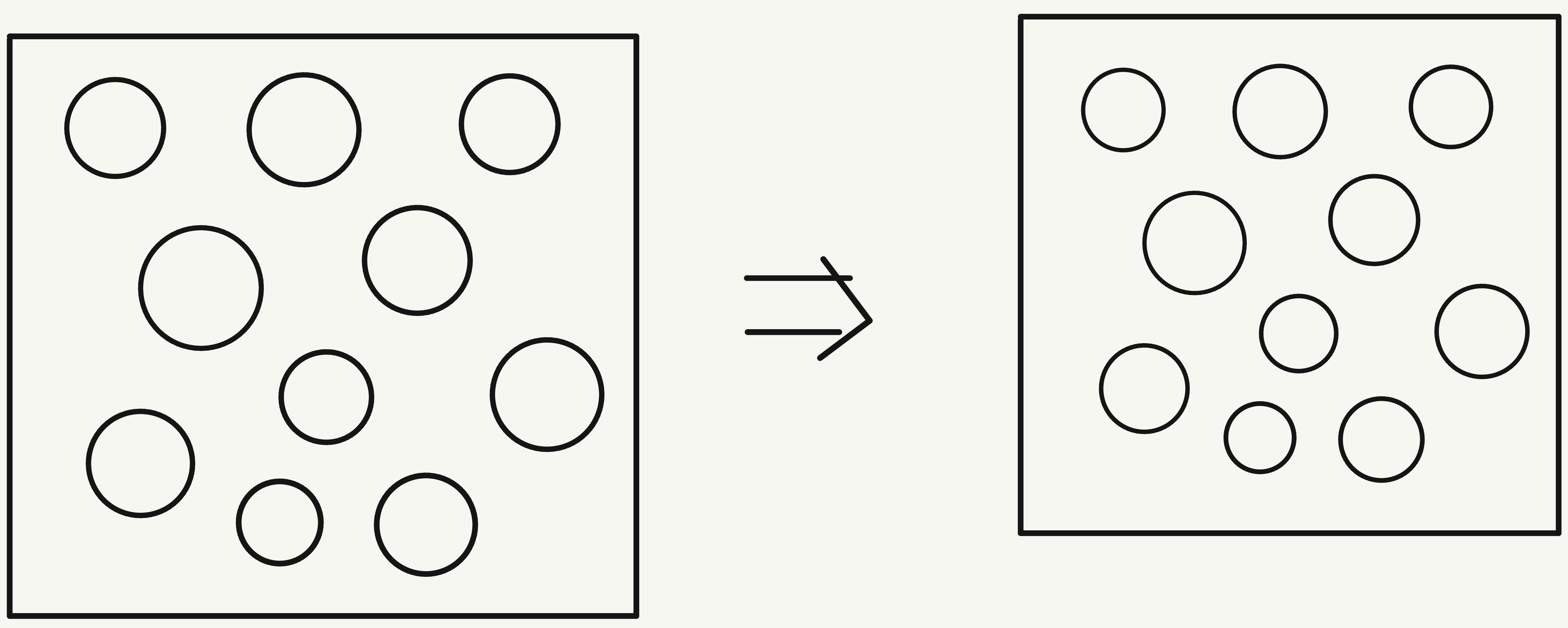
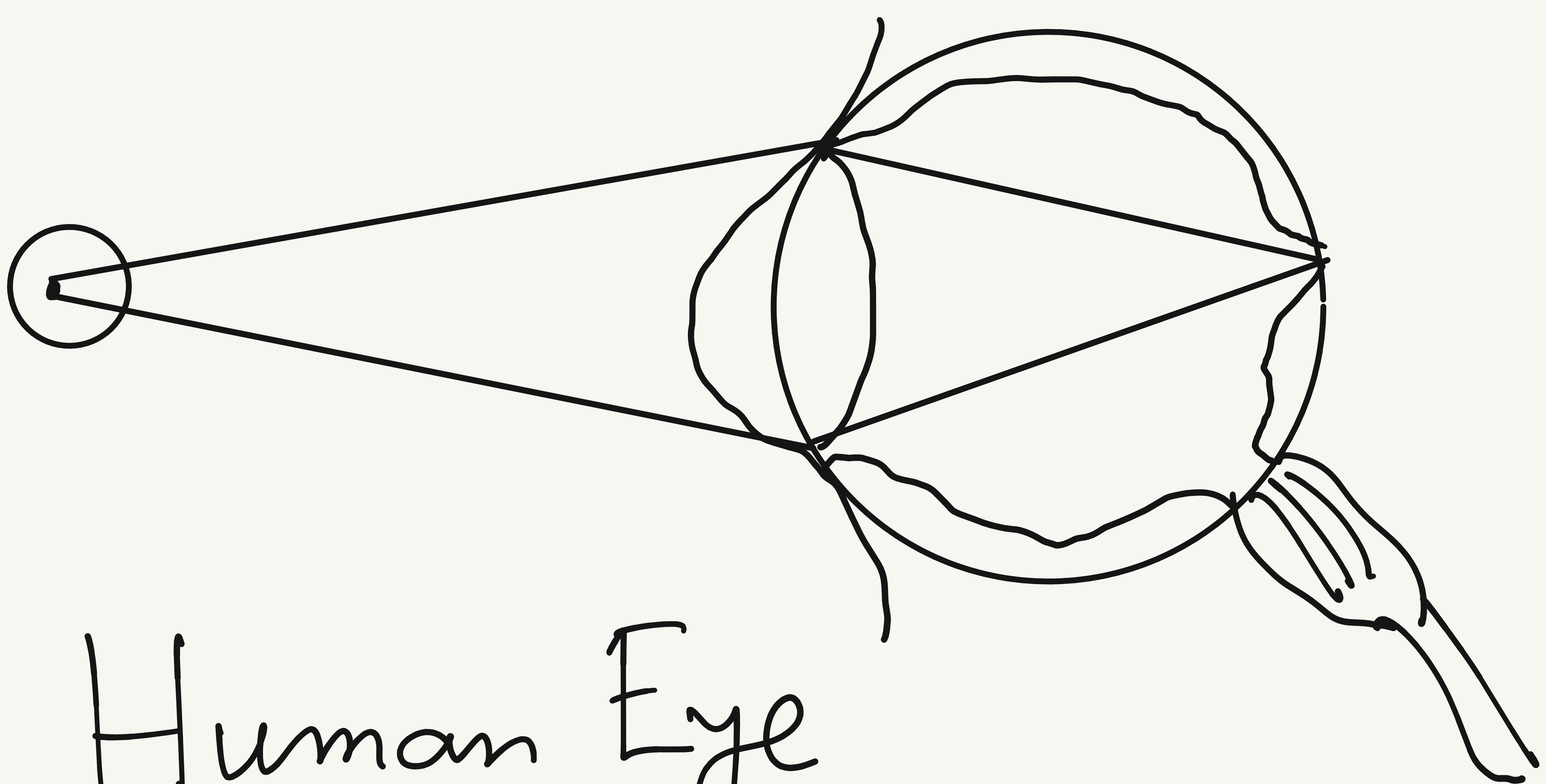


Changed view.

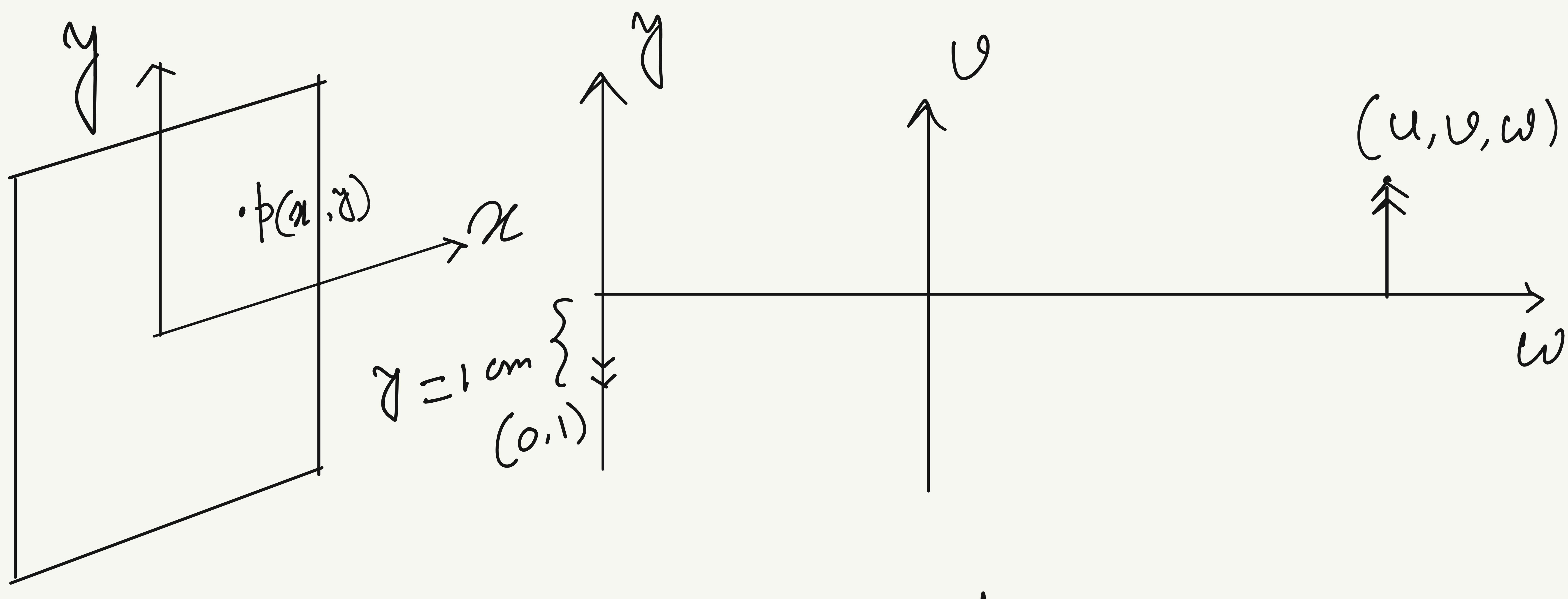


Human Eye

$$\begin{pmatrix} 0 \\ 0 \\ b \end{pmatrix}$$

R	G	R	
G	B	G	B
R	G	R	G

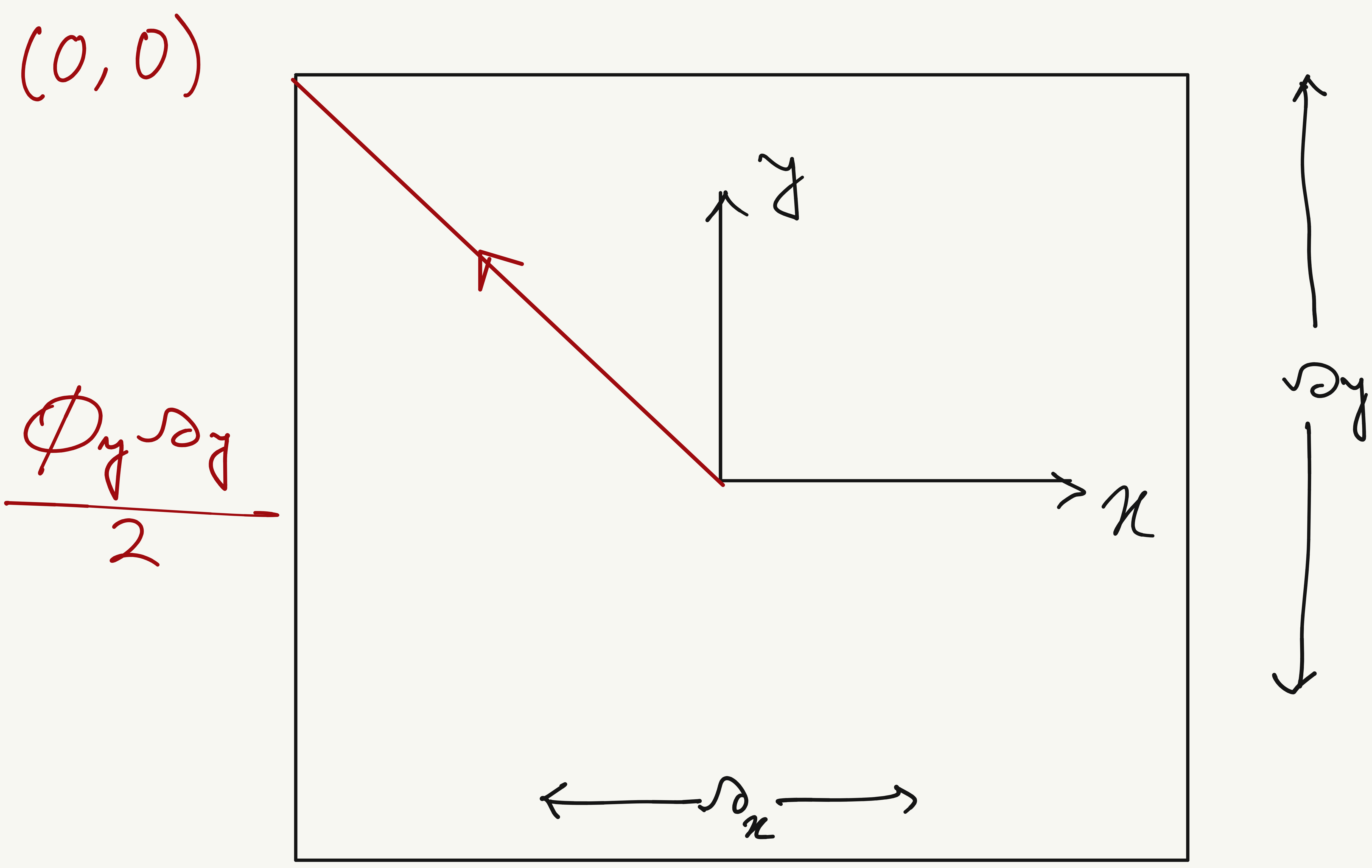
$$\begin{pmatrix} r \\ 0 \\ 0 \end{pmatrix} \qquad \begin{pmatrix} 0 \\ g \\ 0 \end{pmatrix}$$



$y \equiv \phi_y y$ [$\phi_y \rightarrow$ No of photo sensors per unit length (y).]

$x \equiv f \cdot \frac{u}{w} \phi_x$ (no. of pixel)

Similarly, $y \equiv f \cdot \frac{v}{w} \cdot \phi_y$



$d_y = \frac{\phi_y s_y}{2}$

$d_x = \frac{\phi_x s_x}{2}$

$x \equiv f \frac{u}{w} \cdot \phi_x + d_x = x' + d_x$

$y \equiv f \cdot \frac{v}{w} \phi_y + d_y = y' + d_y$

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & d_x \\ 0 & 1 & d_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix}$$

Also,

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & d_x \\ 0 & 1 & d_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \phi_x & 0 & 0 \\ 0 & \phi_y & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1/f \end{bmatrix} \begin{bmatrix} u \\ v \\ w \end{bmatrix}$$

$$\begin{bmatrix} x' \\ y' \\ \lambda \end{bmatrix} = \begin{bmatrix} \phi_x & 0 & d_x/f \\ 0 & \phi_y & d_y/f \\ 0 & 0 & 1/f \end{bmatrix} \begin{bmatrix} u \\ v \\ w \end{bmatrix}$$

ie

$$\left.\begin{aligned} x' &= \phi_x u + \frac{w\, d_x}{f} \\ y' &= \phi_y v + \frac{w\, d_y}{f} \\ \lambda &= w/f \end{aligned}\right\} \text{Homogeneous System}$$

Now,

$$\left.\begin{aligned} x &= \frac{x'}{\lambda} = \phi_x u \cdot \frac{f}{w} + d_x \\ y &= \frac{y'}{\lambda} = \phi_y v \cdot \frac{f}{w} + d_y \end{aligned}\right\} \text{Non-homogeneous System}$$

$$\left.\begin{aligned} x &= f \cdot \frac{u}{w} \\ x' &= f \cdot \frac{u-B}{w} \end{aligned}\right\} \qquad w = \frac{fB}{x-x'}$$

$$\therefore\ x' = \frac{f\,(u-B)}{f \cdot B/(x-x')}$$

$$u = \frac{wx}{f}$$

$$\begin{bmatrix} u' \\ v' \\ w' \end{bmatrix} = \begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{bmatrix} \begin{bmatrix} u \\ v \\ w \end{bmatrix}$$

$$\begin{bmatrix} u'' \\ v'' \\ w'' \\ \lambda \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & t_u \\ 0 & 1 & 0 & t_v \\ 0 & 0 & 1 & t_w \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} u' \\ v' \\ w' \\ 1 \end{bmatrix}$$

ie. $$\begin{bmatrix} u'' \\ v'' \\ w'' \\ \lambda \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & t_u \\ 0 & 1 & 0 & t_v \\ 0 & 0 & 1 & t_w \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} & 0 \\ r_{21} & r_{22} & r_{23} & 0 \\ r_{31} & r_{32} & r_{33} & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} u \\ v \\ w \\ 1 \end{bmatrix}$$

For 1st Camera. 06/03/2023

$$P\begin{pmatrix} u \\ v \\ w \end{pmatrix} \longrightarrow p\begin{pmatrix} x \\ y \end{pmatrix}$$

$$x = f \cdot \frac{u}{w} \quad , \quad y = f \cdot \frac{v}{w}$$

$$\begin{pmatrix} u^c \\ v^c \\ w^c \end{pmatrix} = TR\begin{pmatrix} u^w \\ v^w \\ w^w \end{pmatrix} \longrightarrow p\begin{pmatrix} x \\ y \end{pmatrix}$$

$$x' = f \cdot \frac{u^c}{w^c} \quad , \quad y' = f \cdot \frac{v^c}{w^c}$$

$$\begin{pmatrix} x' \\ y' \\ z' \\ w^c/f \end{pmatrix} = \begin{pmatrix} K \\ _{3\times3} \end{pmatrix} \begin{pmatrix} R & t \\ _{3\times3} & _{3\times1} \end{pmatrix} \begin{pmatrix} u \\ v \\ w \\ 1 \end{pmatrix}$$

$$\hookrightarrow \begin{pmatrix} x \\ y \end{pmatrix} \text{ as}$$

$$\begin{pmatrix} \lambda x \\ \lambda y \\ \lambda \end{pmatrix} = K \begin{pmatrix} R & t \end{pmatrix} \begin{pmatrix} u \\ v \\ w \\ 1 \end{pmatrix}$$

$$A = [K][R \quad t]$$

$$= [KR \quad Kt]$$

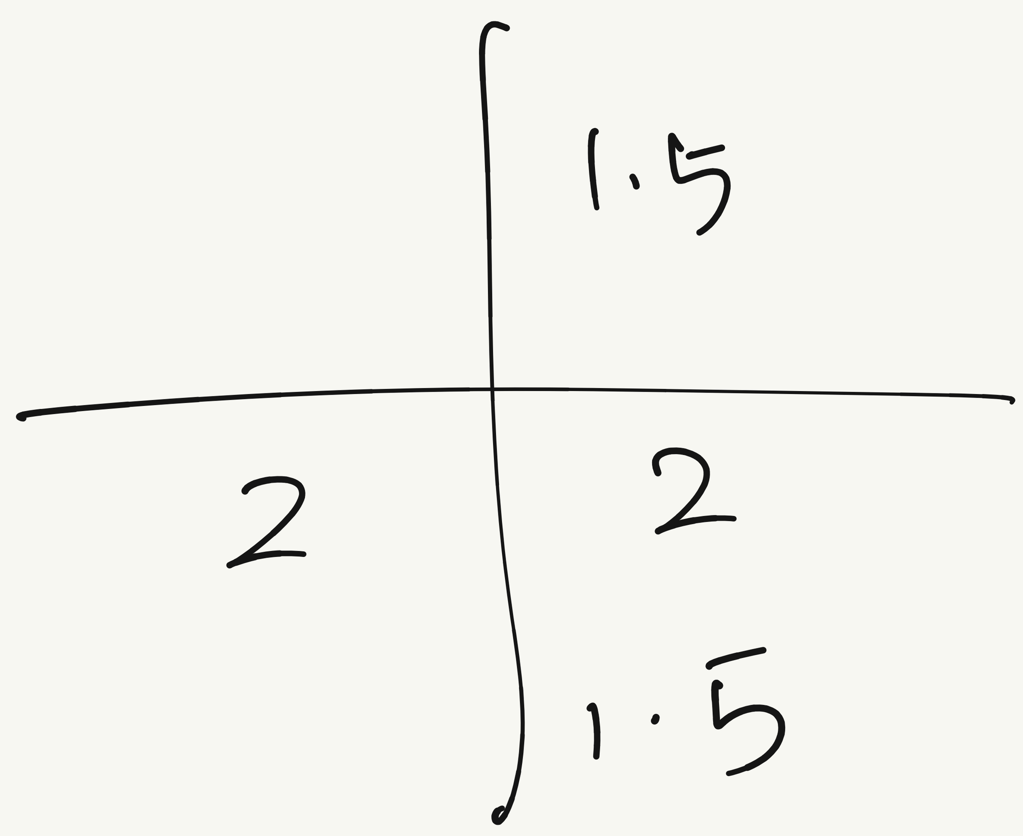
$$= \left[\begin{array}{ccc|c} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \end{array}\right]$$

$$K = \begin{bmatrix} \phi_x & 0 & d_x/f \\ 0 & \phi_y & d_y/f \\ 0 & 0 & 1/f \end{bmatrix}$$ Upper Triangular

---

$$x = (1.5) \cdot \frac{2}{10} \quad , \quad y = (1.5) \cdot \frac{5}{10}$$

$$= 0.3 \quad , \quad = 0.75 .$$



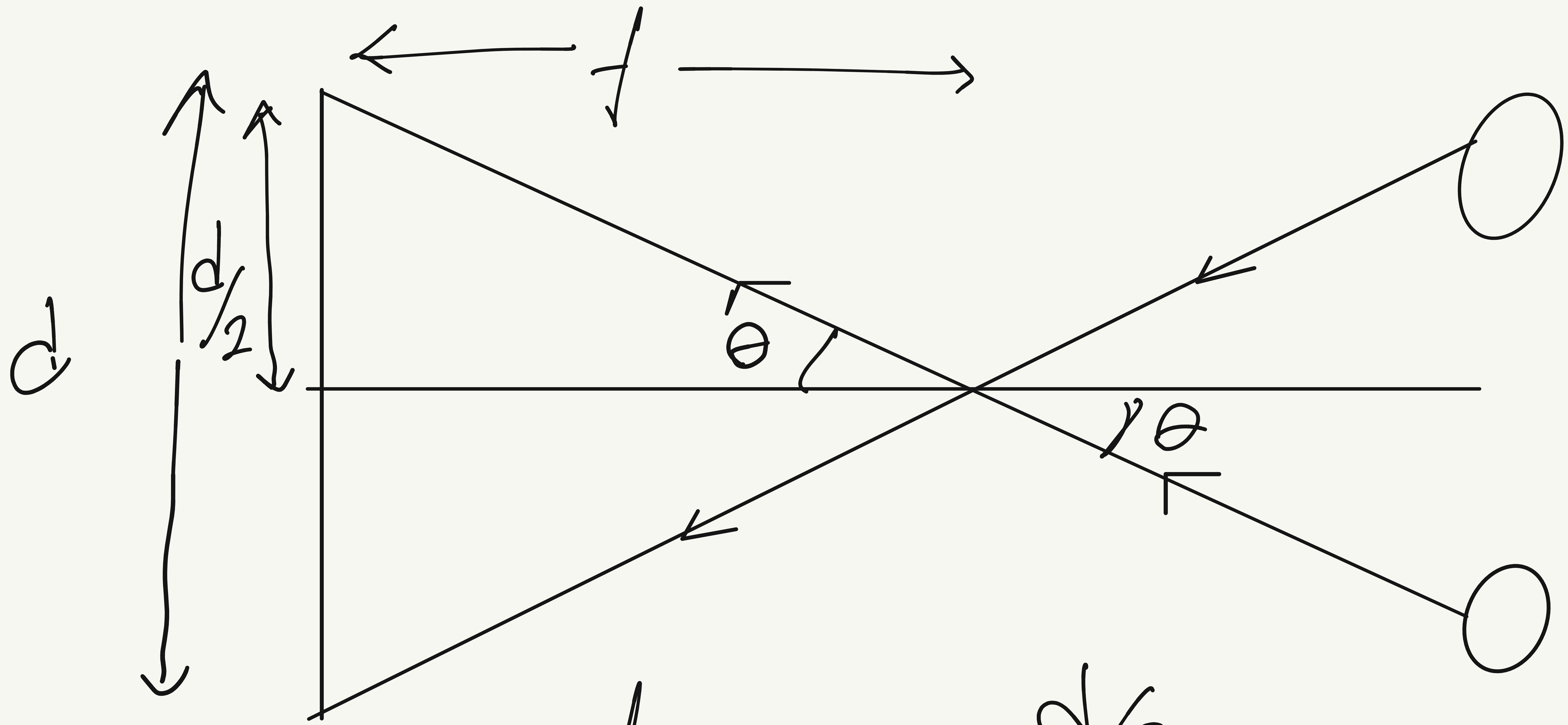
$$0.3 \times 1200 = 360 +$$

$$075 \times 1200 = 900 +$$

$$\frac{4 \times 1200}{2} = 2400$$

$$\frac{3 \times 1200}{2} = 1800$$

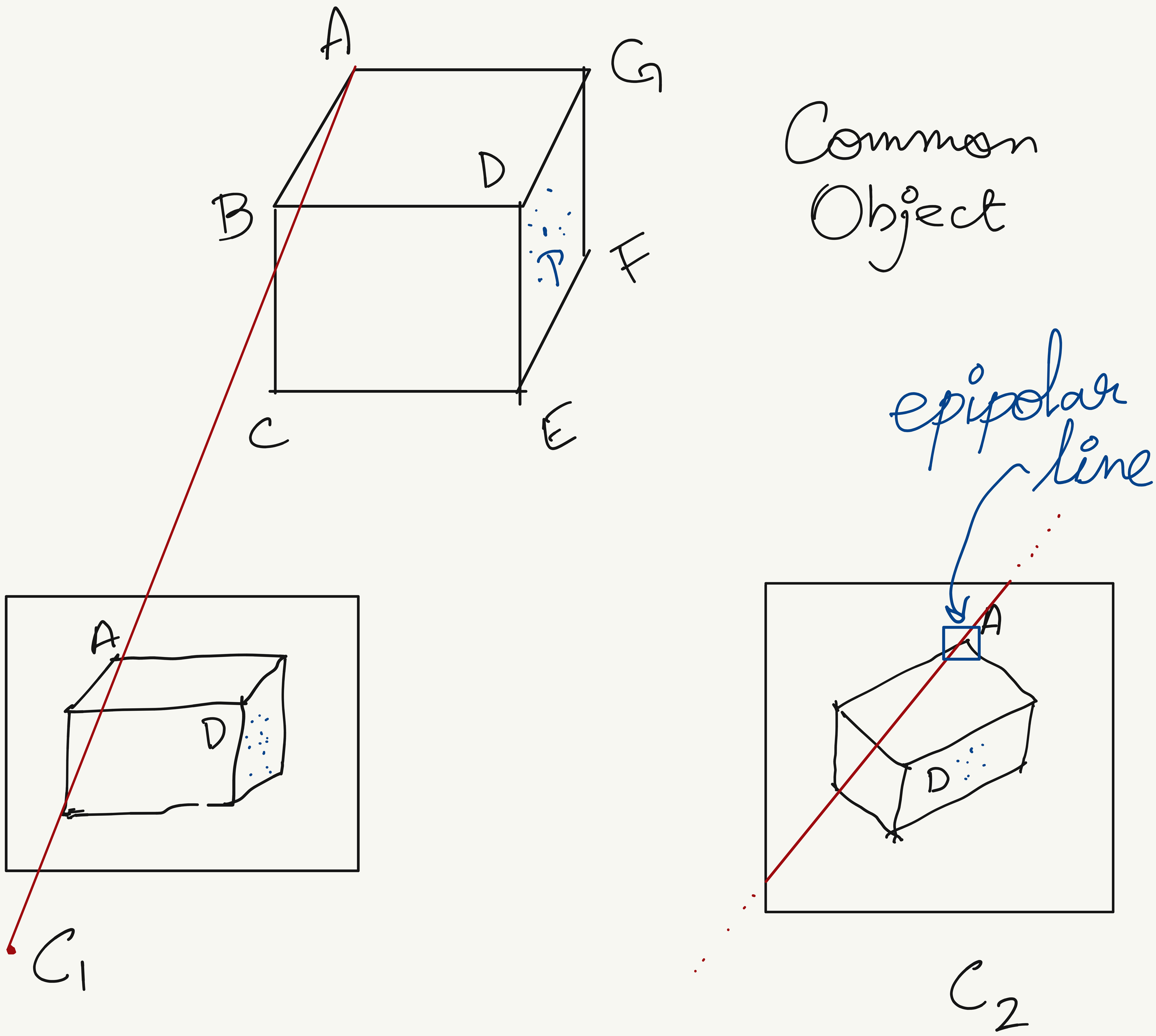
ie Co-ordinate = $(2760, 2700)$



$$\tan\theta = \frac{d/2}{f}$$

$$\Rightarrow \theta = \tan^{-1}\left(\frac{d/2}{f}\right).$$

09/03/2023



To get the points we have to describe the neighbourhood of the point.

For a fixed point their must be an epipolar line, and the image of the point must lie on the epipolar line.

Real

$$\begin{pmatrix} \lambda x \\ \lambda y \\ \lambda \end{pmatrix} = \begin{bmatrix} \phi_x & 0 & d_x/f \\ 0 & \phi_y & d_y/f \\ 0 & 0 & 1/f \end{bmatrix} \begin{pmatrix} u^c \\ v^c \\ w^c \\ 1 \end{pmatrix}^T = \left[R \,|\, t \right] \begin{pmatrix} u^w \\ v^w \\ w^w \\ 1 \end{pmatrix}$$

$$K = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad \text{and} \quad P_h^T = \begin{pmatrix} \lambda x \\ \lambda y \\ \lambda \end{pmatrix}$$

Then, $$\begin{pmatrix} u^c \\ v^c \\ w^c \\ 1 \end{pmatrix} = K^{-1} P_h^T$$

i.e. $$\boxed{\underset{n\times 1}{Y} = \underset{n\times n}{A}\, \underset{n\times 1}{V}}$$

$$\hat{P}_h^{I} = RP^{w} + t$$

For camera 1: $\hat{p}_n^{I_1} = P^{w}$

For Camera 2: $\hat{p}_n^{I_2} = RP^{w} + t$

i.e. $\hat{p}_n^{I_2} = R\,\hat{p}_n^{I_1} + t$

Now,

$$t \times \hat{p}_n^{I_2} = t \times R\hat{p}_n^{I_1} + t \times t$$

$$= t \times R\,\hat{p}_n^{I_1}$$

$$\Rightarrow \hat{p}_n^{I_2} \cdot \left(t \times \hat{p}_n^{I_2}\right) = \hat{p}_n^{I_2} \cdot \left(t \times R\hat{p}_n^{I_1}\right)$$

$$\Rightarrow \hat{p}_n^{I_2} \cdot \left[\underset{3\times1}{t} \times \underset{3\times3}{R}\,\underset{3\times1}{\hat{p}_n^{I_1}}\right] = 0$$

$$\vec{a} = a\hat{i} + b\hat{j} + c\hat{k}$$
$$\vec{t} = t_u\hat{i} + t_v\hat{j} + t_w\hat{k}$$

$$\vec{t} \times \vec{a} = \begin{vmatrix} \hat{i} & \hat{j} & \hat{k} \\ t_u & t_v & t_w \\ a & b & c \end{vmatrix} = (ct_v - bt_w)\hat{i} + (at_w - ct_u)\hat{j} + (bt_u - at_v)\hat{k}$$

$$= \underbrace{\begin{bmatrix} 0 & -t_w & t_v \\ t_w & 0 & -t_u \\ -t_v & t_u & 0 \end{bmatrix}}_{T'} \begin{bmatrix} a \\ b \\ c \end{bmatrix}$$

Thus,

$$\hat{p}_n^{I_2} \cdot \left[\underset{3\times 1}{t} \times \underset{3\times 3}{R} \underset{3\times 1}{\hat{p}_n^{I_1}} \right] = 0$$

$$\Rightarrow \hat{p}_n^{I_2} \left(T' R \, \hat{p}_n^{I_1} \right) = 0$$

$$\Rightarrow \hat{p}_n^{I_2} \left(E \hat{p}_n^{I_1} \right) = 0$$

$$\Rightarrow \left(\hat{p}_n^{I_2} \right)^T E \, \hat{p}_n^{I_1}$$

where, $E = T'R$ = Essential matrix

Camera 2 :

$$\begin{pmatrix} x \\ y \\ z \end{pmatrix}^T E \, \hat{p}_n^{I_2} = 0$$

$\Rightarrow$ Equation of a st. line

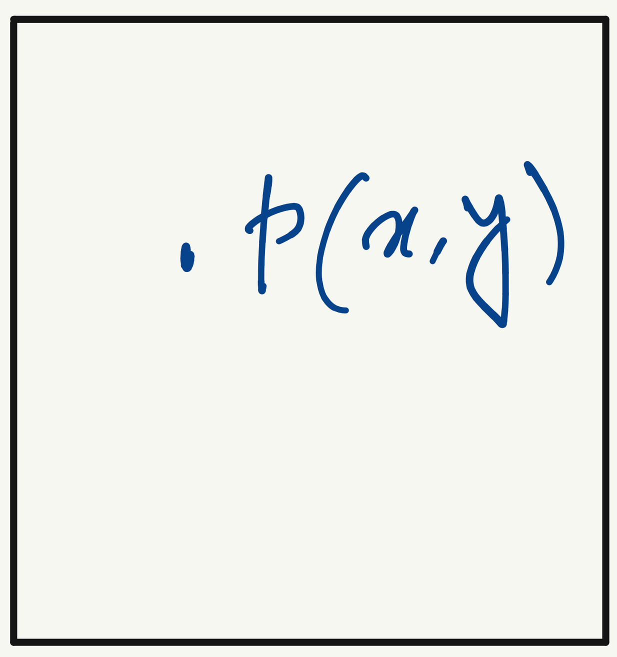
i.e. epipolar line on camera 1.

$$\left(K_2^{-1} p_n^{I_2} \right)^T E \left(K_1^{-1} p_n^{I_1} \right) = 0$$

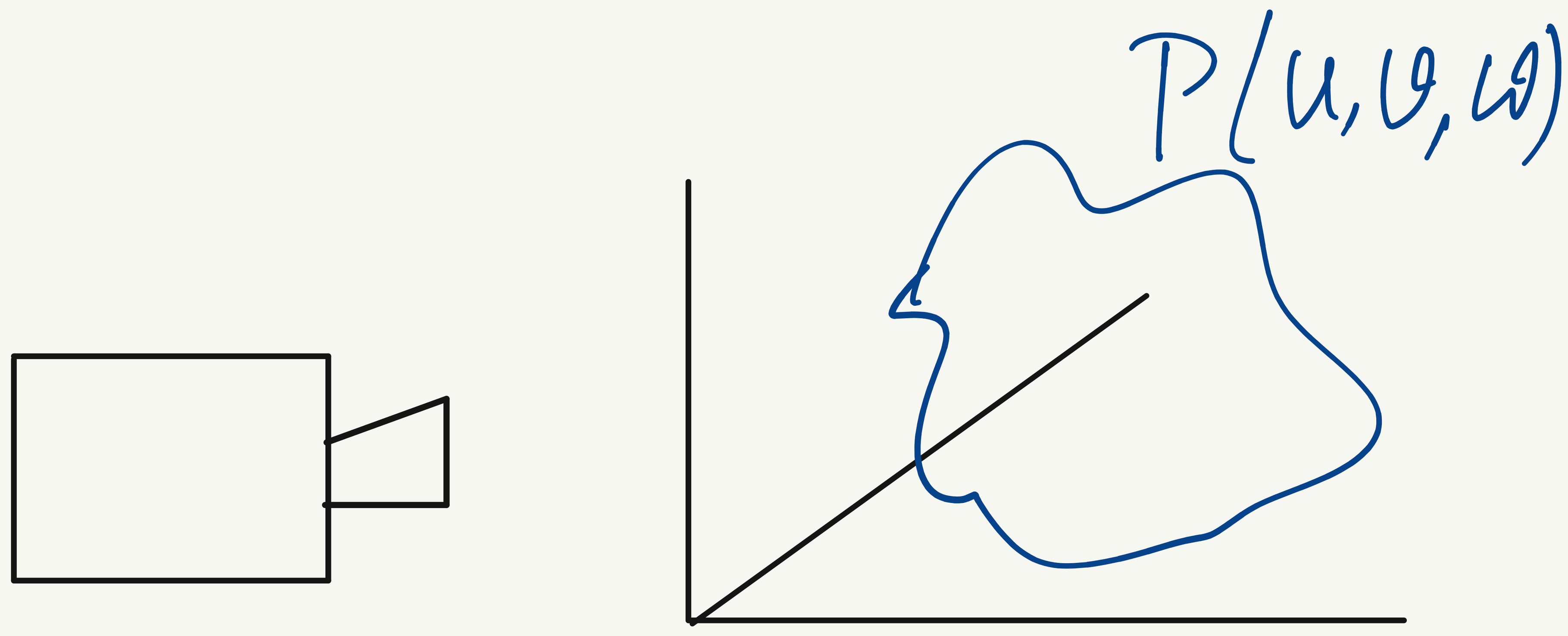
$$\Rightarrow \left(p_n^{I_2} \right)^T \left(\left(K_2^{-1} \right)^T E \left(K_1^{-1} \right) \right) p_n^{I_1} = 0$$

$$\Rightarrow \left(p_n^{I_2}\right)^T F \left(p_n^{I_1}\right) = 0$$

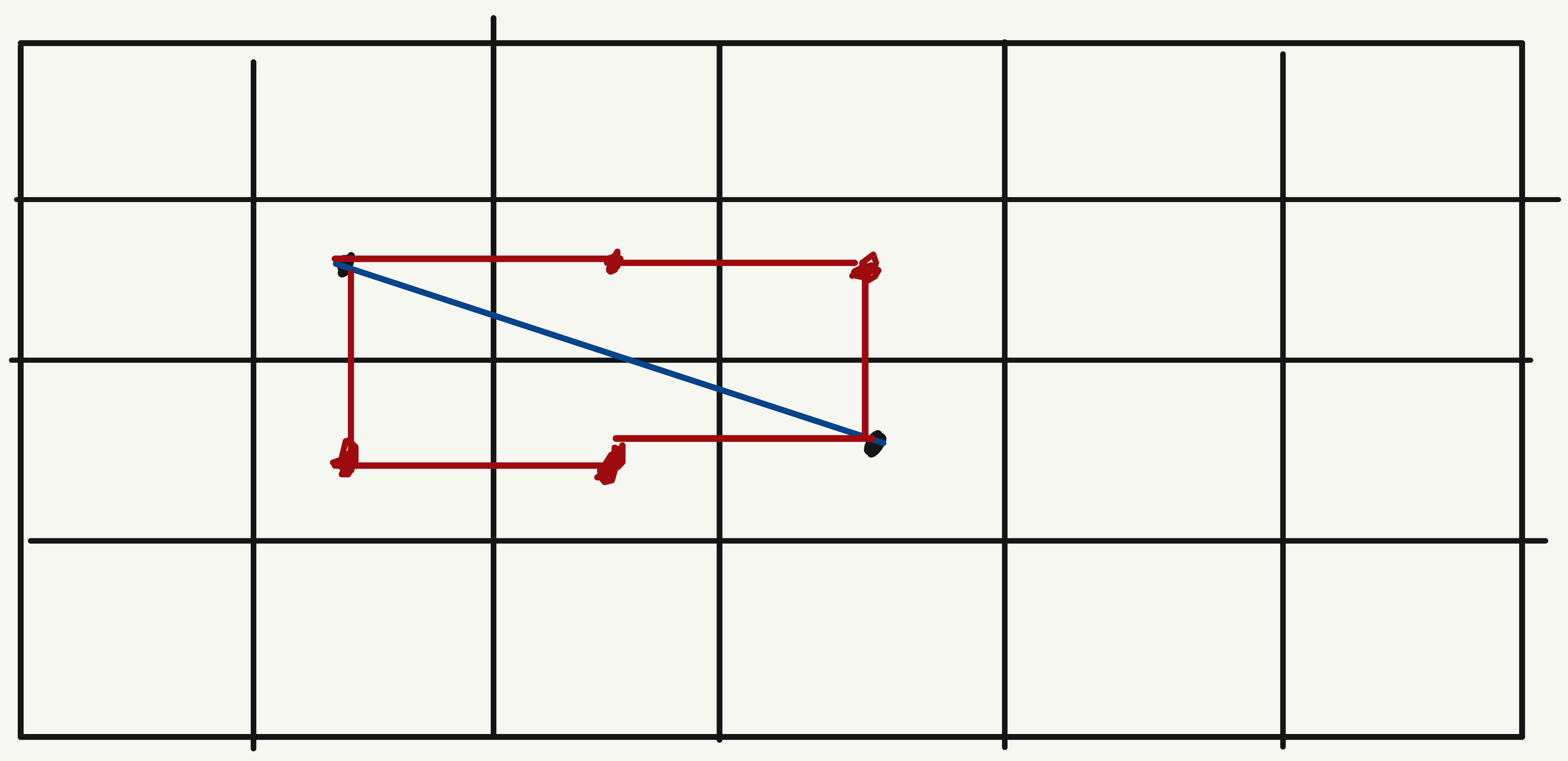
13/03/2023



$$x = f\frac{u}{w}$$
$$y = f\frac{v}{w}$$



Object/ Foreground:



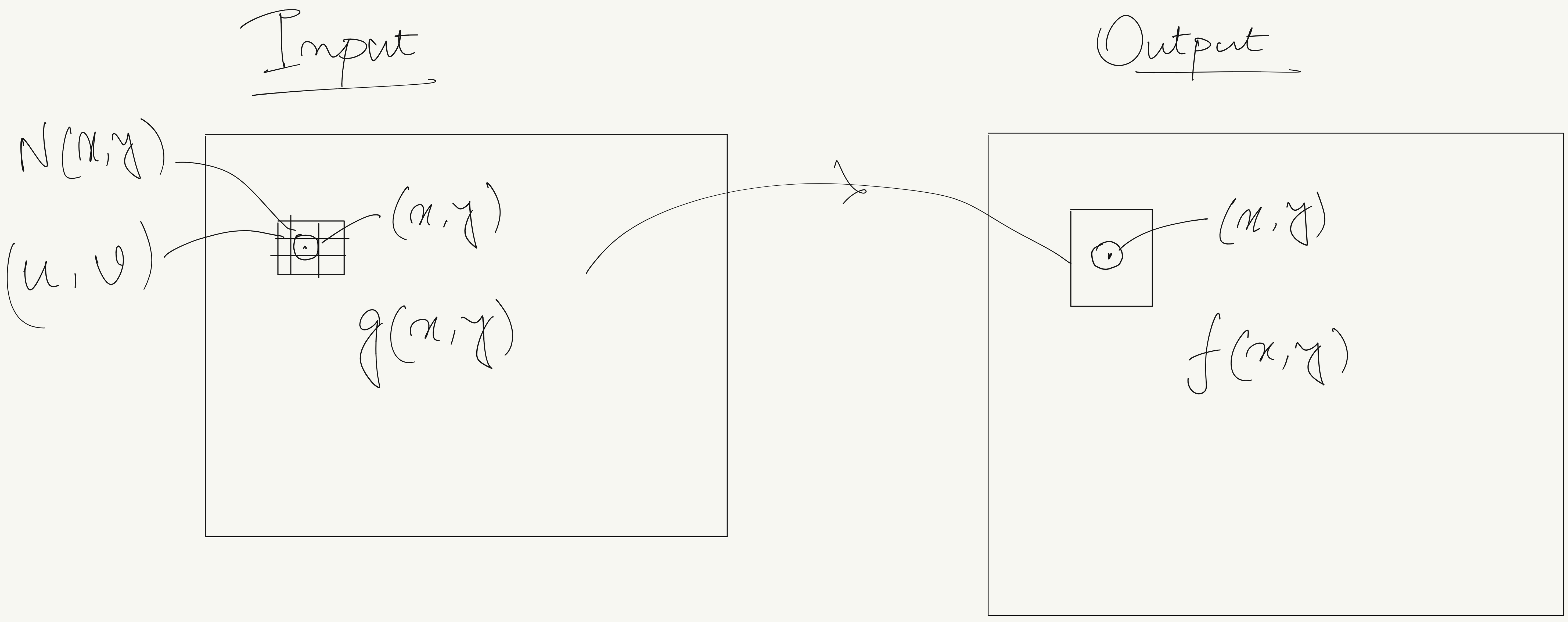
$$dist_E(p_0, q_0) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$$

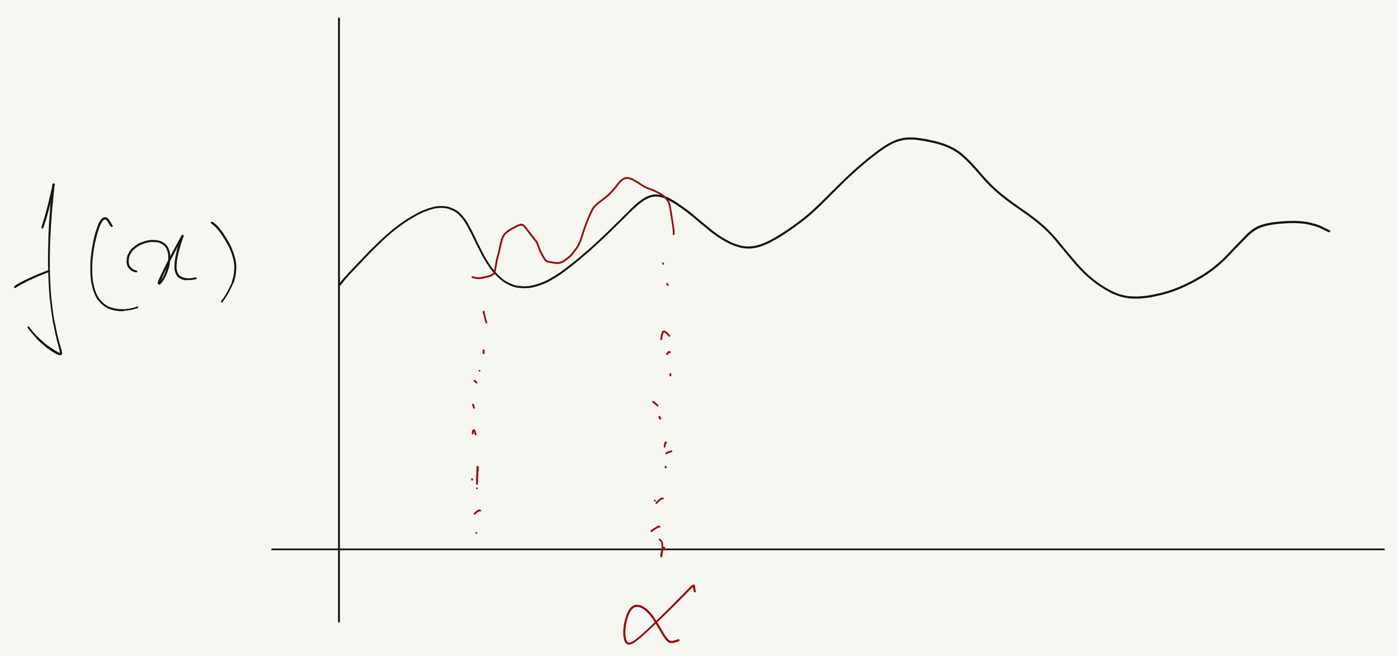
Euclidean Distance doesn't work Since it is a discrete map

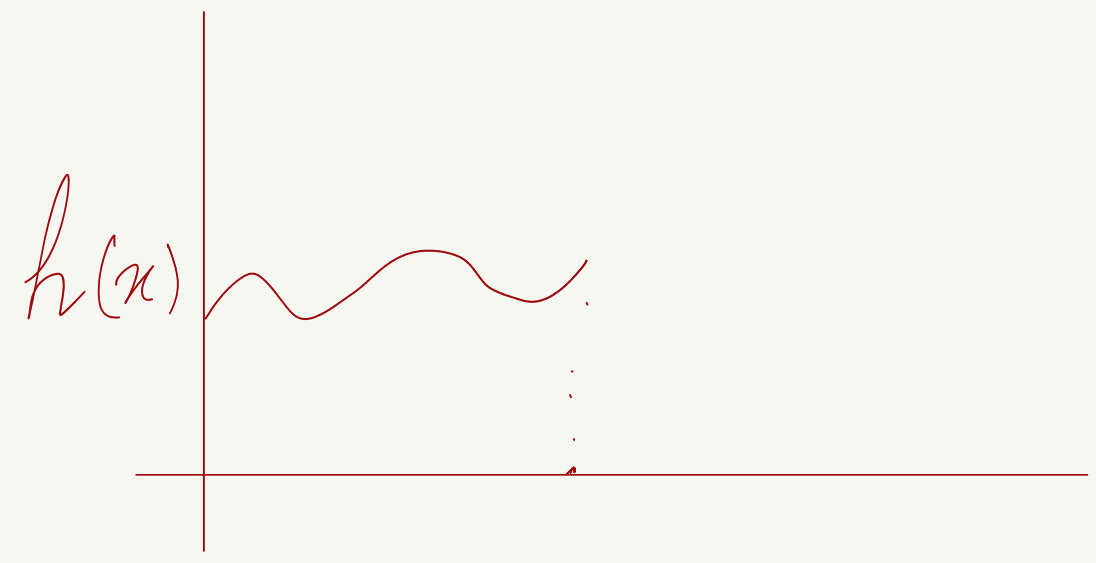
$$dist_4(p_0, q_0) = |x_1 - x_2| + |y_1 - y_2|$$

$$dist_8(p_0, q_0) = \max\{|x_1 - x_2|, |y_1 - y_2|\}$$

15/03/2023

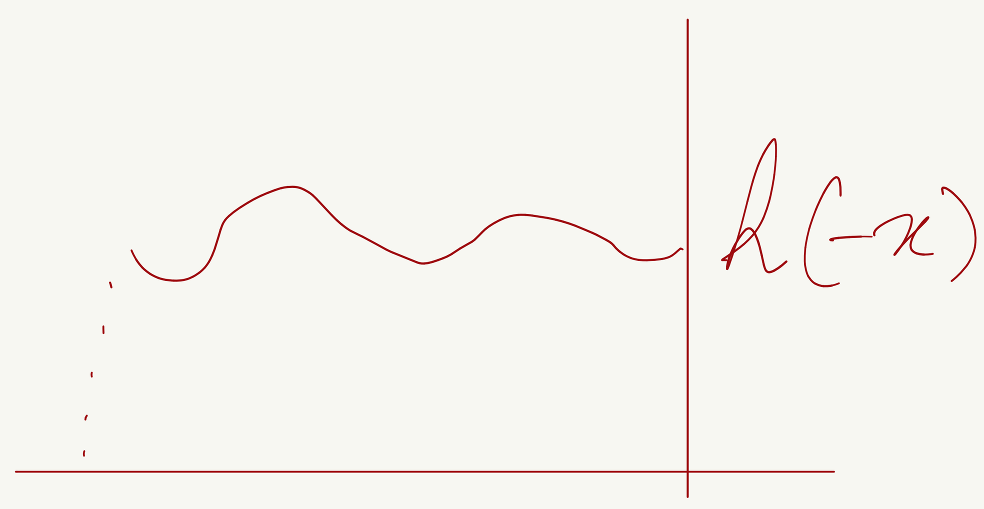


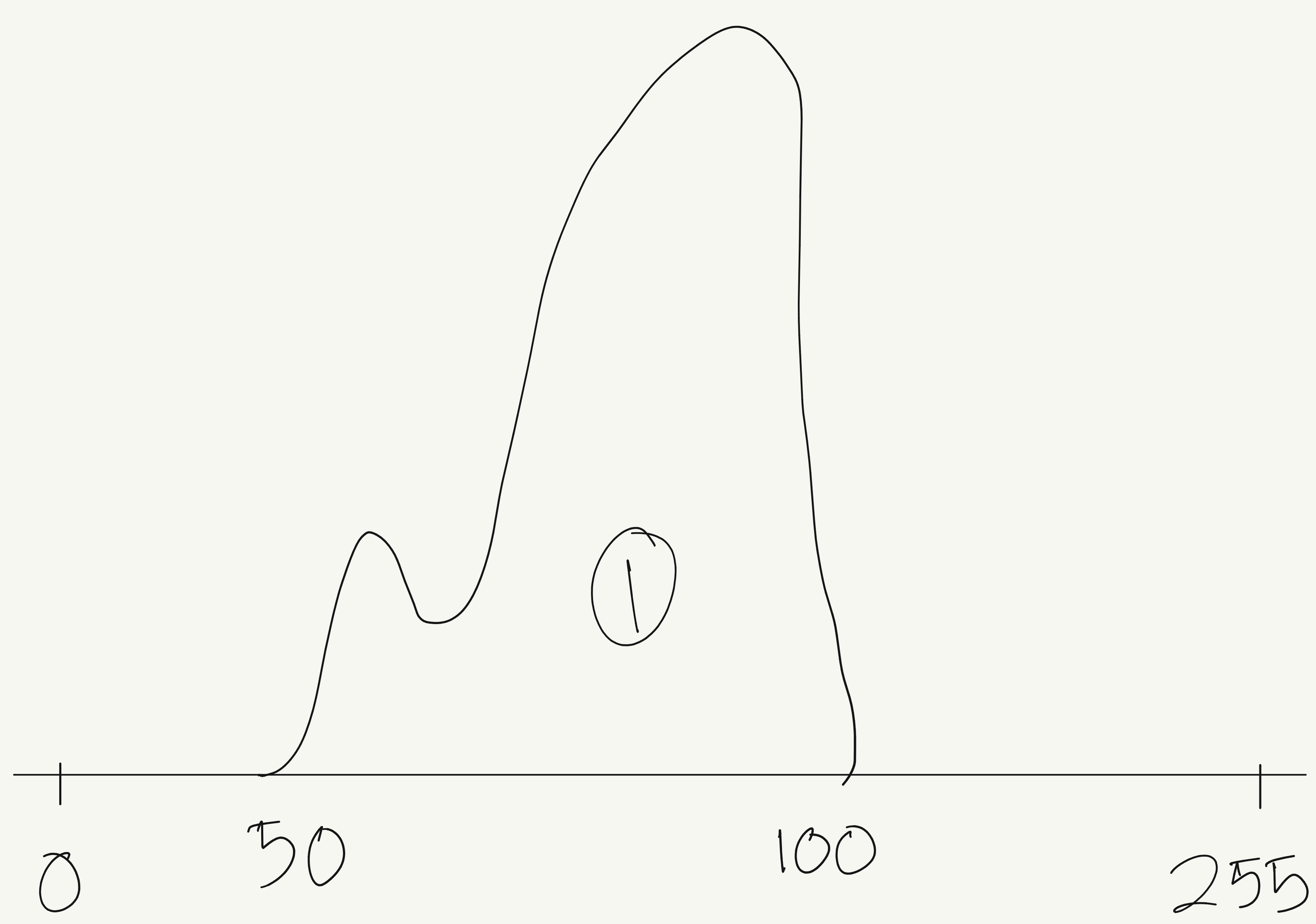




Convolution. $f(x) * h(x)$

$$= \int f(\alpha)\, h(\alpha - x)\, d\alpha$$





$s = a(r - b) + c \;=\; 2.5(r - 50) + 0$

we are changing (50-100) range to (0-250) range.

If the range (0-255) exceed then the computer store the data as (x mod 256).

$$\begin{pmatrix} R \\ G \\ B \end{pmatrix} \rightarrow \begin{pmatrix} Y \\ C_B \\ C_R \end{pmatrix} \xrightarrow[\text{Equalization}]{\text{Histogram}} \begin{pmatrix} Y' \\ C_B' \\ C_R' \end{pmatrix} \rightarrow \begin{pmatrix} R' \\ G' \\ B' \end{pmatrix}$$

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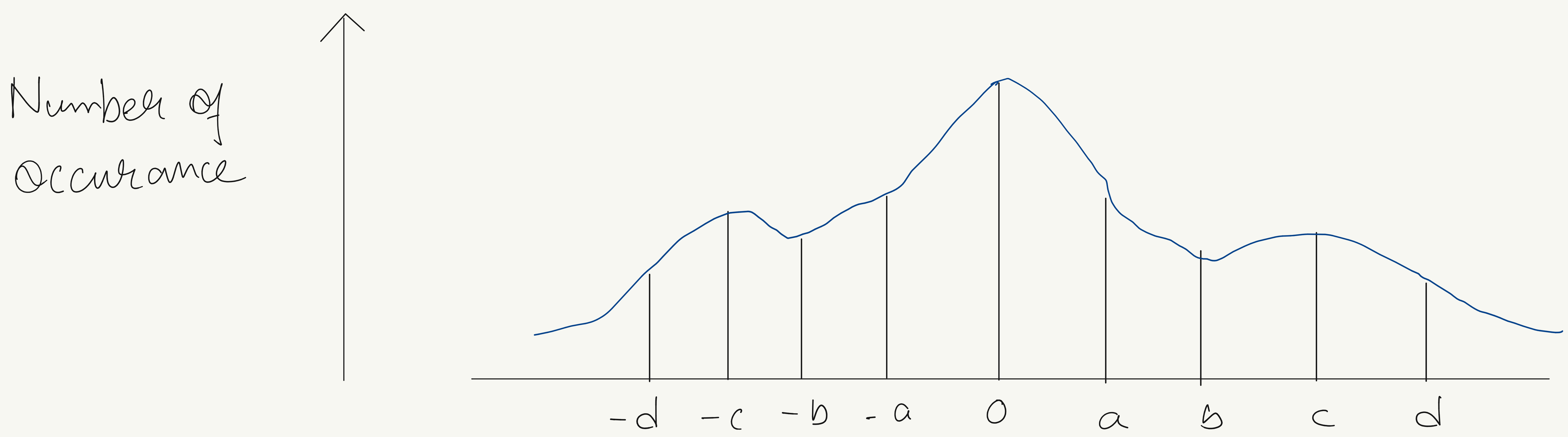
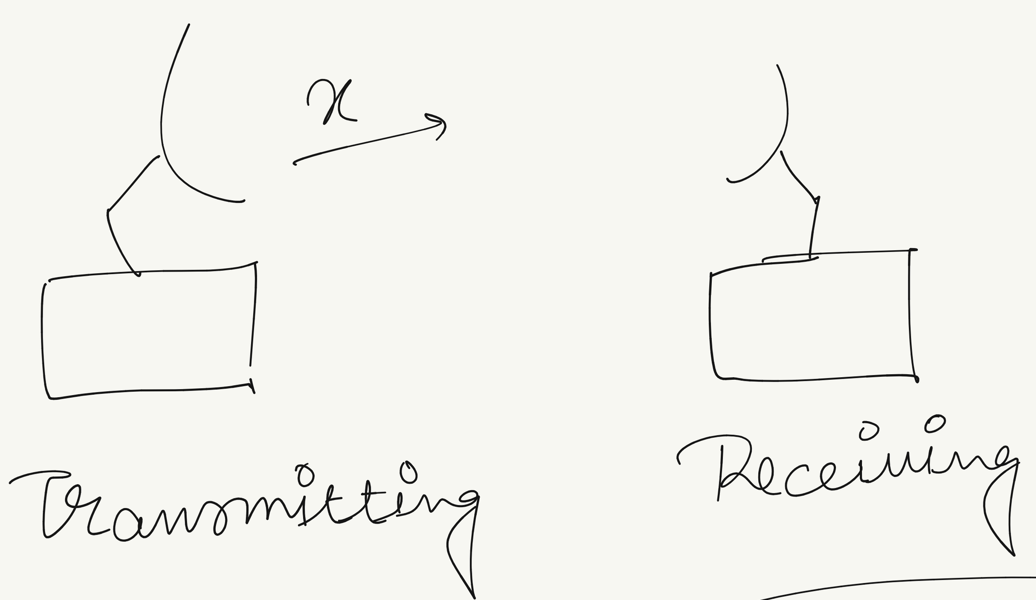
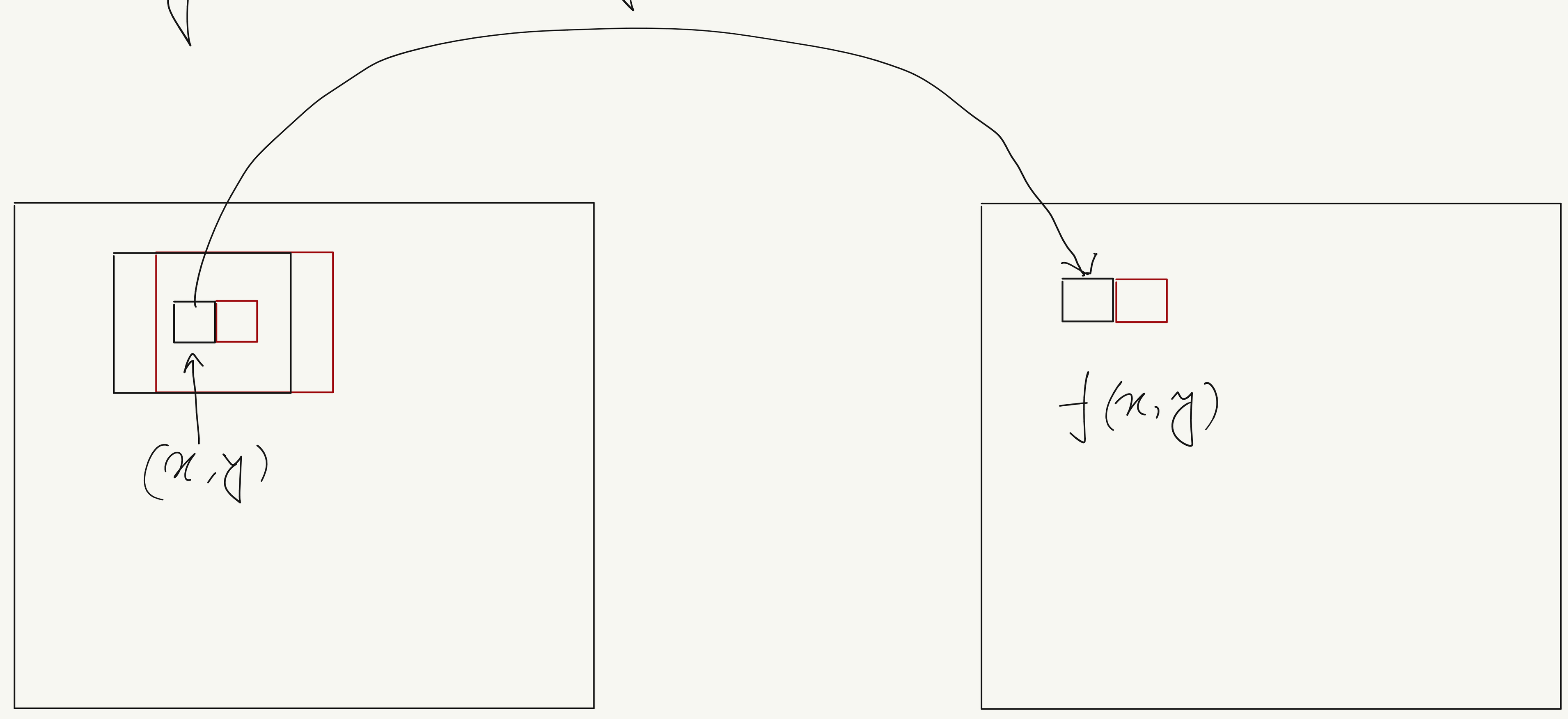




$$\left.\begin{aligned} y_1 &= x + \eta_1 \\ y_2 &= x + \eta_2 \\ &\vdots \\ y_n &= x + \eta_n \end{aligned}\right\} \quad y = \frac{y_1 + y_2 + \dots + y_n}{n} = x + 0$$

[$\because$ mean of noise is zero]



$ax + by + cz + d = 0$ (Eq. of a plane in 3D)

$$\Rightarrow \frac{a}{c}x + \frac{b}{c}y + z + \frac{d}{c} = 0$$

$$\Rightarrow z = -\frac{a}{c}x - \frac{b}{c}y - \frac{d}{c}$$

ie $f(x,y) = Ax + By + C = A(x - x_0) + B(y - y_0) + C$

But in reality.

$$g(x,y) = A(x - x_0) + B(y - y_0) + C + \eta(x,y) \leftarrow \underline{\text{Noise}}$$

ie. $g(x,y) = f(x,y) + \eta(x,y)$

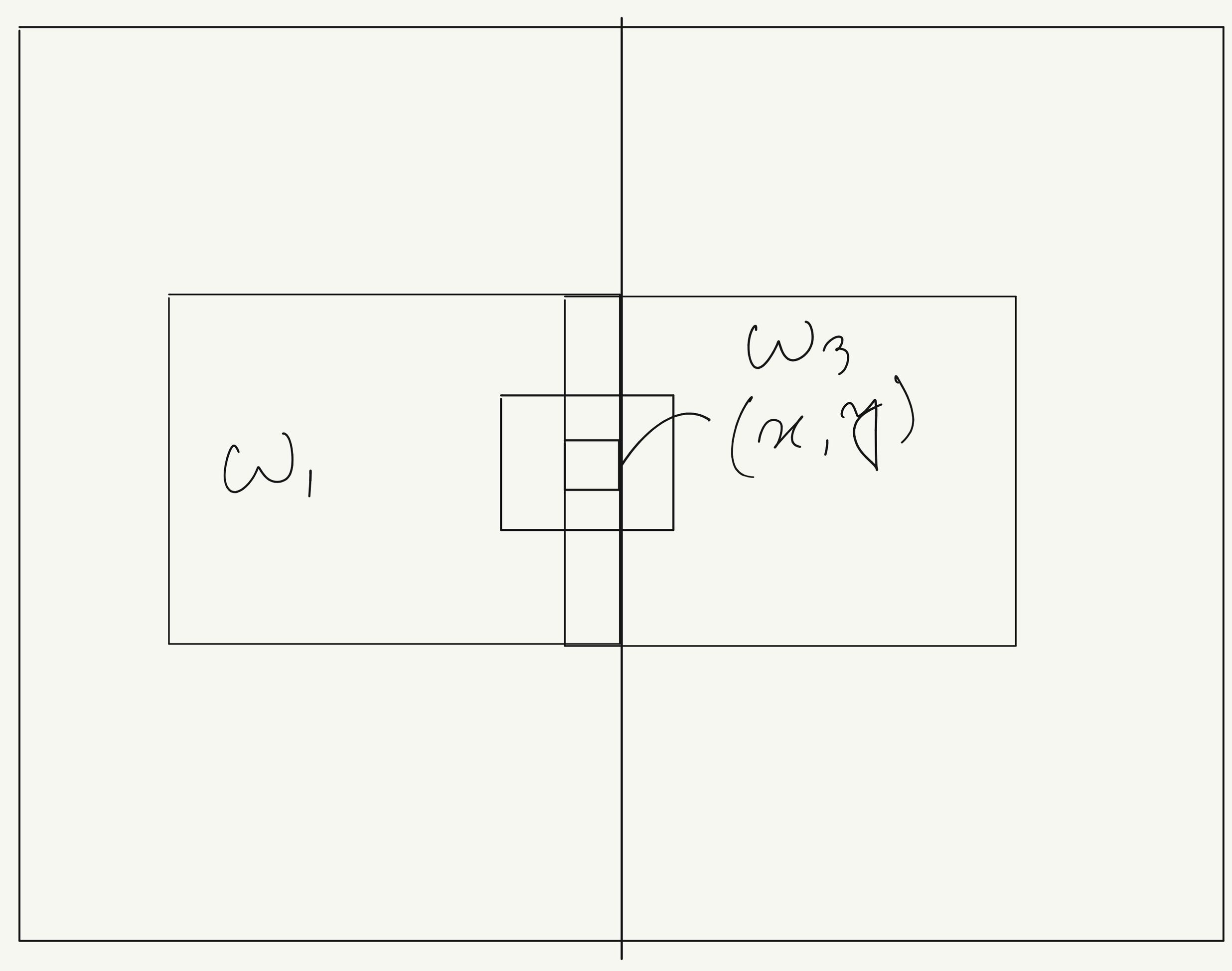
Now, if we get the values of A, B, C then we can estimate the $f(x,y)$.

Thus,

$$\left[g(x,y) - A(x-x_0) - B(y-y_0) - C\right]^2 = \left[\eta(x,y)\right]^2$$

Let, $e(A,B,C) = \sum_{(x,y)\in W} \left[g(x,y) - A(x-x_0) - B(y-y_0) - C\right]^2 - \sum_{(x,y)\in W} \left[\eta(x,y)\right]^2$

Now, we are minimizing the error term $e(A,B,C)$



Var (ω_1 region) ~ 0
Var (ω_3 region) is some significant value > 0

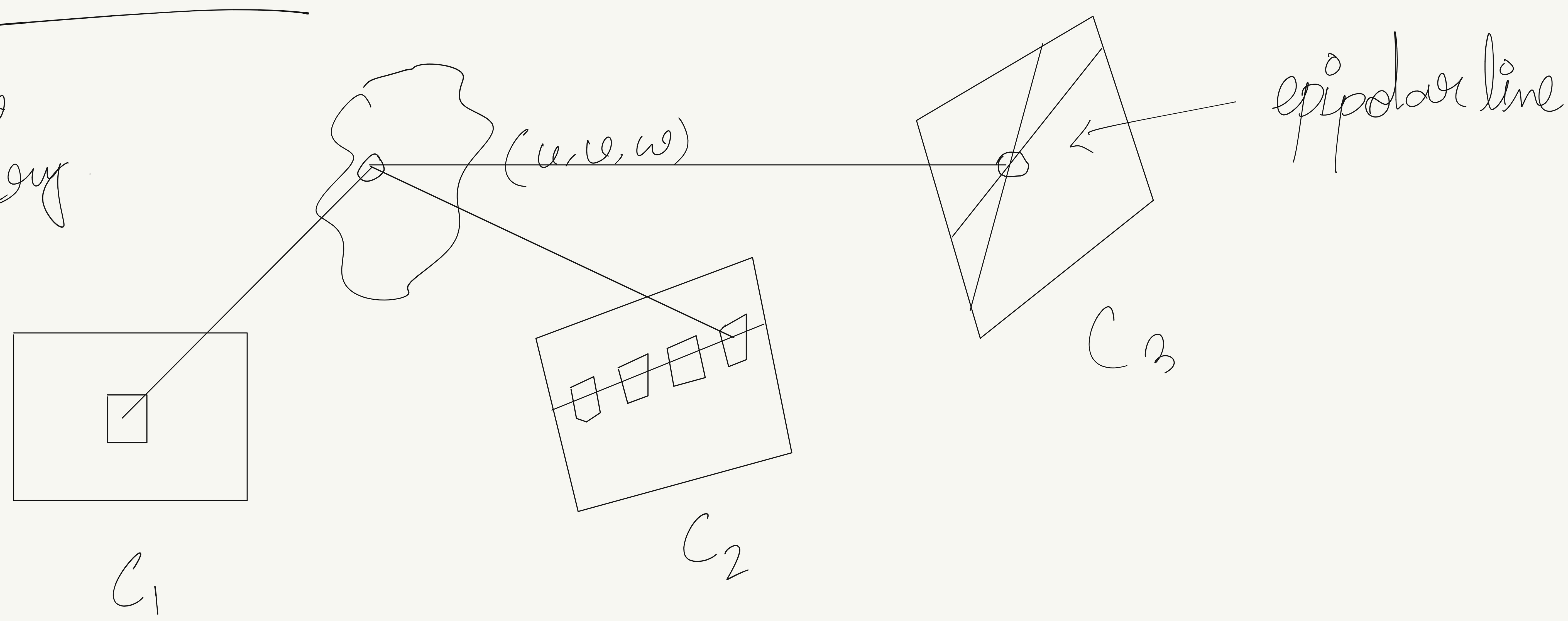
Fourier Series :

$$f(x) = \sum a_i \phi_i(x)$$

as i goes higher the frequency of $\phi_i(x)$ goes higher.

Assignment :

Multiview Geometry



3D Zepher / Mesh room ⟵ packages.

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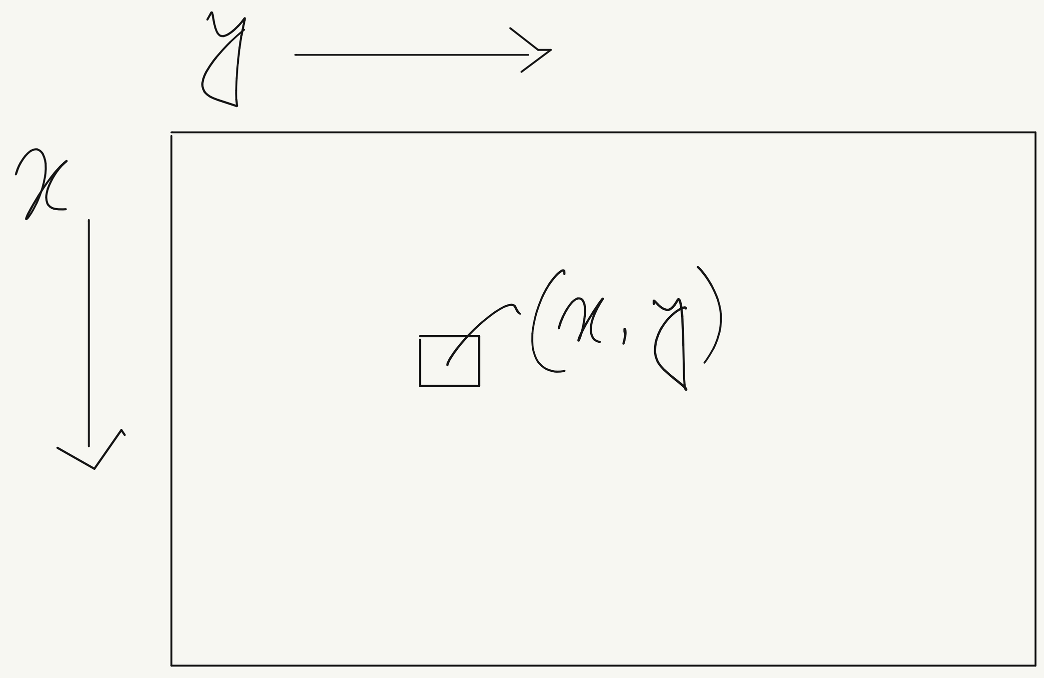
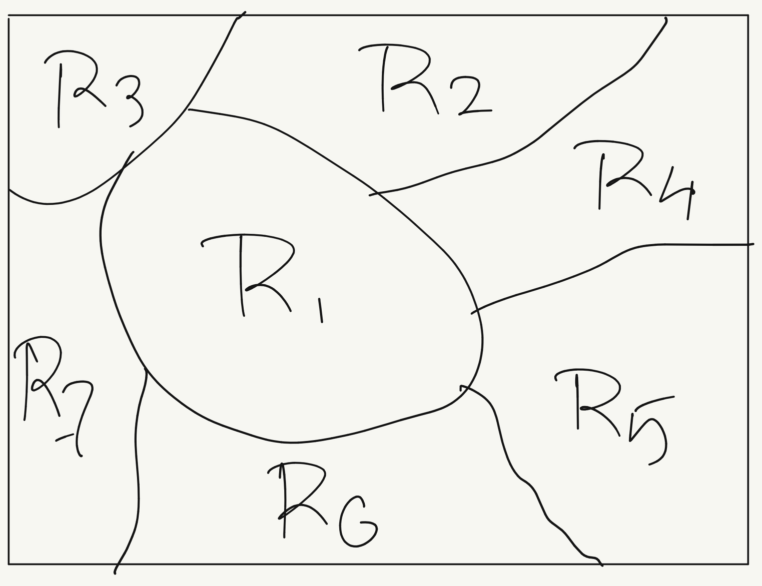
Objective :



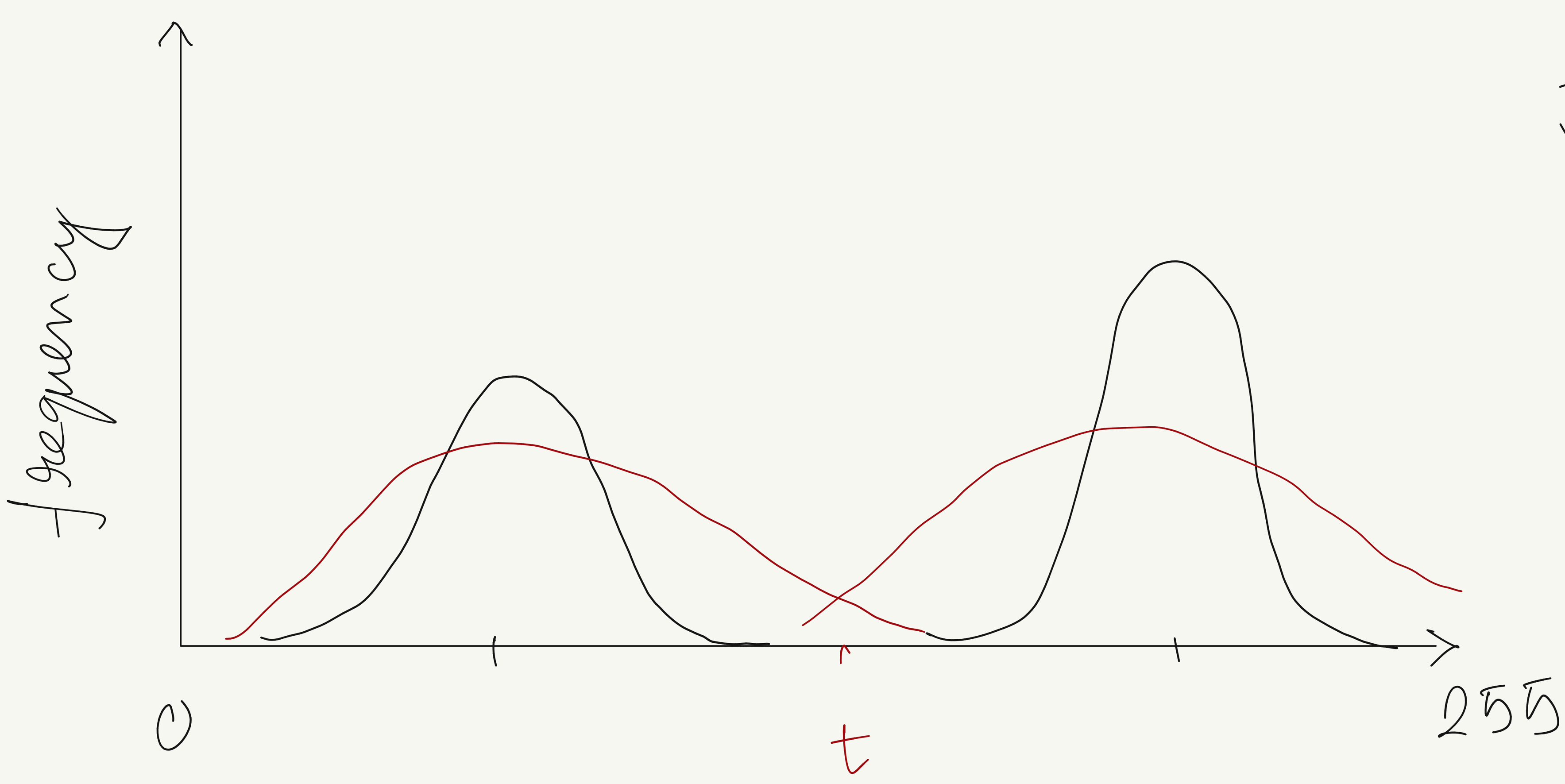
Domain

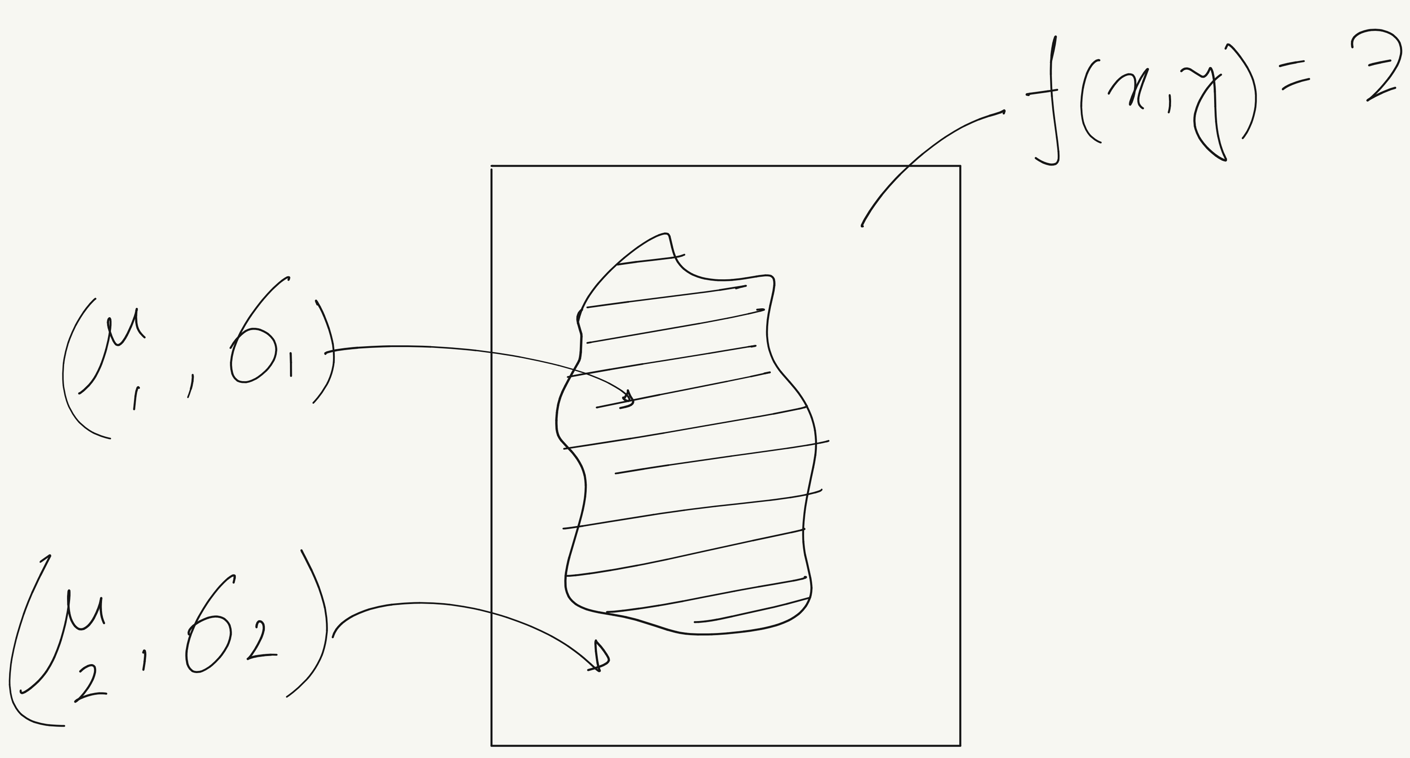


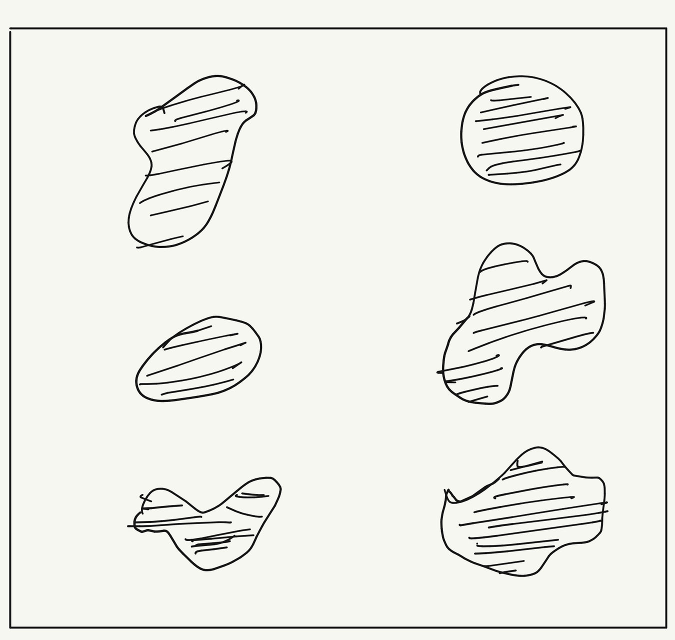
Domain : $R_i : i = \{1, 2, \dots, 7\}$

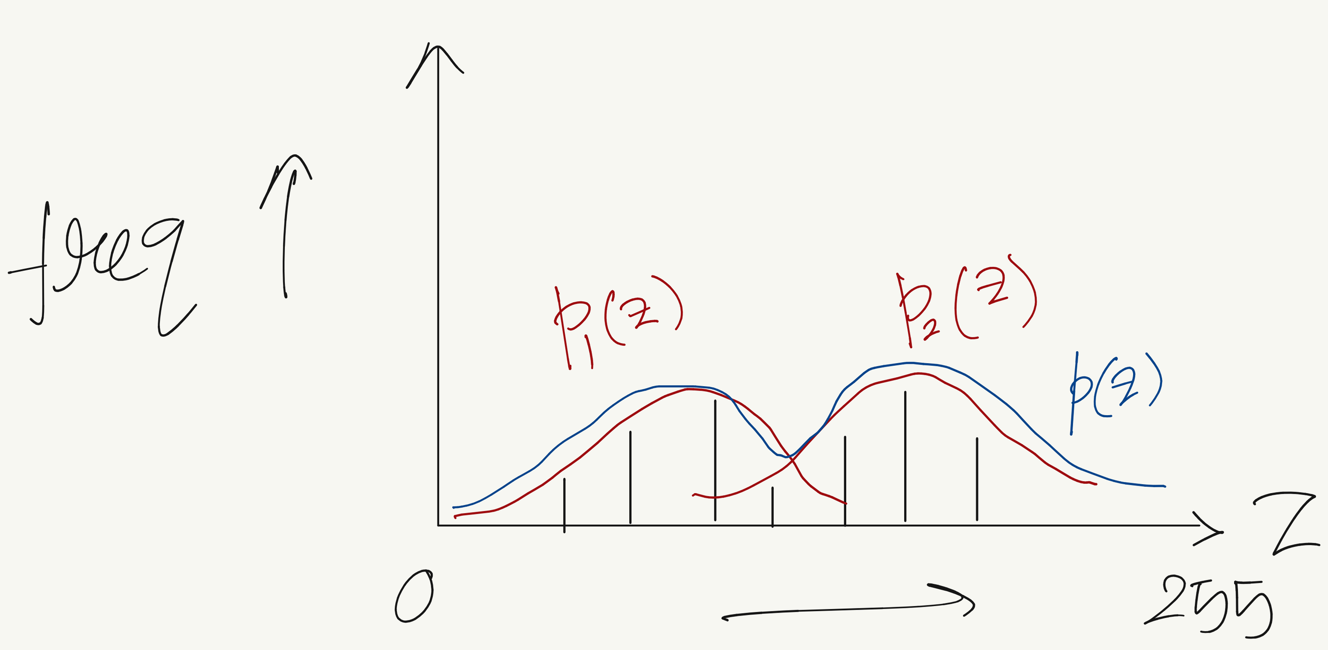
In general, $\bigcup_{i=1}^{n} R_i = D$, $R_i \cap R_j = \phi \;\; \forall\, i \neq j$.

$Prop(R_i) = True$, $Prop(R_i \cup R_j) = False$ if R_i and R_j are adjacent.









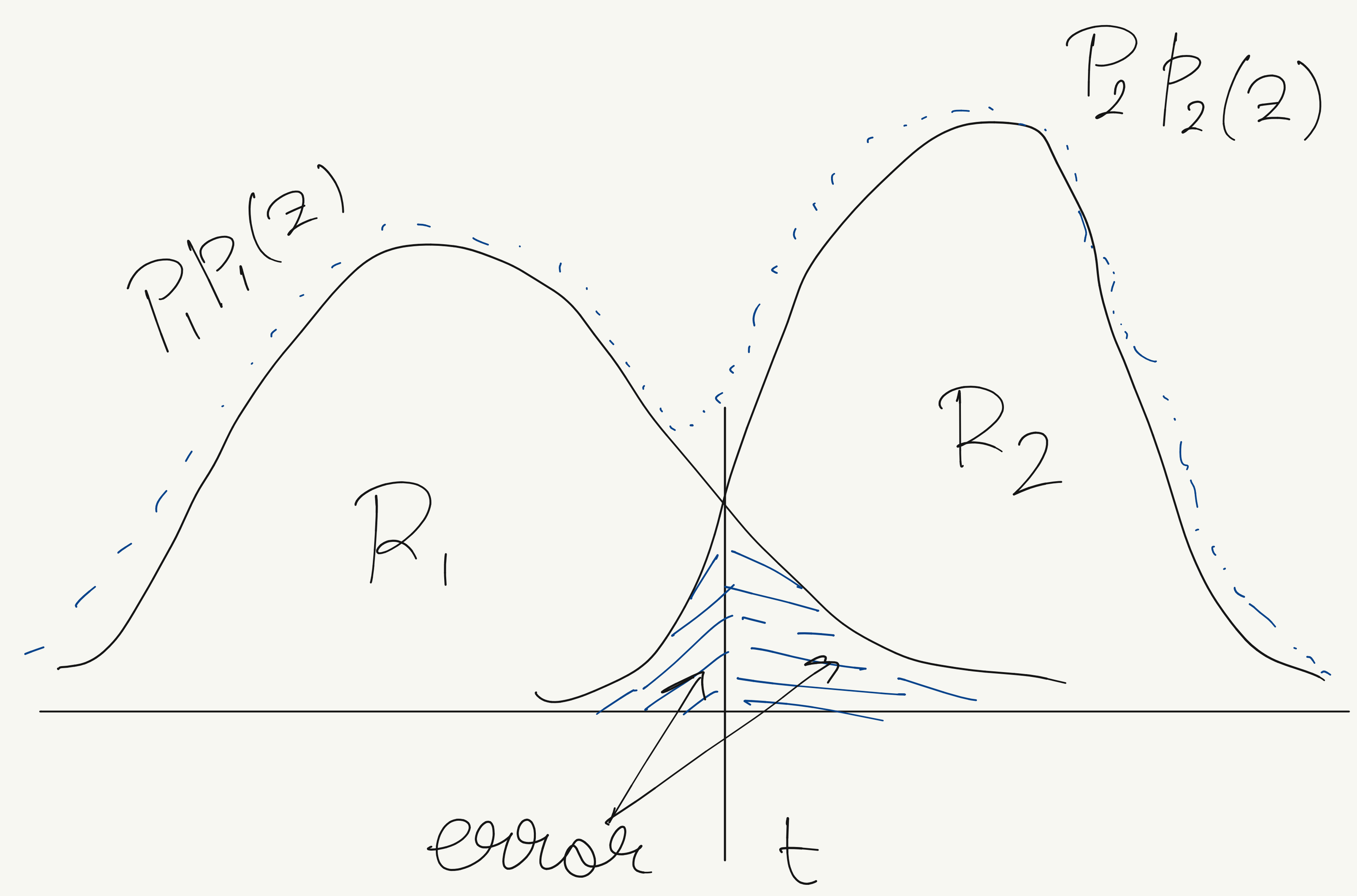
mean = μ_1 , std = σ_1

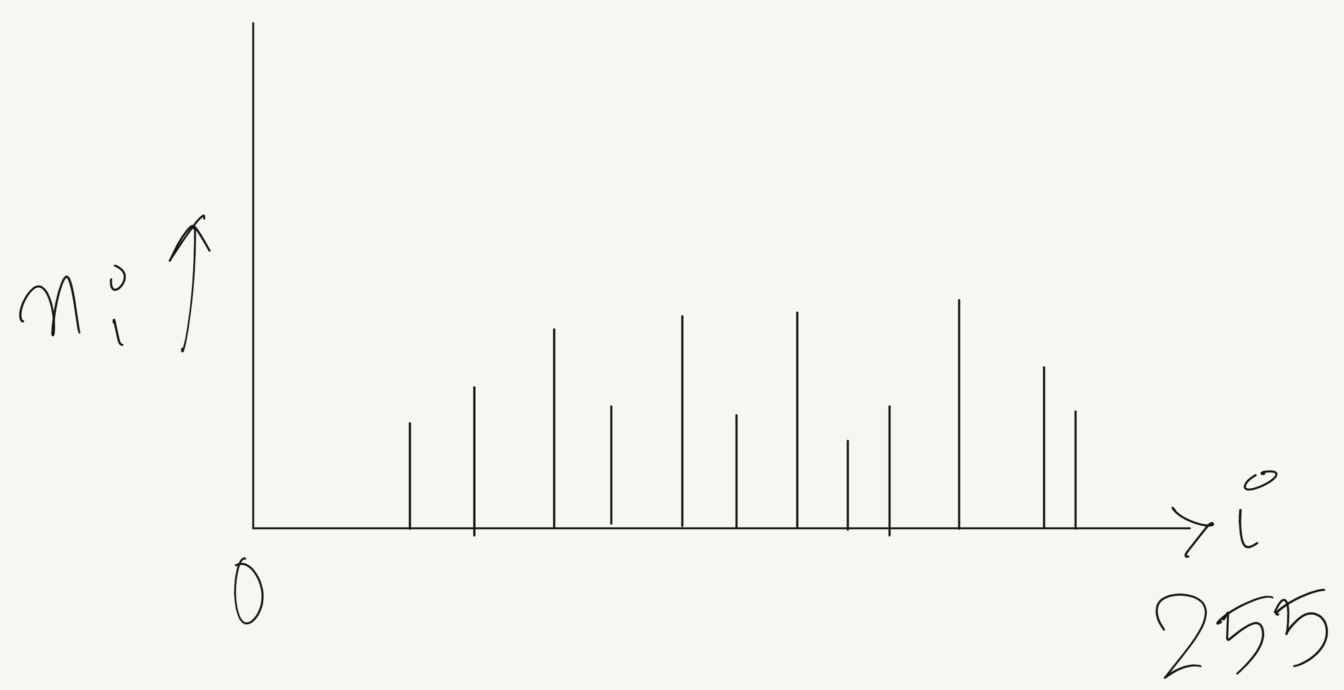
$$p_1(z) = \frac{1}{\sqrt{2\pi\sigma_1^2}}\, e^{-\frac{1}{2}\left(\frac{z-\mu_1}{\sigma_1}\right)^2}$$

And, $$p_2(z) = \frac{1}{\sqrt{2\pi\sigma_2^2}} e^{-\frac{1}{2}\left(\frac{z-\mu_2}{\sigma_2}\right)^2} \quad (\text{Assume, } \mu_1 < \mu_2)$$

$$p(z) = P_1 p_1(z) + P_2 p_2(z)$$

$$e(t) = \int_{-\infty}^{t} P_2 p_2(z)\,dz + \int_{t}^{\infty} P_1 p_1(z)\,dz$$





Then, $\sum_{i=0}^{255} n_i = N$

Thus, $\sum_{i=0}^{t-1} n_i = N_1$ and $\sum_{i=t}^{255} n_i = N_2$

Let, prior probability $= \frac{n_i}{N} = p_i$, then,

$$\sum_{i=0}^{t-1} p_i = P_1, \quad \sum_{i=t}^{255} p_i = P_2 \quad \text{and}$$

$$\sum_{i=0}^{t-1} i\,p_i = \mu_1, \quad \sum_{i=t}^{255} i\,p_i = \mu_2, \quad \sum_{i=0}^{255} i\,p_i = \mu = P_1\mu_1 + P_2\mu_2$$

$$\sum_{i=0}^{t-1} p_i(i-\mu_1)^2 = \sigma_1^2, \quad \sum_{i=t}^{255} p_i(i-\mu_2)^2 = \sigma_2^2, \quad \sigma^2 = P_1\sigma_1^2 + P_2\sigma_2^2$$

$$P_1 + P_2 = 1 \Rightarrow P_2(t) = 1 - P_1(t)$$

$$\sigma_b^2 = P_1(t)(\mu_1(t) - \mu)^2 + P_2(t)(\mu_2(t) - \mu)^2$$

$$P_1(t) = \sum_{i=0}^{t-1} p_i, \quad \mu_1(t) = \sum_{i=0}^{t-1} i\,p_i$$

$$P_1(t+1) = P_1(t) + p_{t+1} \quad \text{and} \quad \mu_1(t+1) = \mu_t + (t+1)\,p_{t+1}$$

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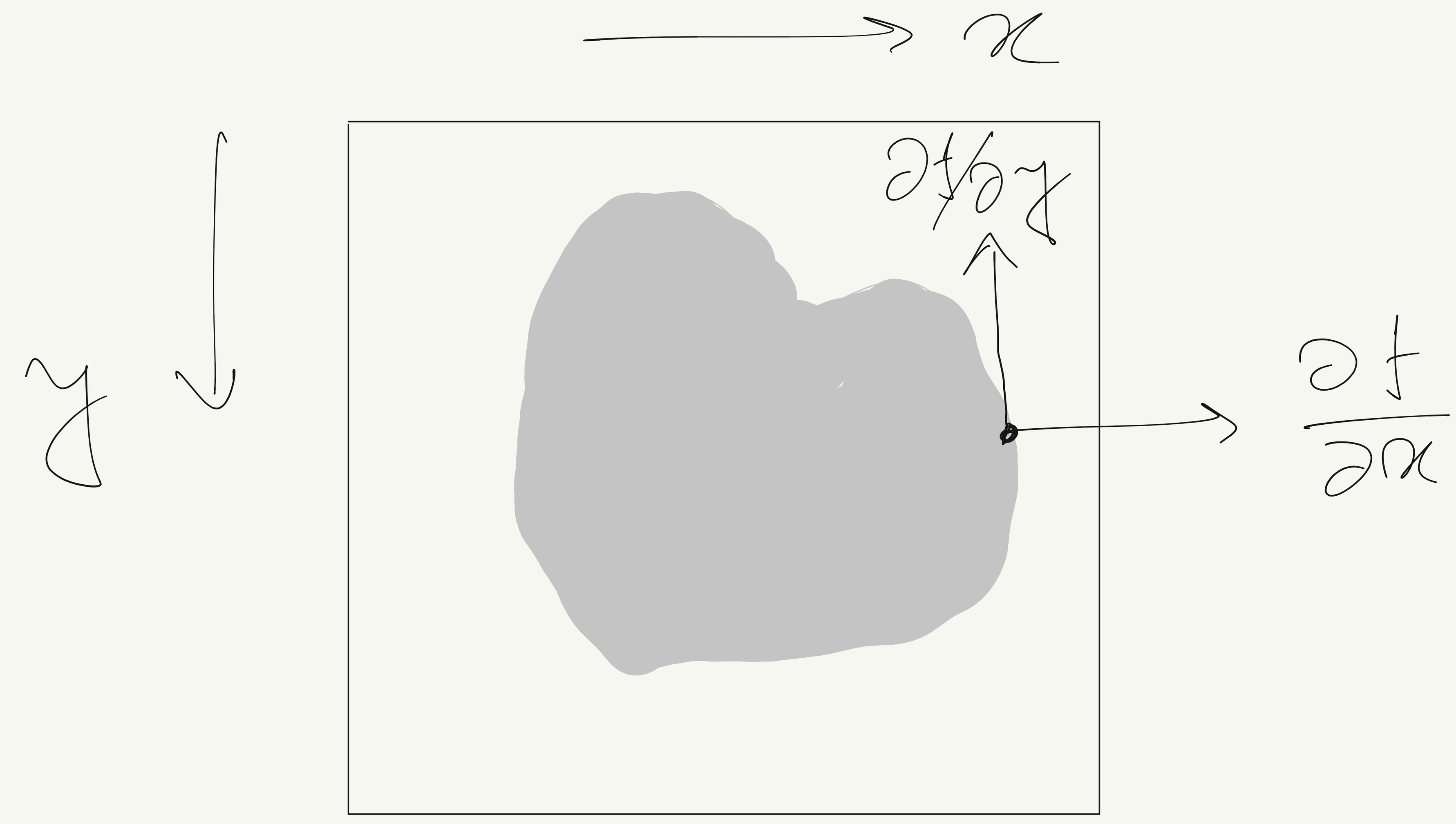
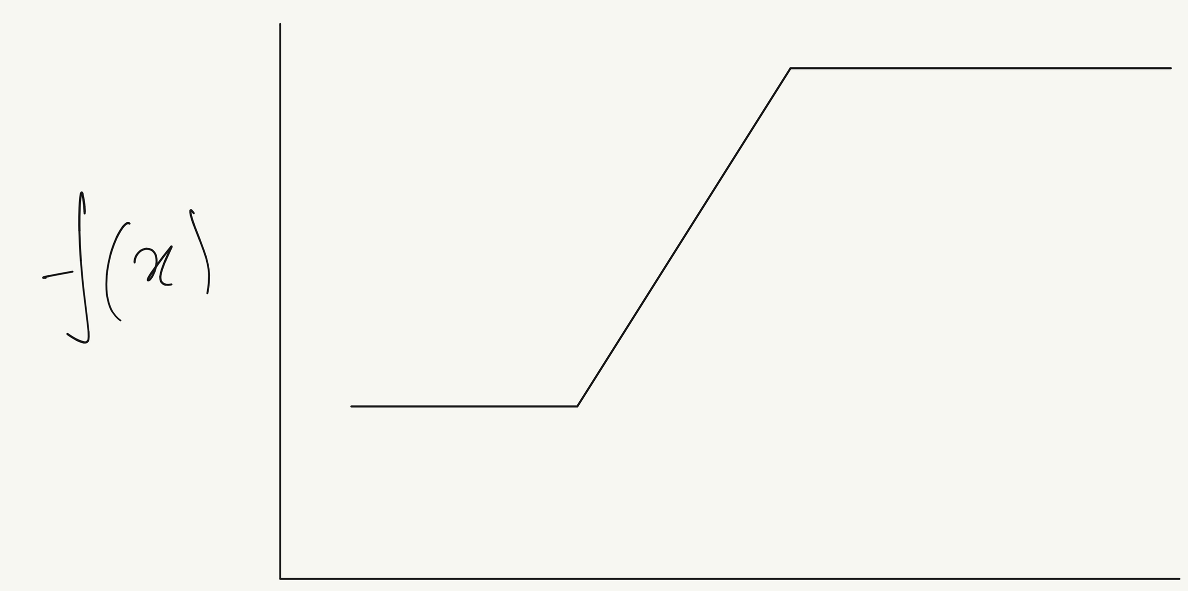
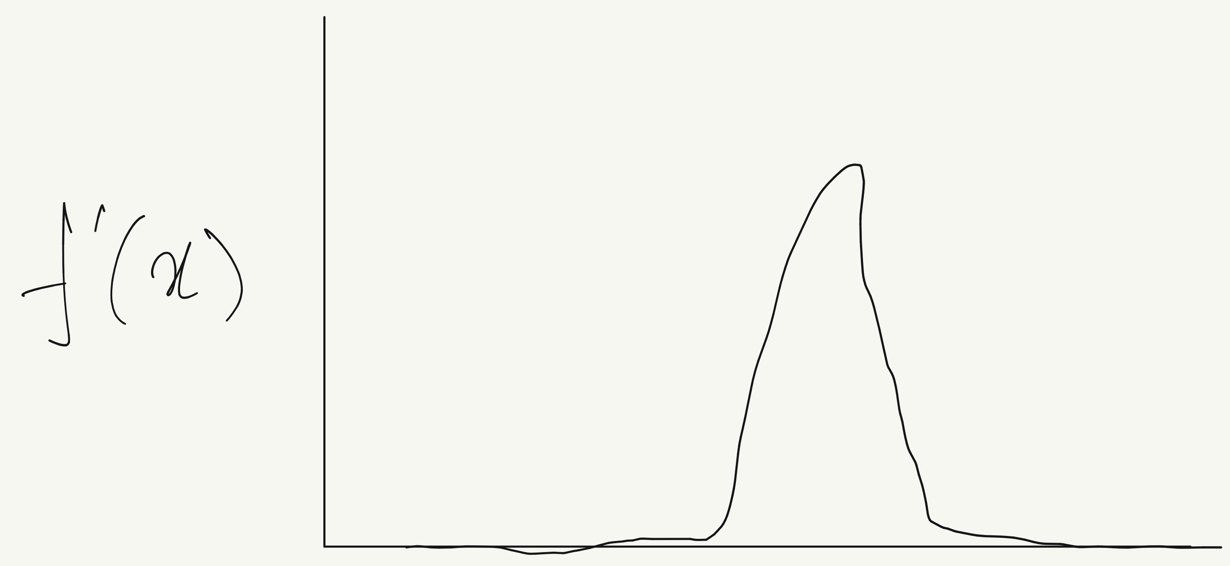
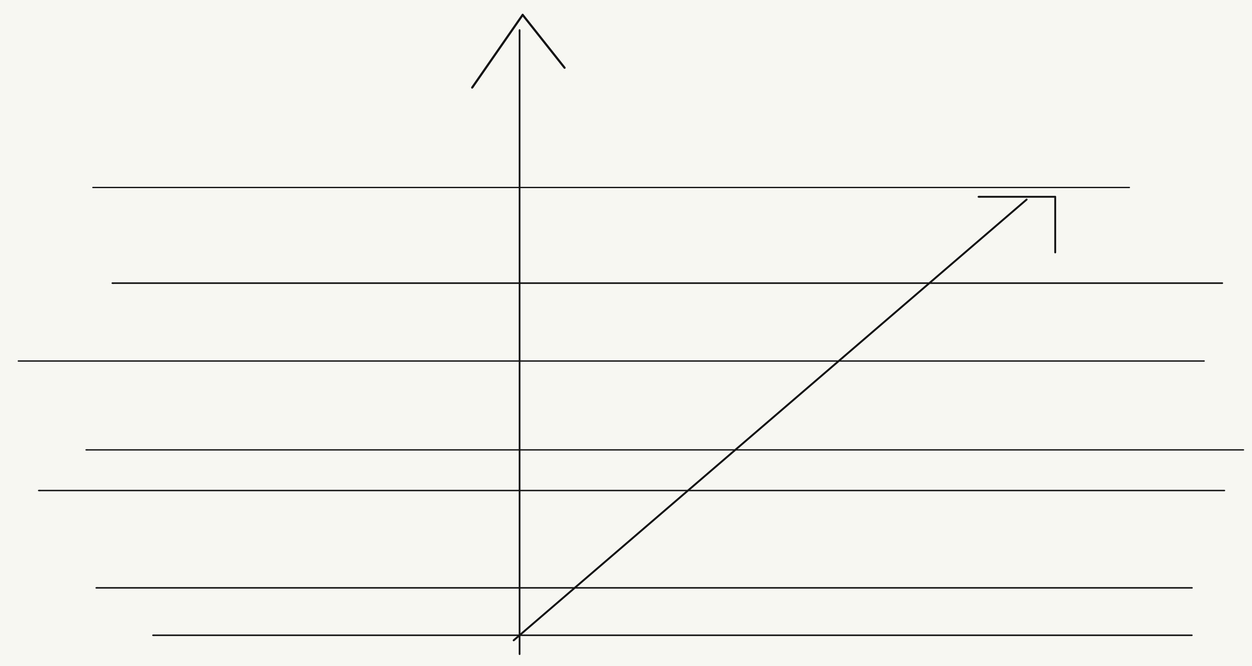
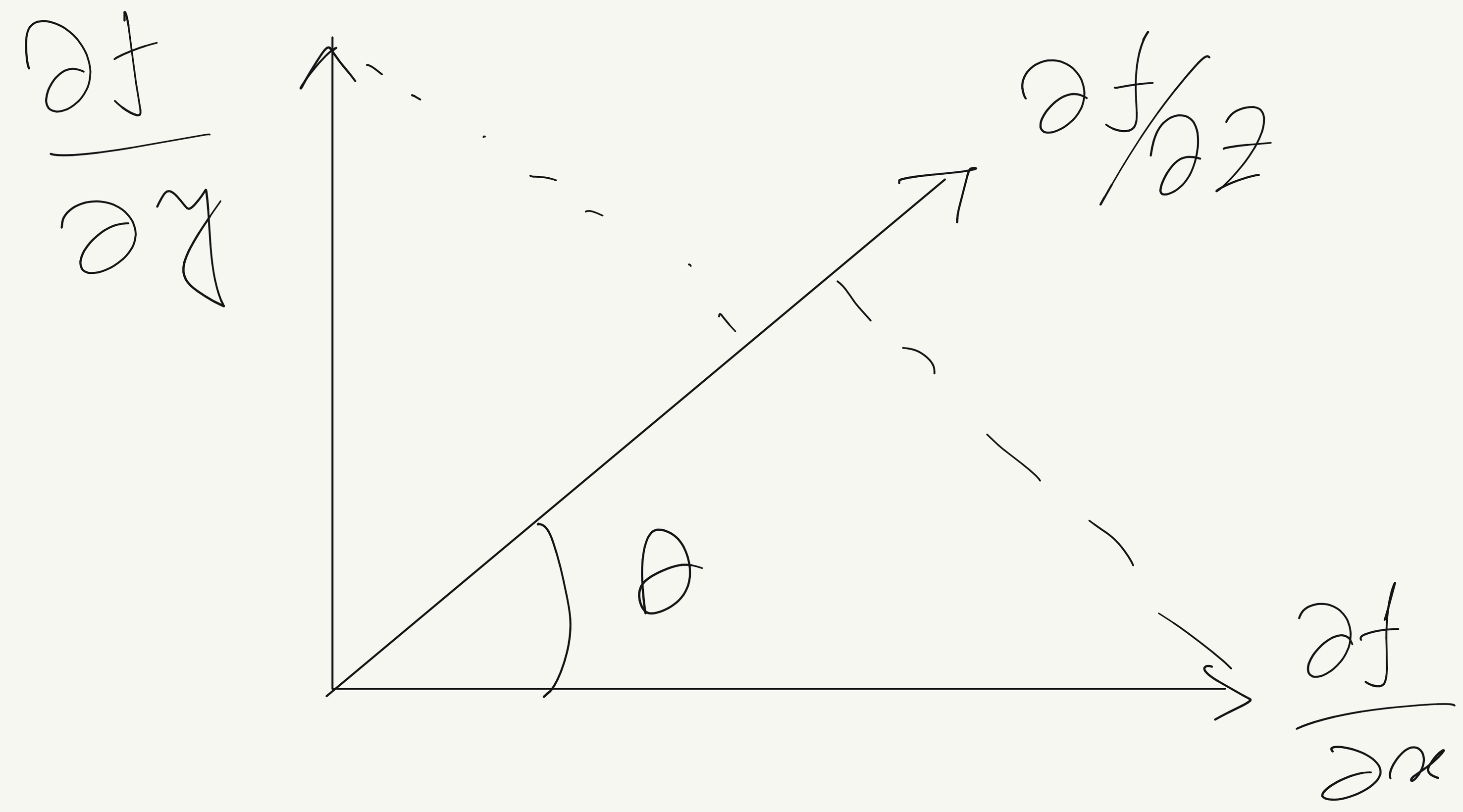
Edge Detection :











$$\therefore \frac{\partial f}{\partial z} = \frac{\partial f}{\partial x}\cos\theta + \frac{\partial f}{\partial y}\sin\theta$$

$$\therefore \frac{\partial}{\partial \theta}\left(\frac{\partial f}{\partial z}\right) = -\frac{\partial f}{\partial x}\sin\theta + \frac{\partial f}{\partial y}\cos\theta = 0$$

$$\Rightarrow \theta = \tan^{-1}\left(\frac{\partial f}{\partial y}\Big/\frac{\partial f}{\partial x}\right)$$

$$\therefore \frac{\partial^2}{\partial \theta^2}\left(\frac{\partial f}{\partial z}\right) = -\frac{\partial f}{\partial x}\cos\theta - \frac{\partial f}{\partial y}\sin\theta$$

$$= -\left(\frac{\partial f}{\partial x}\cdot\frac{\partial f/\partial x}{\sqrt{\left(\frac{\partial f}{\partial x}\right)^2+\left(\frac{\partial f}{\partial y}\right)^2}}\right) - \left(\frac{\partial f}{\partial y}\cdot\frac{\partial f/\partial y}{\sqrt{\left(\frac{\partial f}{\partial x}\right)^2+\left(\frac{\partial f}{\partial y}\right)^2}}\right)$$

$$= -\left[\left(\frac{\partial f}{\partial x}\right)^2+\left(\frac{\partial f}{\partial y}\right)^2\right]^{1/2}$$

$$\therefore \frac{\partial f}{\partial z} = \left[\left(\frac{\partial f}{\partial x}\right)^2+\left(\frac{\partial f}{\partial y}\right)^2\right]^{1/2}$$

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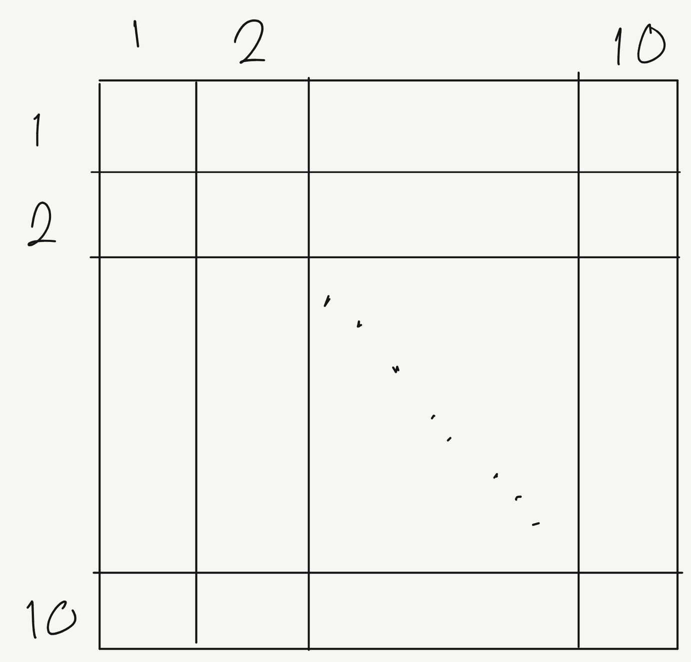
Histogram equilization :

$$T : r_i \rightarrow s_i$$

$r_i \in \{0, 1, 2, \ldots, 255\}$

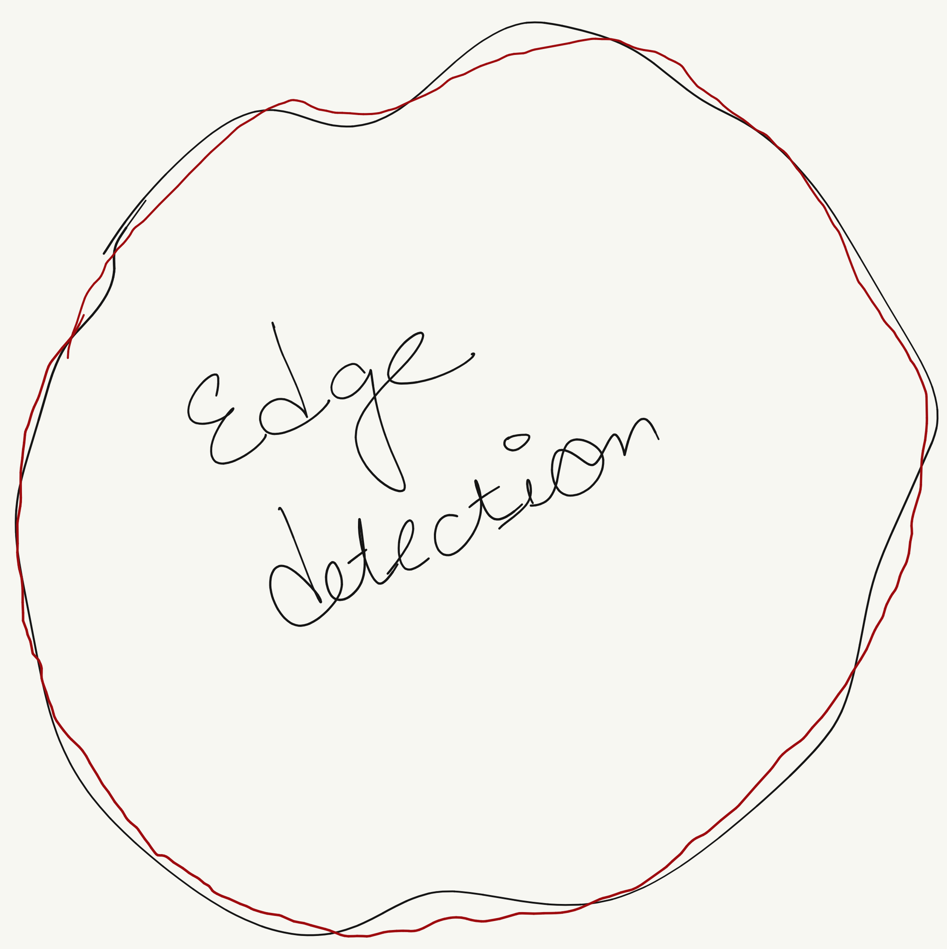
$$s_i = (L-1)\, c_i = (L-1) \sum_{K=0}^{i} p_K$$

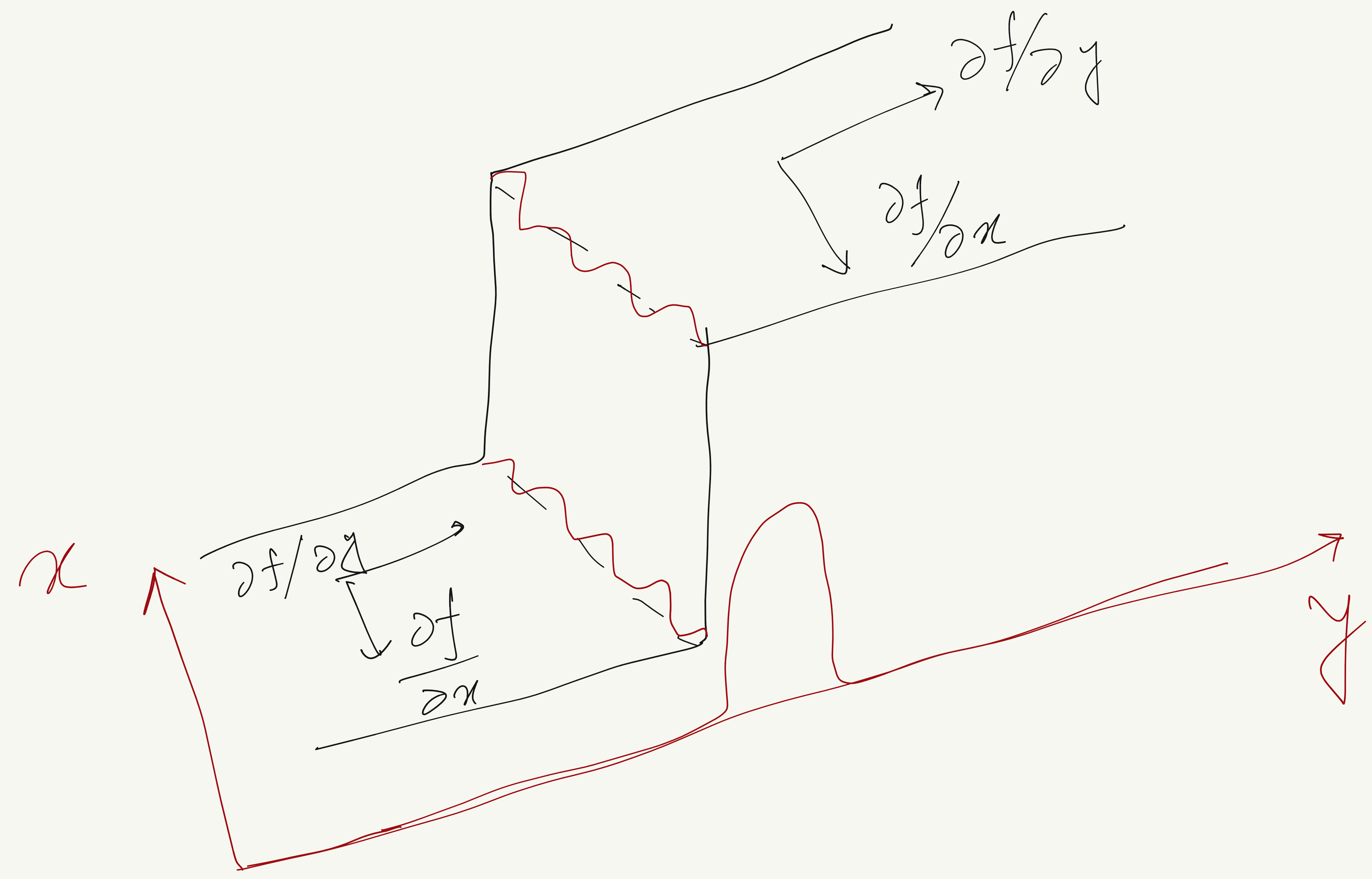


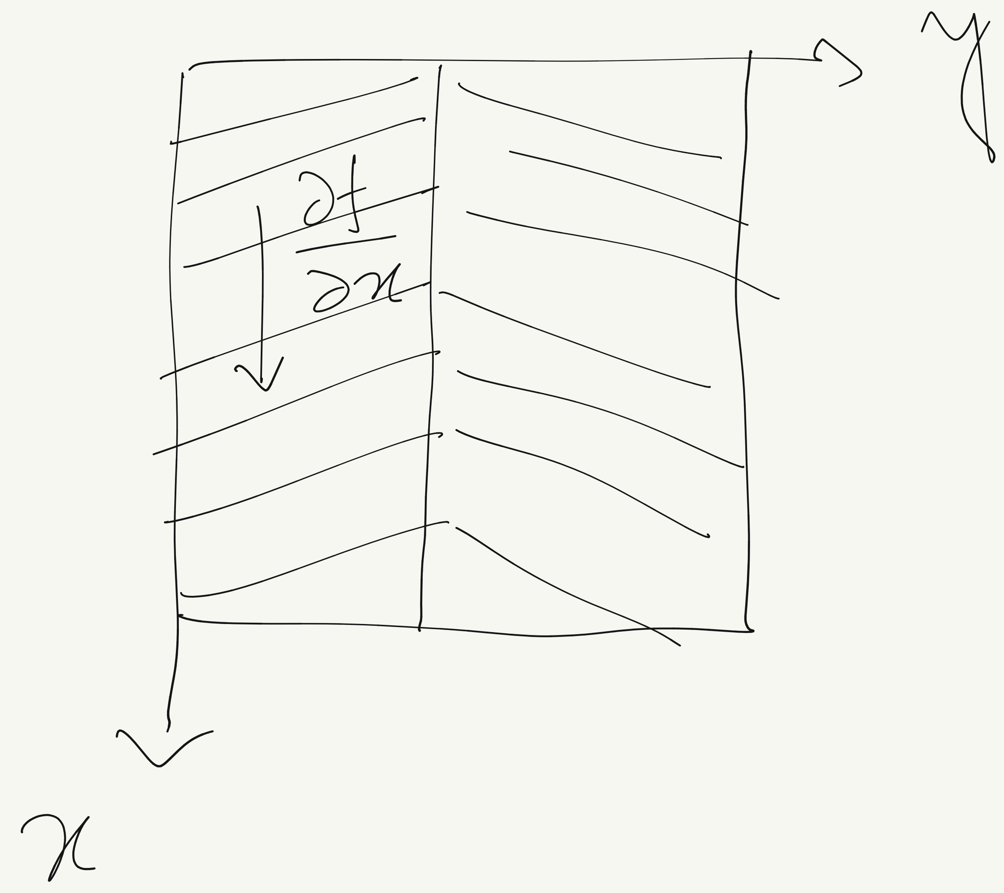
10X10

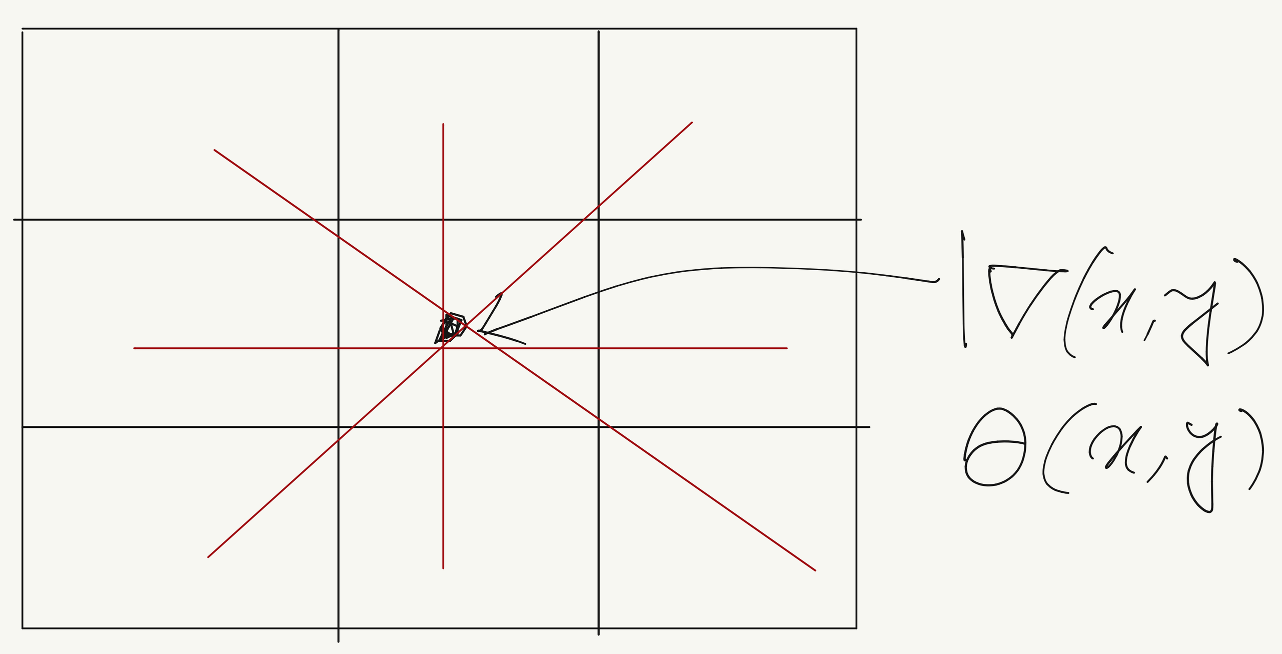
r_i	0	1	2	3	4	5	6	7	Total
n_i	0	4	13	7	35	25	16	0	100
p_i	0	0.04	0.13	0.07	0.35	0.25	0.16	0	1
c_i	0	0.04	0.17	0.24	0.59	0.84	1	1	X
$7c_i$	0	0.28	1.19	1.68	4.13	5.88	7	7	X
s_i	0	0	1	2	4	6	7	7	X

s_i	0	1	2	3	4	5	6	7	Total
n_i	4	13	7	0	35	0	25	16	100



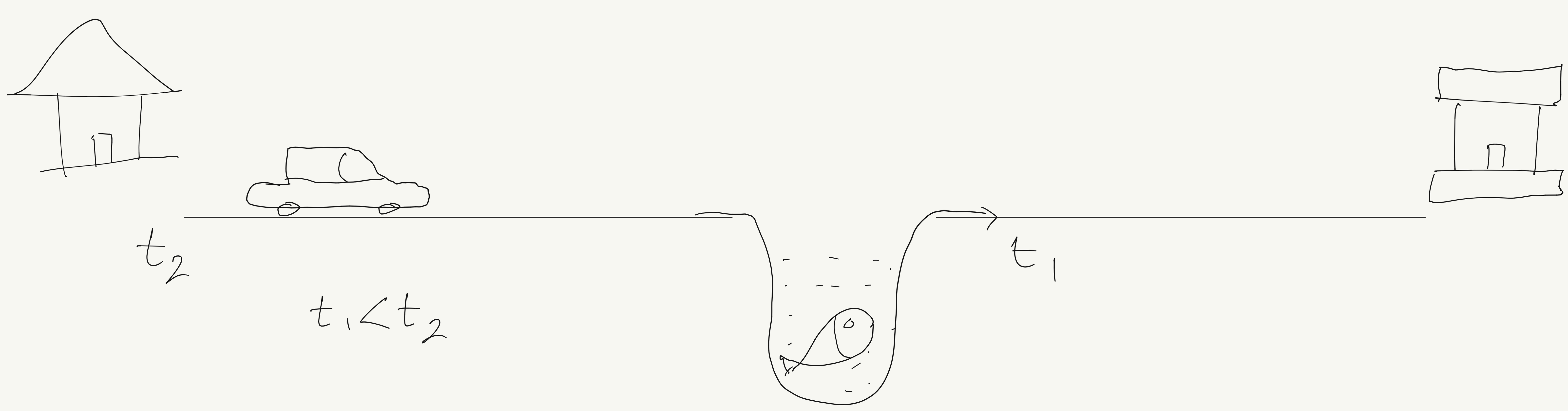






$0^\circ \leq \theta < 360^\circ$

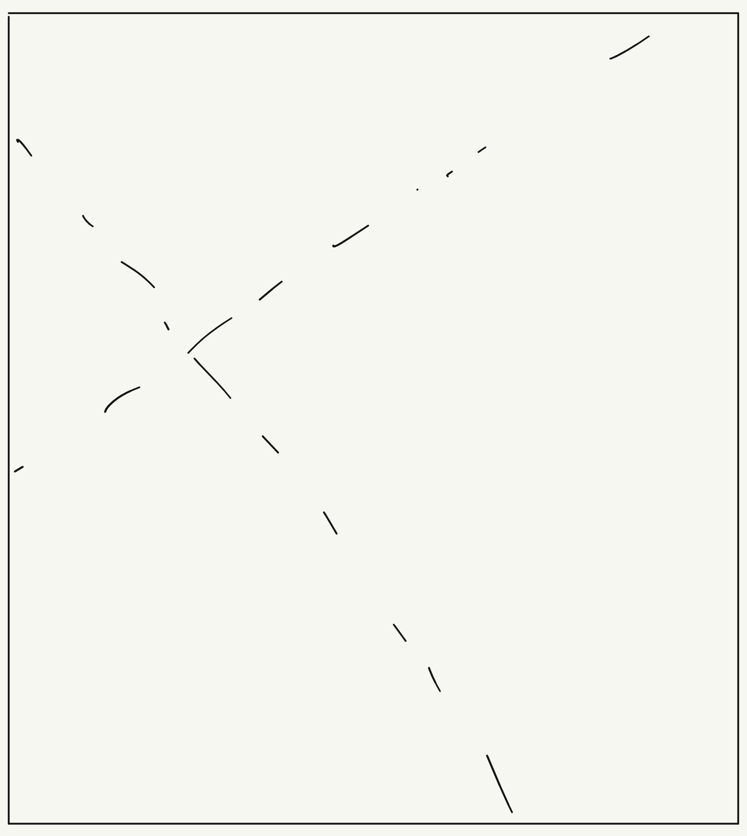
$-22.5^\circ \leq \theta \leq 22.5^\circ$



f	e	d	e	f
e	c	b	c	e
d	b	a	b	d
e	c	b	c	e
f	e	d	e	f

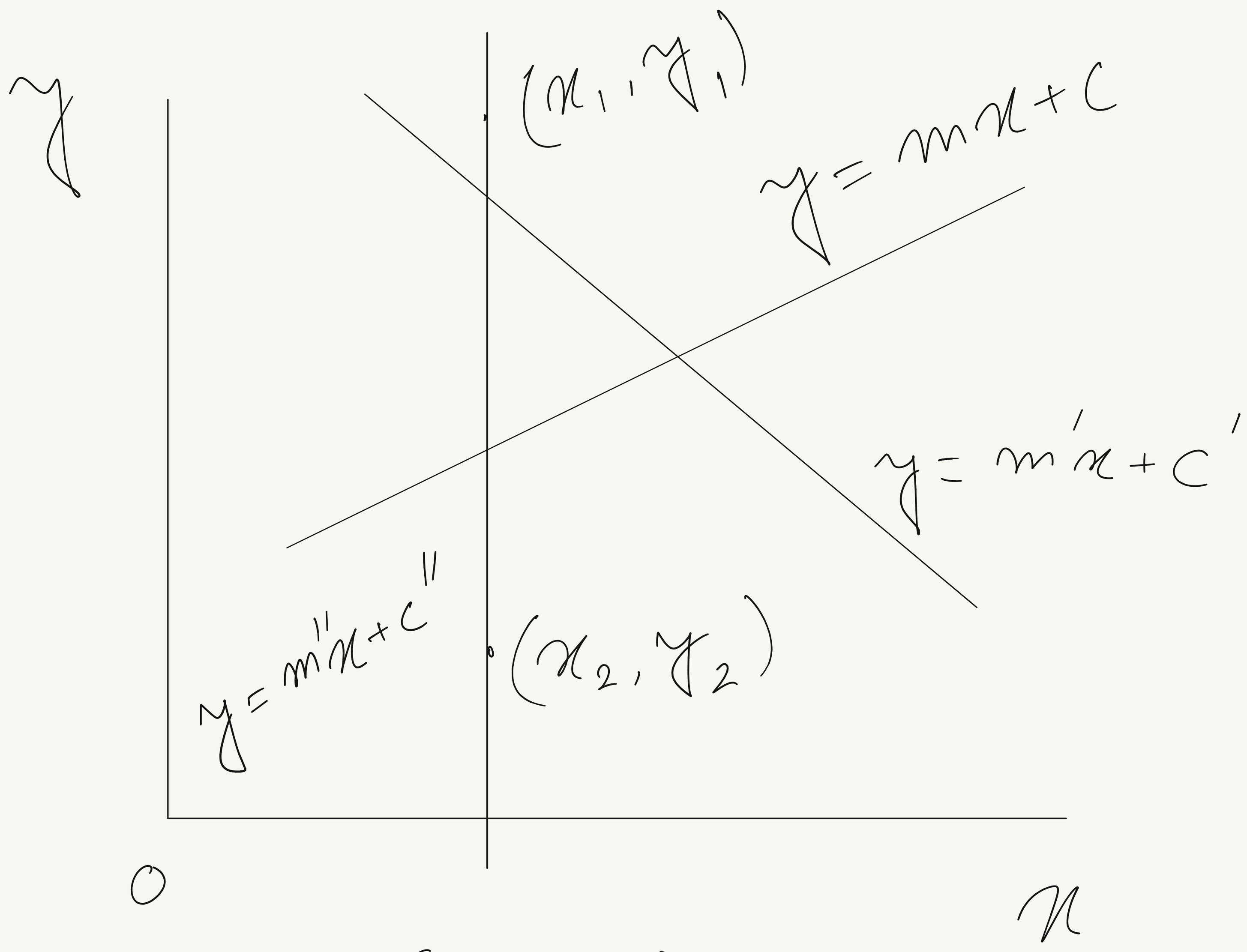
$$a > b > c > d > e > f$$

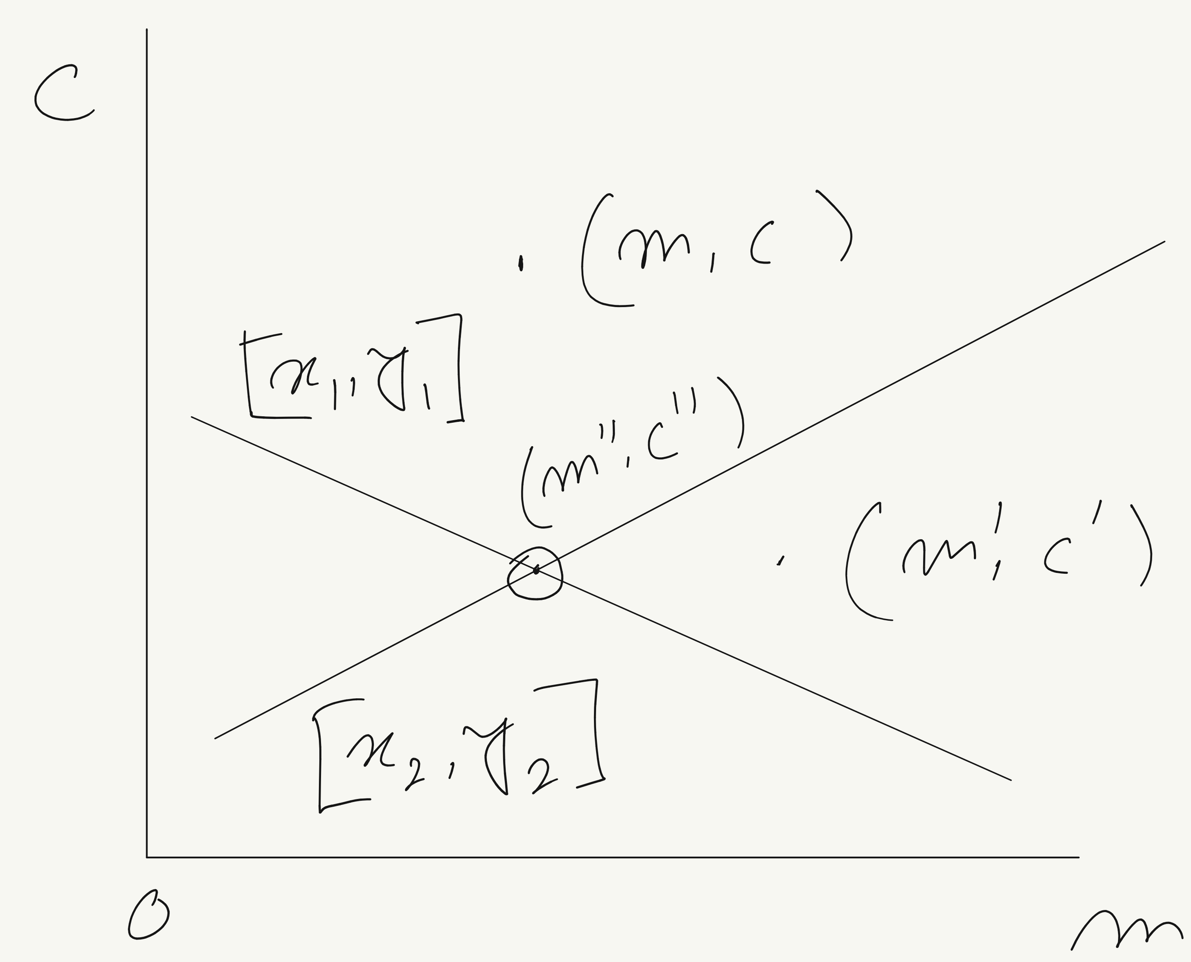
$$\frac{1}{\sum w_{ij}}$$



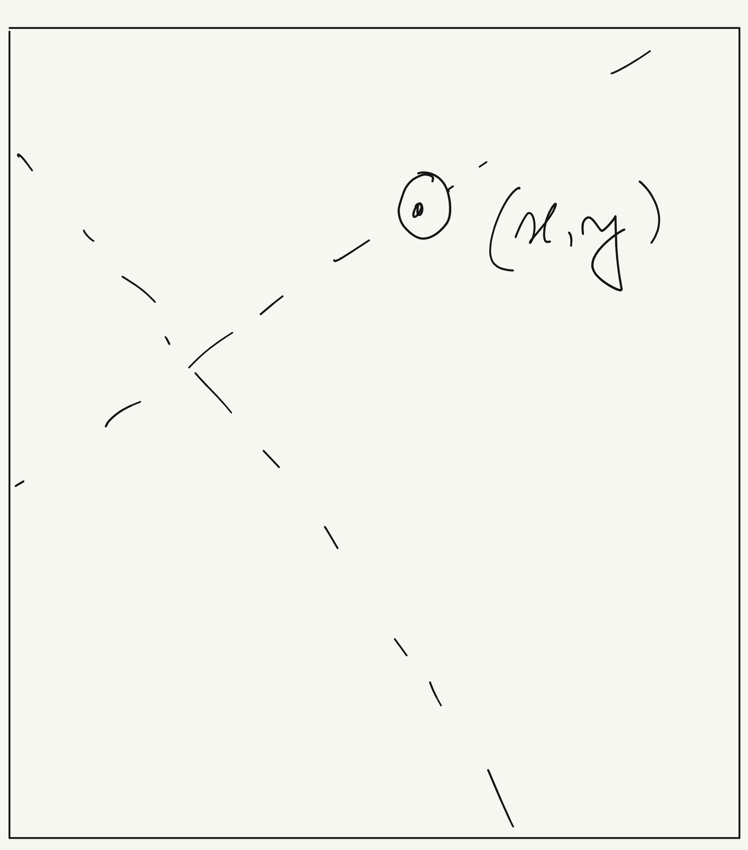
1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9

Smoothing





$$y = m(x - x_1) + y_1$$



$y = mx + c$

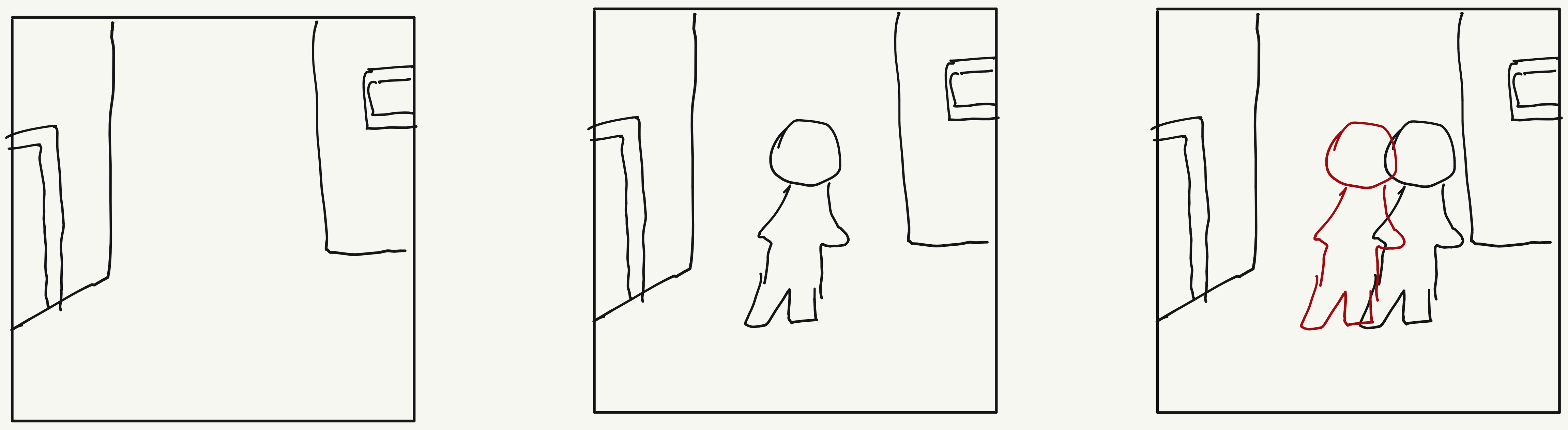
$c \rightarrow$

$m \downarrow$

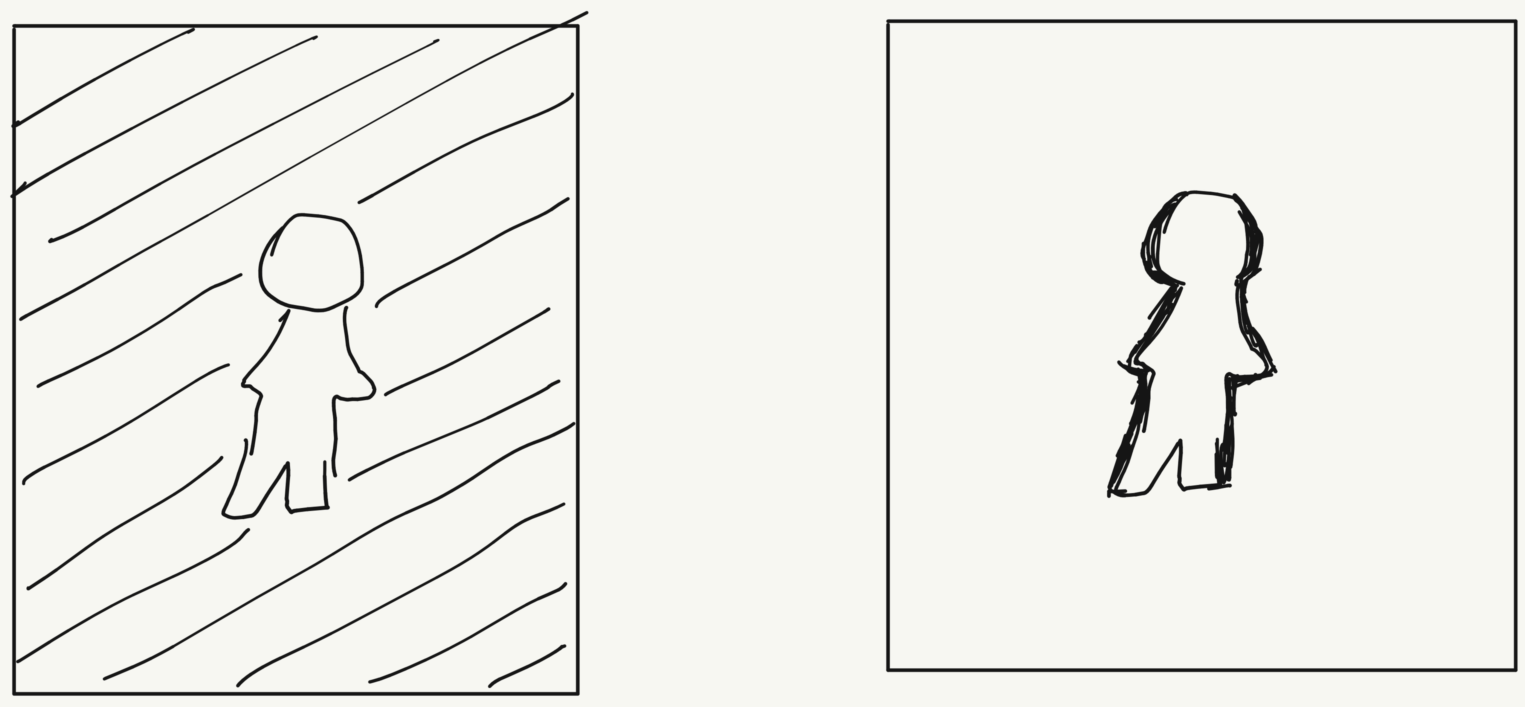
	0	1	2	3	4	...	K
0		1		1			
1		1	1				1
2		1	1	1	1	1	
3	1	1	3				
4	1	1	1				
⋮				1		N	
		1	1				
L			1	1			

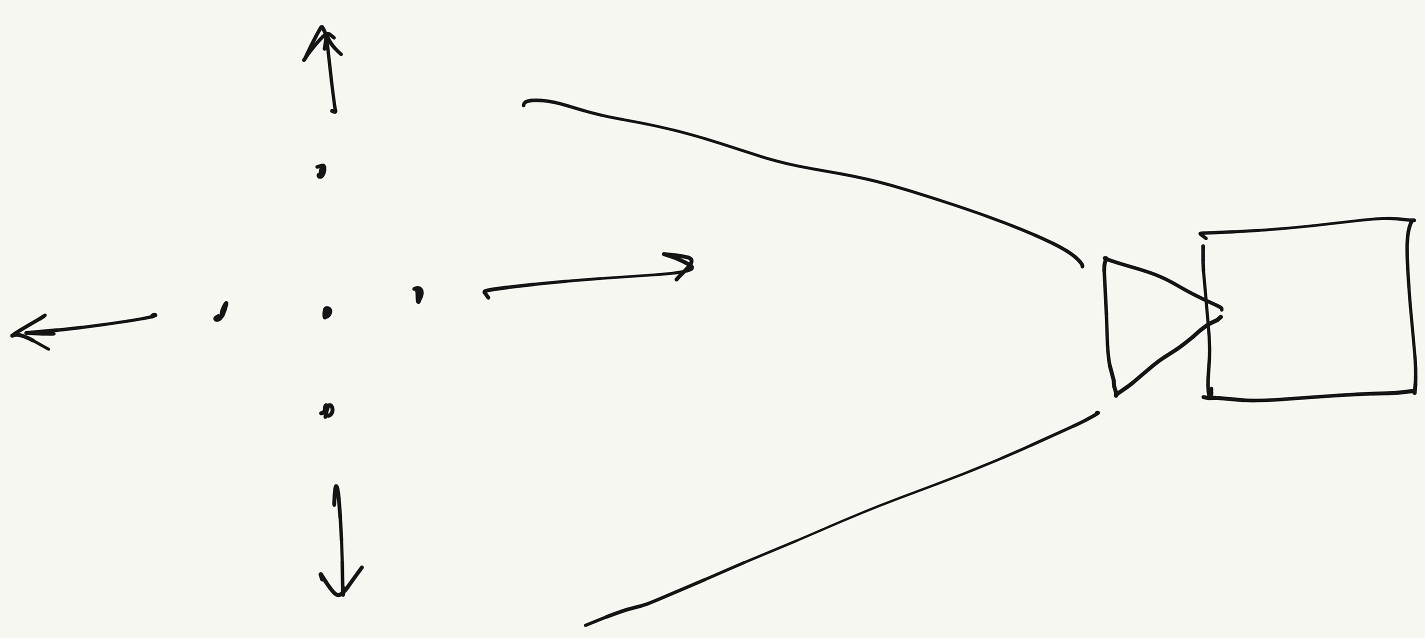
Accumulator

03/04/2023



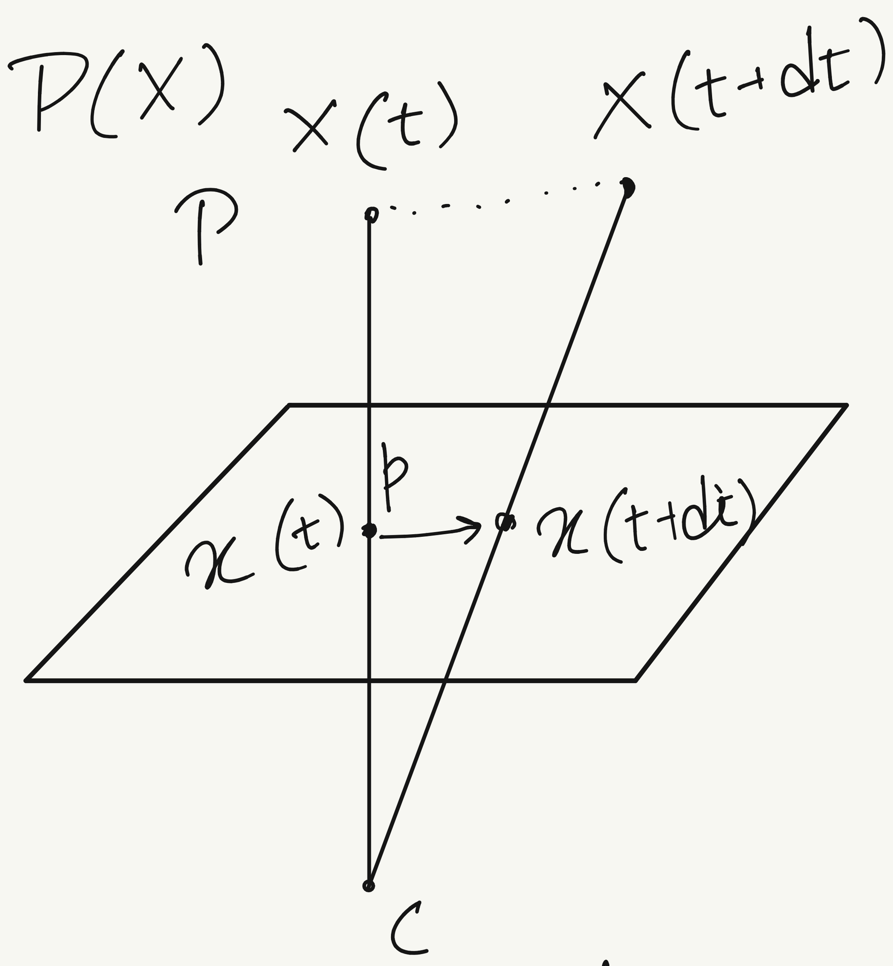
$t=0$ $\qquad$ $t=1$ $\qquad$ $t=2$





Camera position

05/04/2023



$$X = \begin{pmatrix} u \\ v \\ w \end{pmatrix} \quad \text{ie} \quad X(t) = \begin{pmatrix} u(t) \\ v(t) \\ w(t) \end{pmatrix}$$

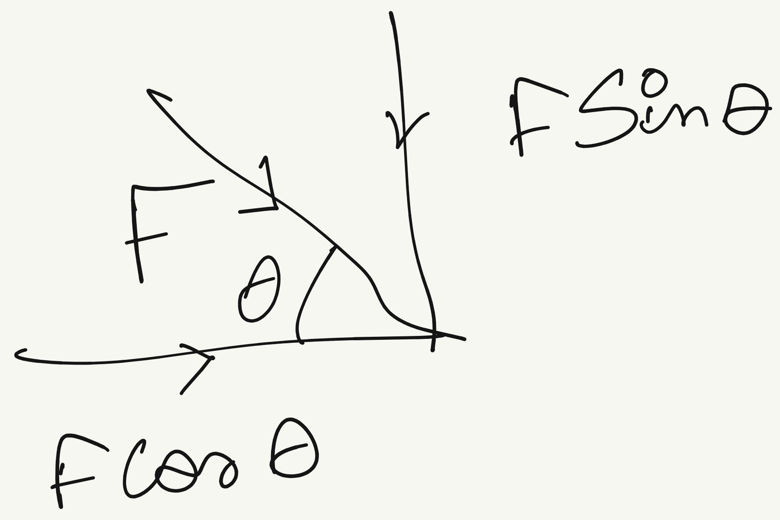
$$x(t) = f \cdot \frac{u(t)}{w(t)} \quad , \quad y(t) = f \cdot \frac{v(t)}{w(t)}$$

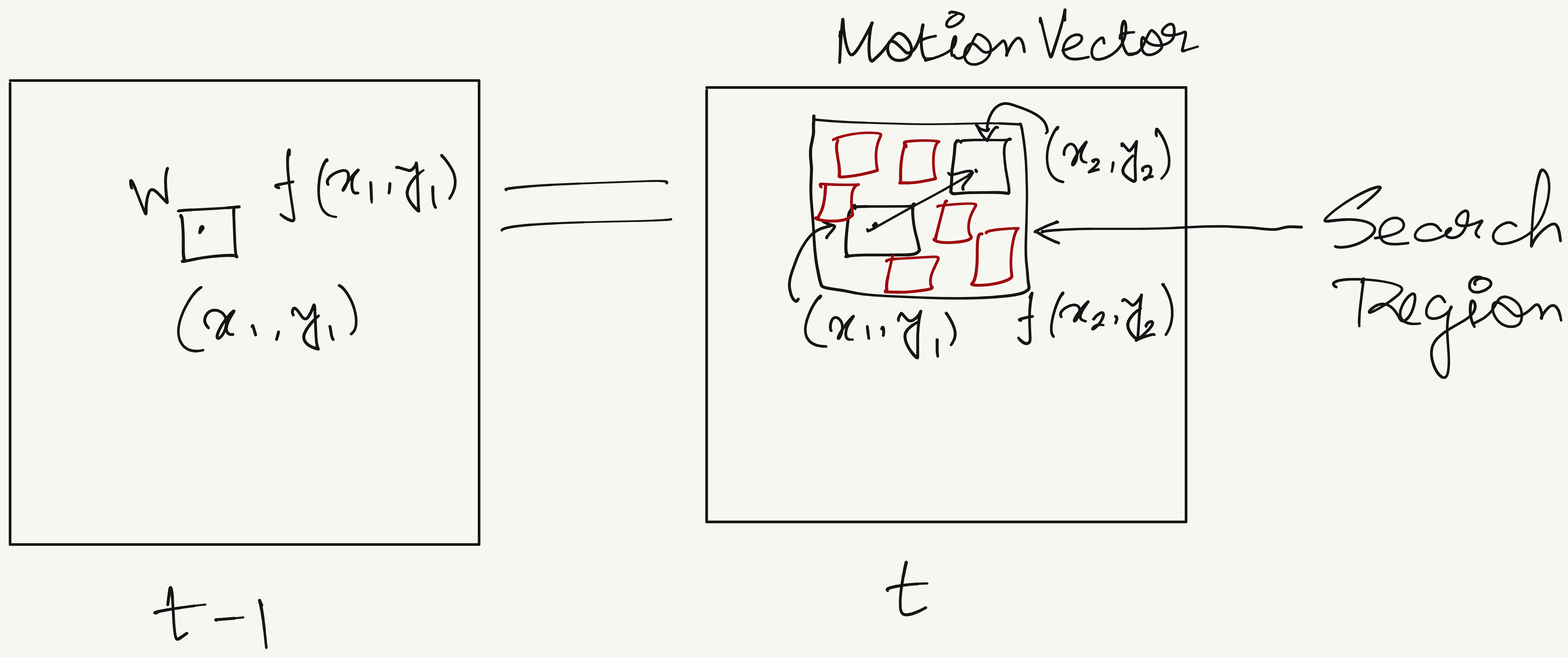
$$V_x = \frac{dx(t)}{dt} = \frac{\frac{du}{dt} w - \frac{dw}{dt} u}{w^2} \cdot f = \frac{f V_u - V_w \cdot x}{w} \qquad \left[f \cdot \frac{u}{w} = x \right]$$

$$V_y = \frac{dy(t)}{dt} = \frac{\frac{dv}{dt} w - \frac{dw}{dt} v}{w^2} \, f = \frac{f \cdot V_v - V_w \cdot y}{w} \qquad \left[f \cdot \frac{v}{w} = y \right]$$

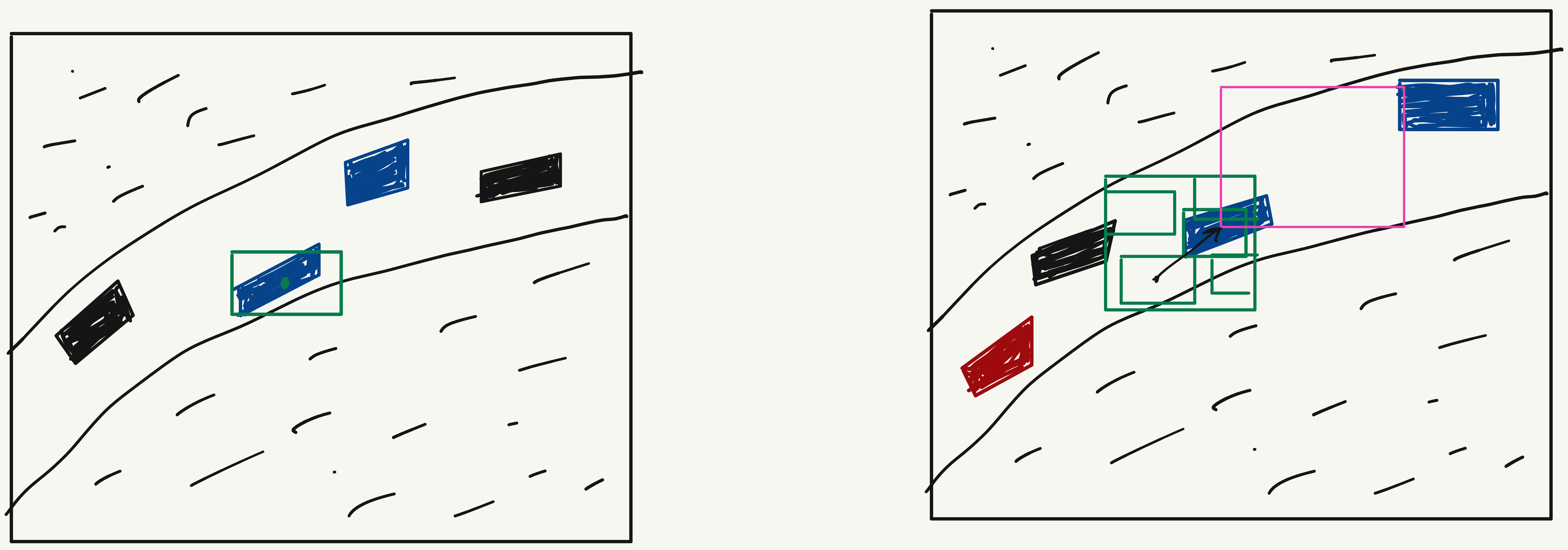
$$\therefore \begin{pmatrix} V_x \\ V_y \end{pmatrix} = \frac{1}{w} \left[\begin{pmatrix} f V_u \\ f V_v \end{pmatrix} - V_w \begin{pmatrix} x \\ y \end{pmatrix} \right]$$

$$\therefore V_x = \frac{1}{w} \left[\underset{2\times 1}{V_0} - V_w \underset{2\times 1}{X} \right] = \begin{pmatrix} V_x \\ V_y \end{pmatrix} \equiv \text{Optical Flow.}$$





$$\sum_{(x,y)\in W} \left| f(x,y) - f(x+u, y+v) \right|^2$$

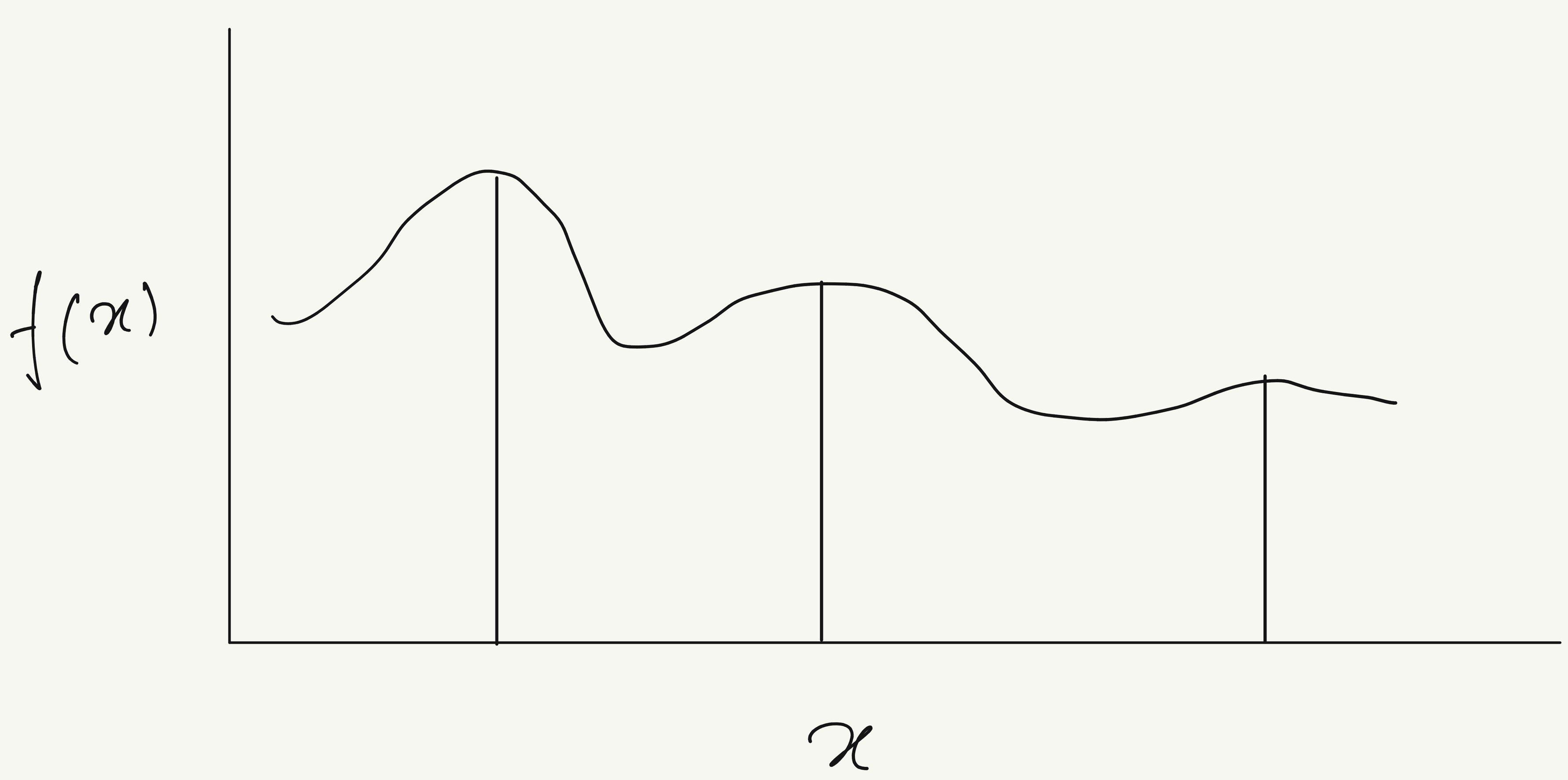


$$I(x, y, t-1) = I(x+u, y+v, t) \quad \forall (x,y)$$

$$u(x,y) = \frac{dx}{dt}\Delta t \quad , \quad v(x,y) = \frac{dy}{dt}\Delta t \, .$$

$$(x_1, y_1) \longrightarrow (x_2, y_2)$$

$$\begin{array}{ccc} (x_1, y_1) & & (x_2, y_2) \\ \parallel\!\mid & & \parallel\!\mid \\ (x, y, t-1) & & (x+u, y+v, t) \end{array}$$



$$f(x) = x^2 \sin x + 3x$$

$$I(x,y,t) = I(x+\Delta x, y+\Delta y, t+\Delta t)$$

$$= I(x,y,t) + \frac{\partial I}{\partial x}\Delta x + \frac{\partial I}{\partial y}\Delta y + \frac{\partial I}{\partial t}\Delta t + H.O.T. \ldots$$

$$\simeq I(x,y,t) + \frac{\partial I}{\partial x}\Delta x + \frac{\partial I}{\partial y}\Delta y + \frac{\partial I}{\partial t}\Delta t$$

$$\Rightarrow \frac{\partial I}{\partial x}\Delta x + \frac{\partial I}{\partial y}\Delta y + \frac{\partial I}{\partial t}\Delta t = 0$$

$$\Rightarrow \frac{\partial I}{\partial x} \cdot \frac{\Delta x}{\Delta t} + \frac{\partial I}{\partial y} \cdot \frac{\Delta y}{\Delta t} + \frac{\partial I}{\partial t} = 0$$

$$\Rightarrow \frac{\partial I}{\partial x} \cdot V_x + \frac{\partial I}{\partial y} \cdot V_y + \frac{\partial I}{\partial t} = 0$$

$$\Rightarrow \vec{\nabla} I \cdot \vec{v} = - I_t$$

$$ax + by = c$$

$$\Rightarrow \begin{pmatrix} a & b \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = c$$

$$\Rightarrow \begin{pmatrix} a \\ b \end{pmatrix} \cdot \begin{pmatrix} x \\ y \end{pmatrix} = c$$

$$\Rightarrow \begin{pmatrix} \frac{\partial I}{\partial x} & \frac{\partial I}{\partial y} \end{pmatrix} \begin{pmatrix} V_x \\ V_y \end{pmatrix} = - I_t$$

where, $\vec{\nabla} I = \begin{pmatrix} \frac{\partial I}{\partial x} & \frac{\partial I}{\partial y} \end{pmatrix}^T$, $\vec{v} = \begin{pmatrix} V_x & V_y \end{pmatrix}^T$

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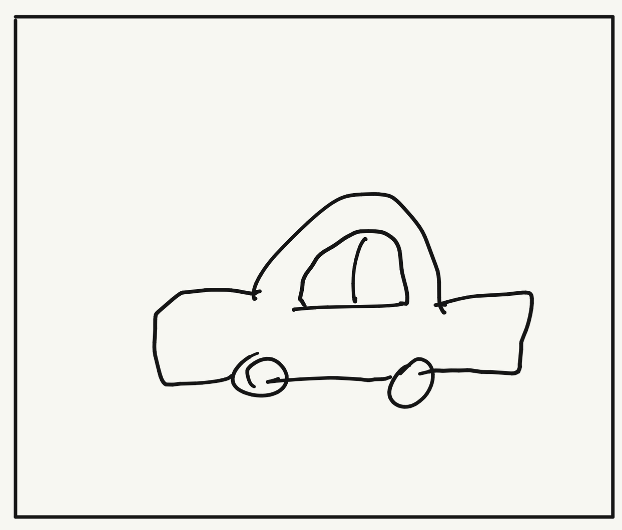
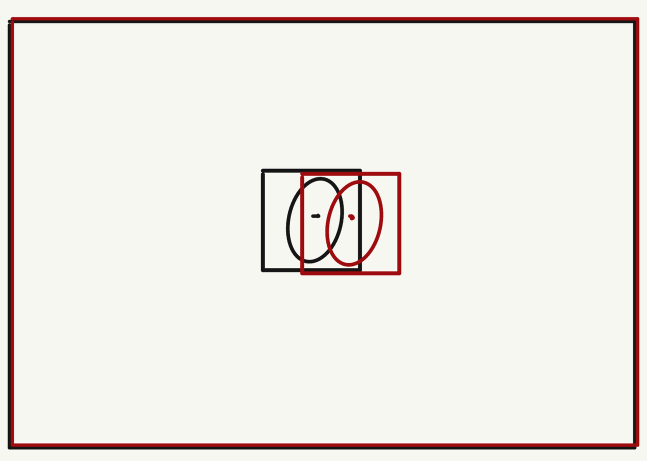
$$I_x u + I_y v + I_t = 0$$

$$\begin{pmatrix} u \\ v \end{pmatrix} \qquad \nabla I = (I_x, I_y)$$





$t = 1$

$t = 0$

Tracking the moving object.

Assignment 2 $\rightarrow$ Tracking an object first manually then automatically. (Software: Any)

Types of Detector :

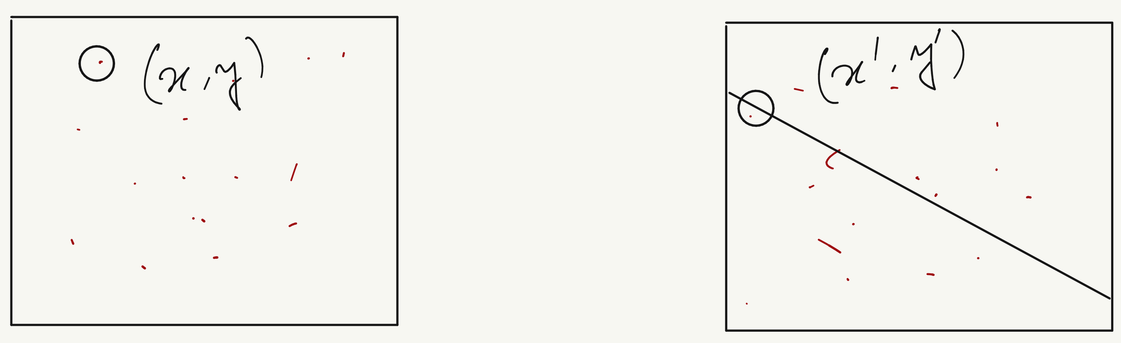
20/04/2023

1) Harris Corner Detector
2) Histogram of Oriented Gradient (HOG)
3) Scale Invariant Feacture Transformation

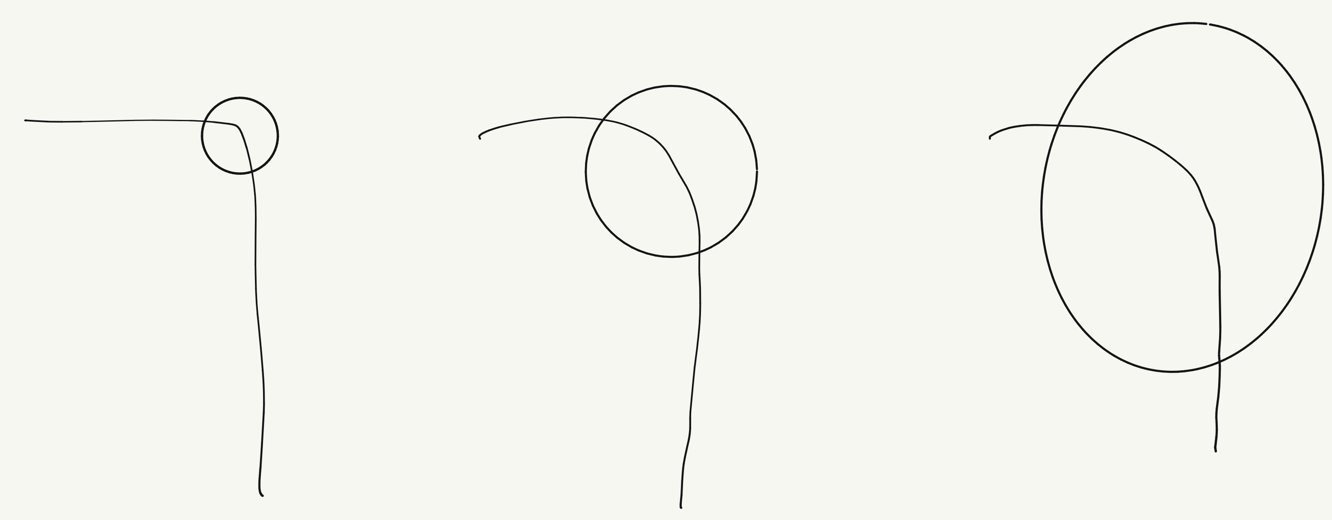
24/04/2023

⊙ P

$$\boxed{\omega = f \cdot \frac{B}{x - x'}}$$

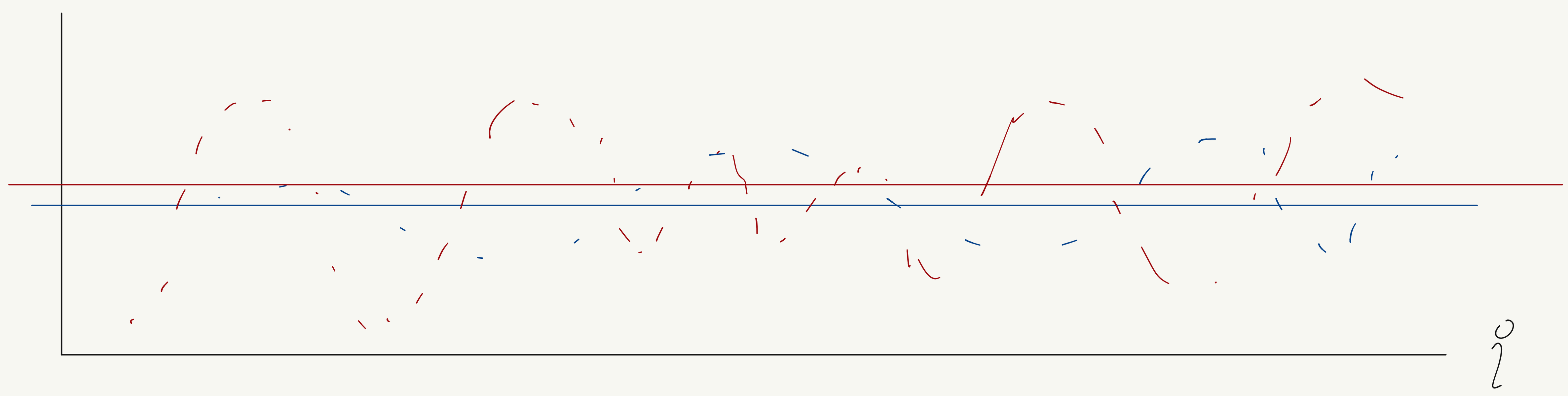


C_1 C_2

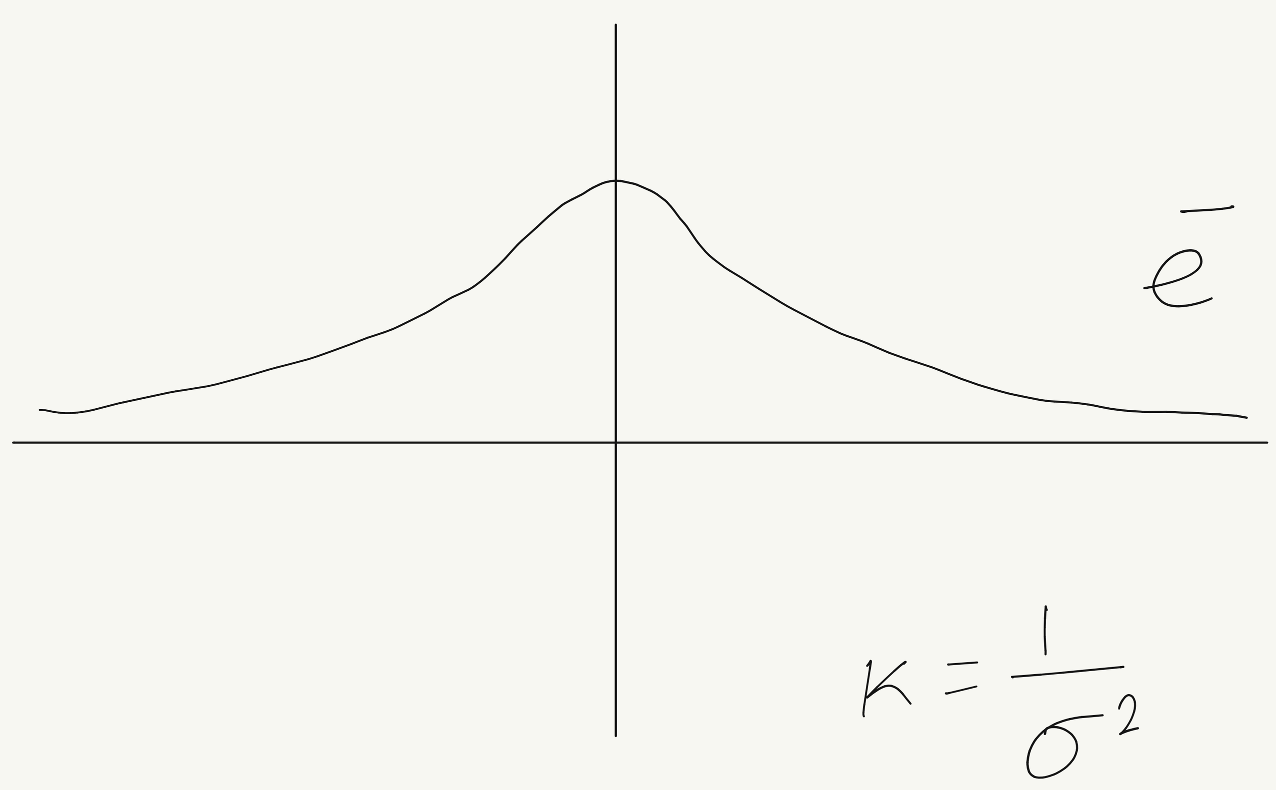


Edge and Corner of a Object

$$\rho(x, y) = \frac{\mathrm{Cov}(x, y)}{\sigma_x \cdot \sigma_y} = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2} \sqrt{\sum (y_i - \bar{y})^2}}$$



e^{-Kx^2} is a gaussian function.



$e^{-\frac{x^2}{\sigma^2}}$

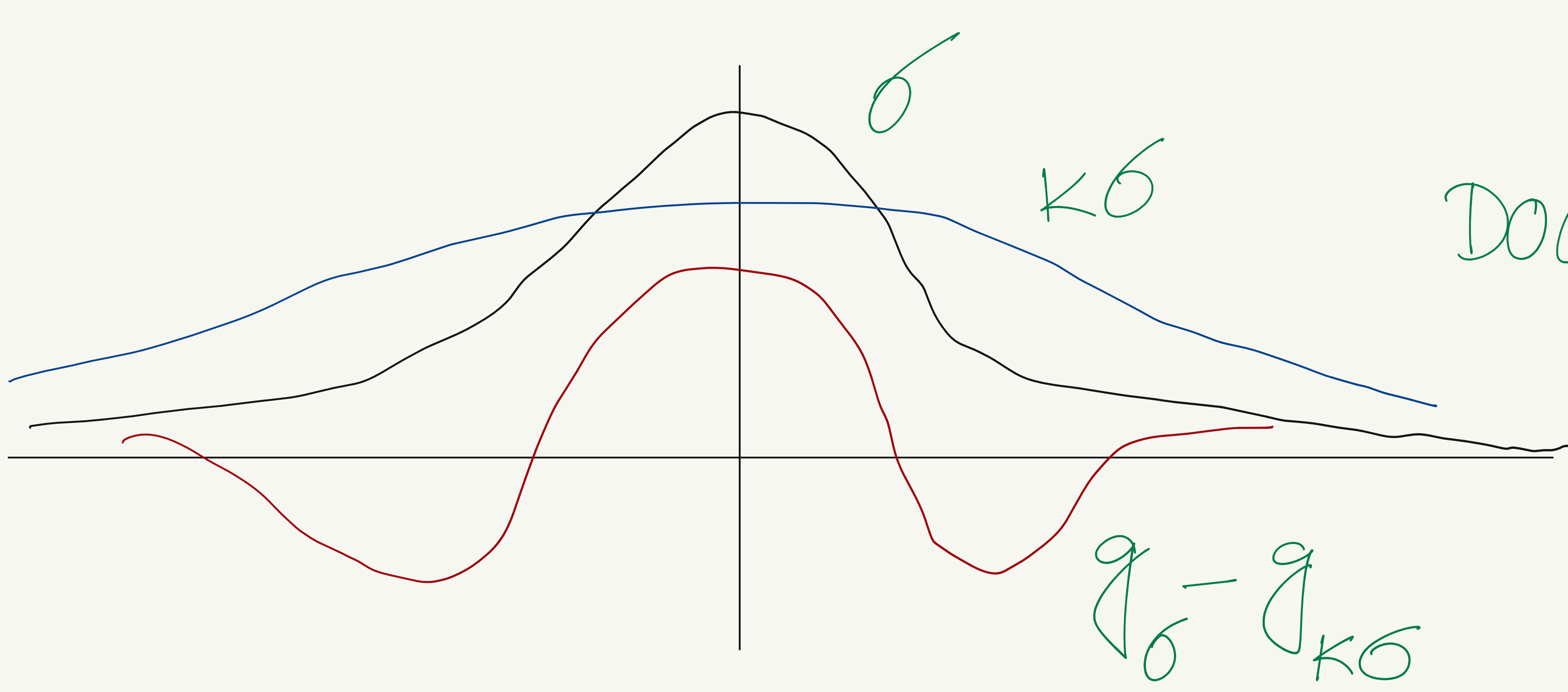
where, σ is the scale parameter.

$K = \frac{1}{\sigma^2}$

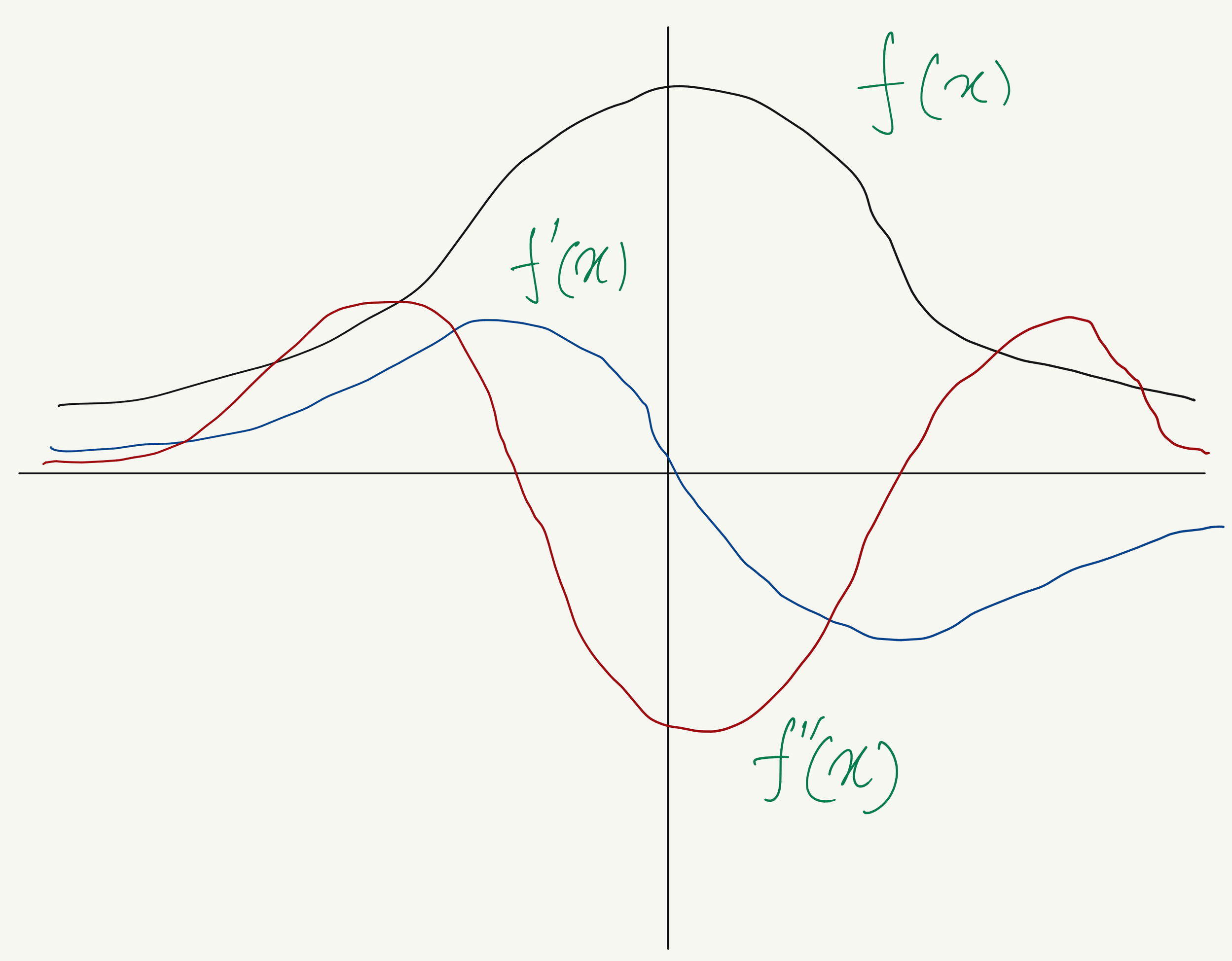
$$\frac{d}{dx}\left(e^{-x^2/\sigma^2}\right)$$

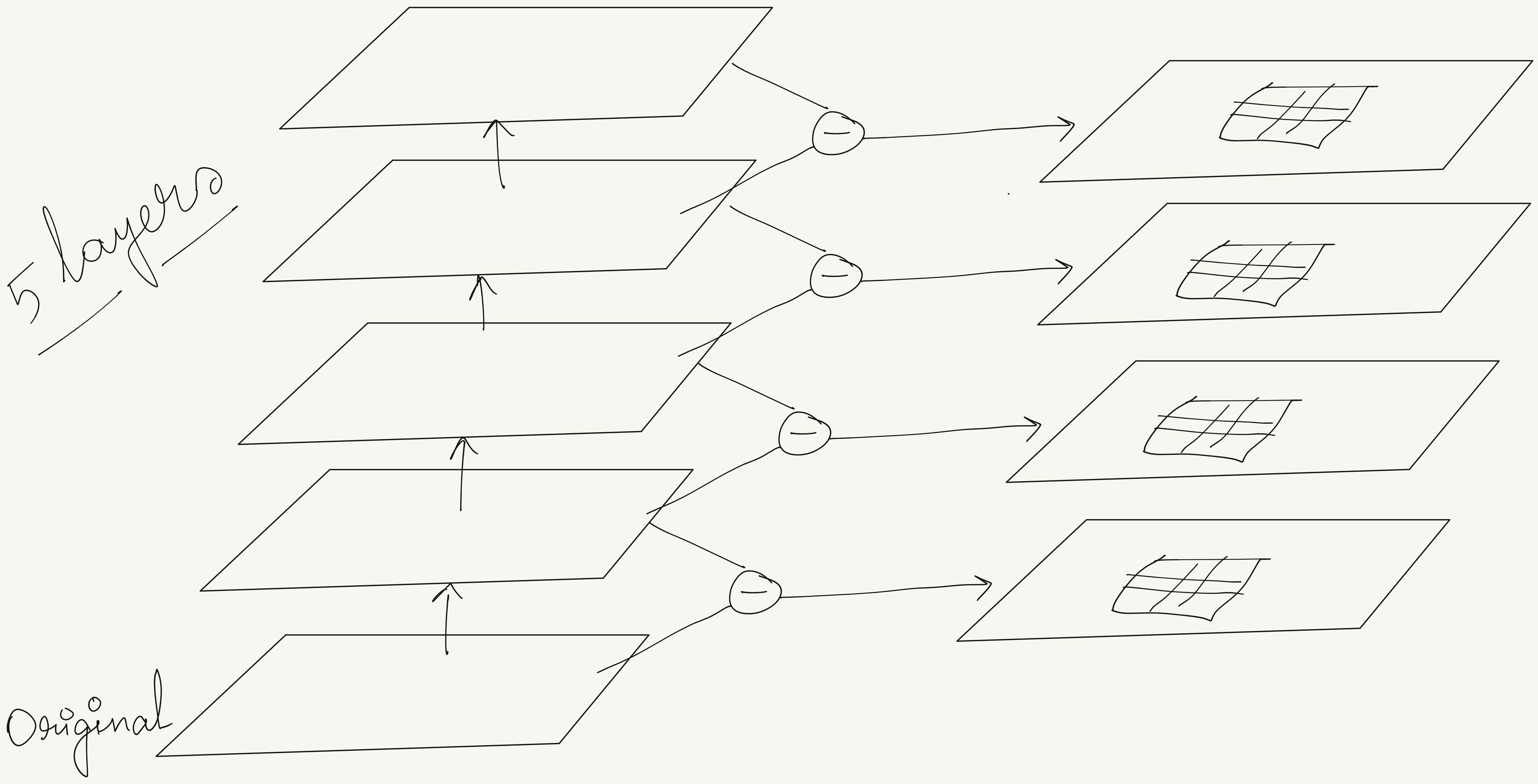
$$= e^{-x^2/\sigma^2} \cdot \frac{1}{\sigma^2}(-2x)$$

Thus, as σ increases
the curve will be more flat.



DOG ≈ LOG





In Harries Corner Detector,

$$R = \text{Det}(H) - K(\text{Trace}(H)^2) = \alpha\beta - K(\alpha+\beta)^2.$$

$[\alpha \gg 0,\ \beta \approx 0$ or $\beta \gg 0,\ \alpha \approx 0] \longrightarrow$ Edge.

$[\alpha \gg 0,\ \beta \gg 0] \longrightarrow$ Corner

$$\frac{\text{Trace}(H)^2}{\text{Det}(H)} = \frac{(\alpha+\beta)^2}{\alpha\beta} = \frac{(\beta r + \beta)^2}{\beta^2 r} = \frac{(r+1)^2}{r}$$

Let, $\alpha = r\beta$, $r > 1.0$

$$f(r) = \frac{(r+1)^2}{r}$$

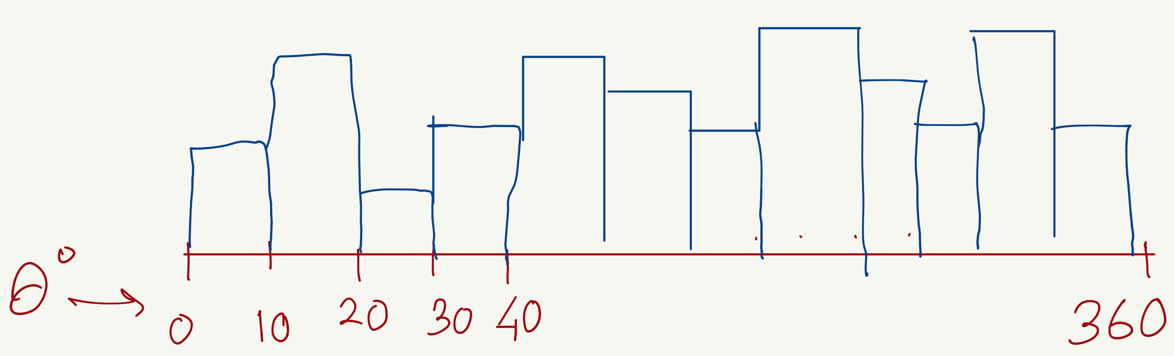
$$\Rightarrow f'(r) = \frac{2(r+1)}{r} - \frac{(r+1)^2}{r^2} = 0$$

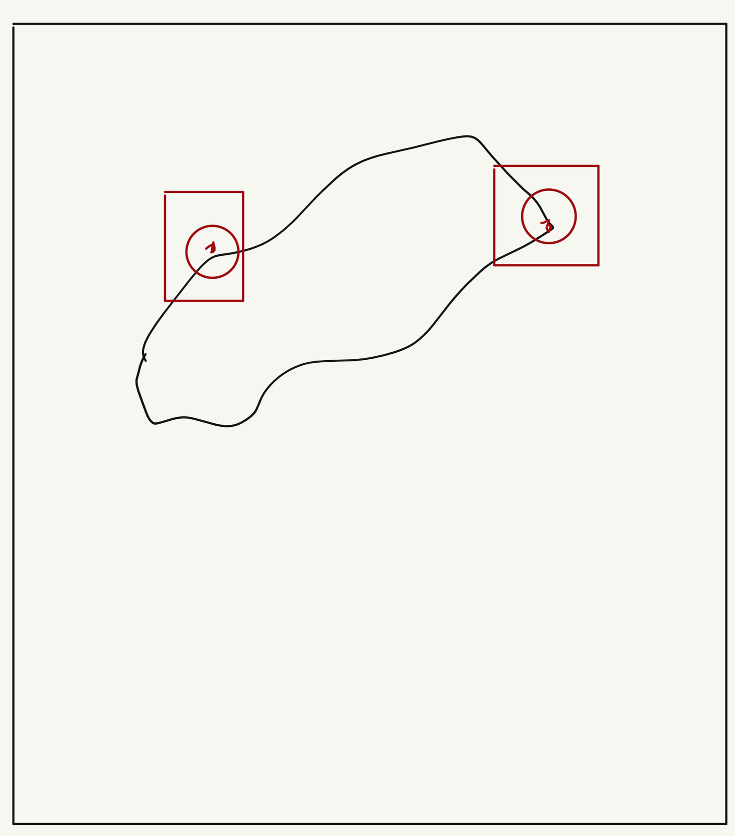
$$\Rightarrow f''(r) > 0 \quad \Rightarrow \frac{r+1}{r} = 2$$

$$\Rightarrow r+1 = 2r \Rightarrow r = 1$$

for $r = 1$, we get the minimum value.

Orientation Assignment:





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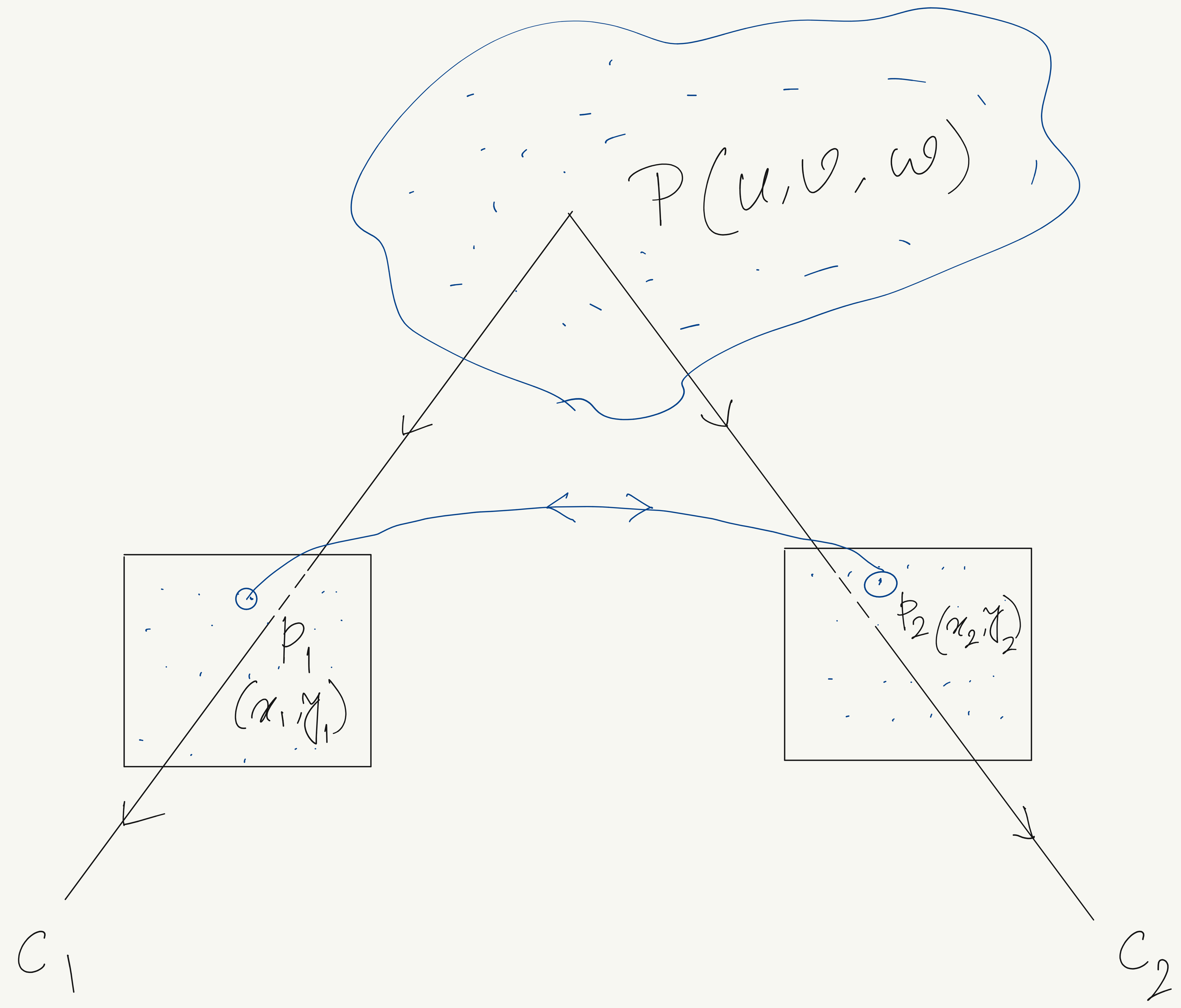
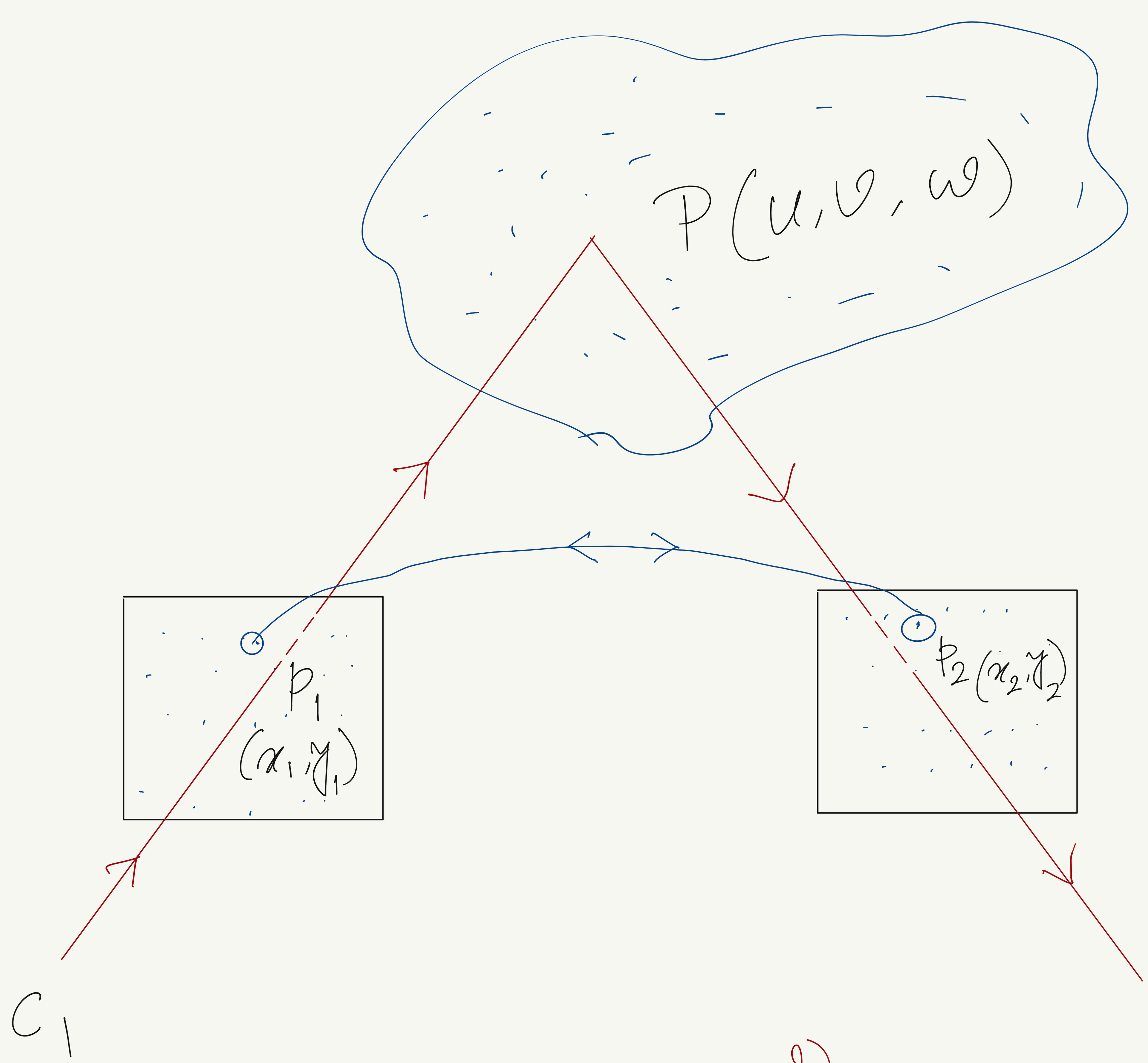
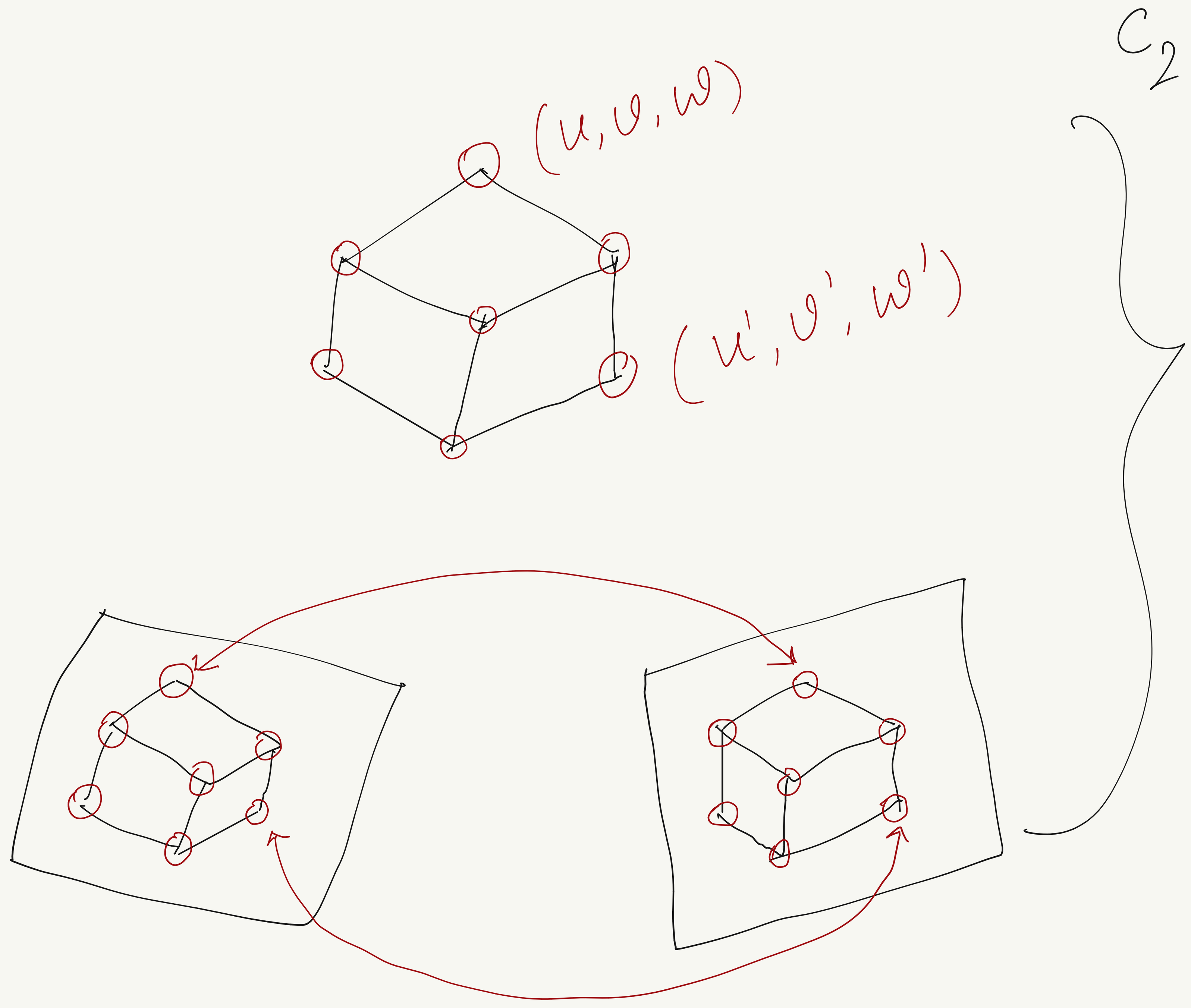
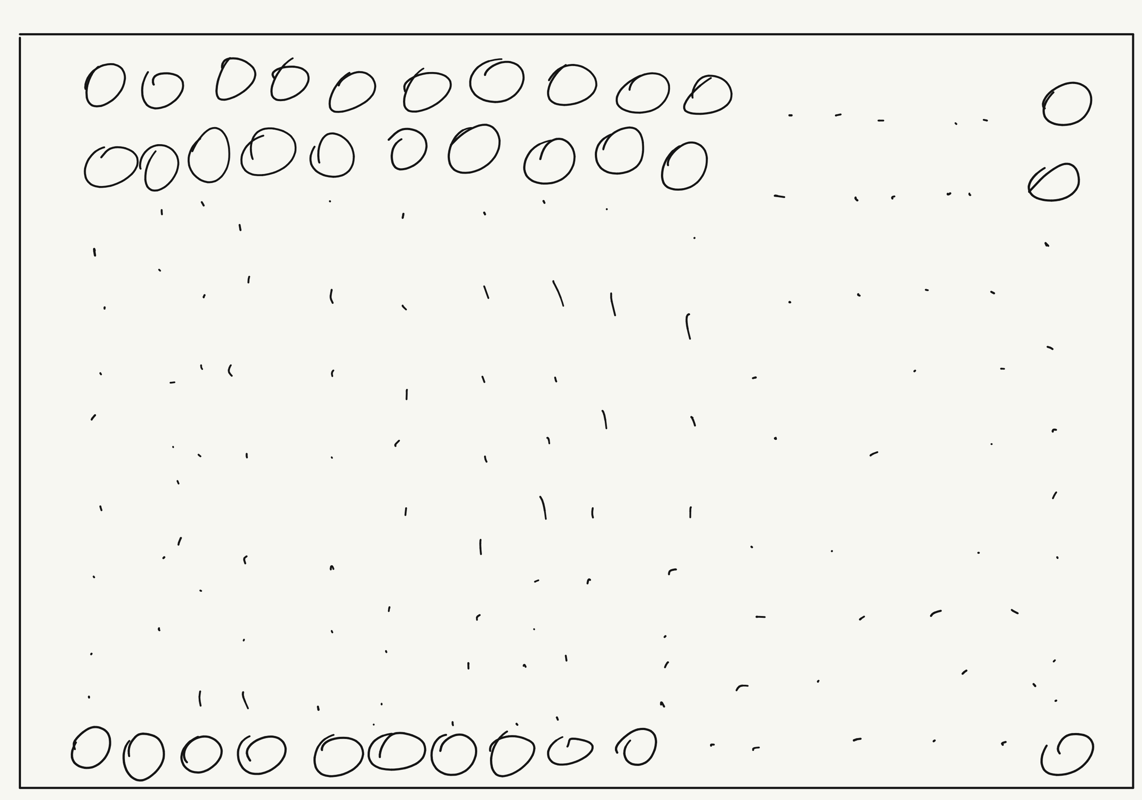


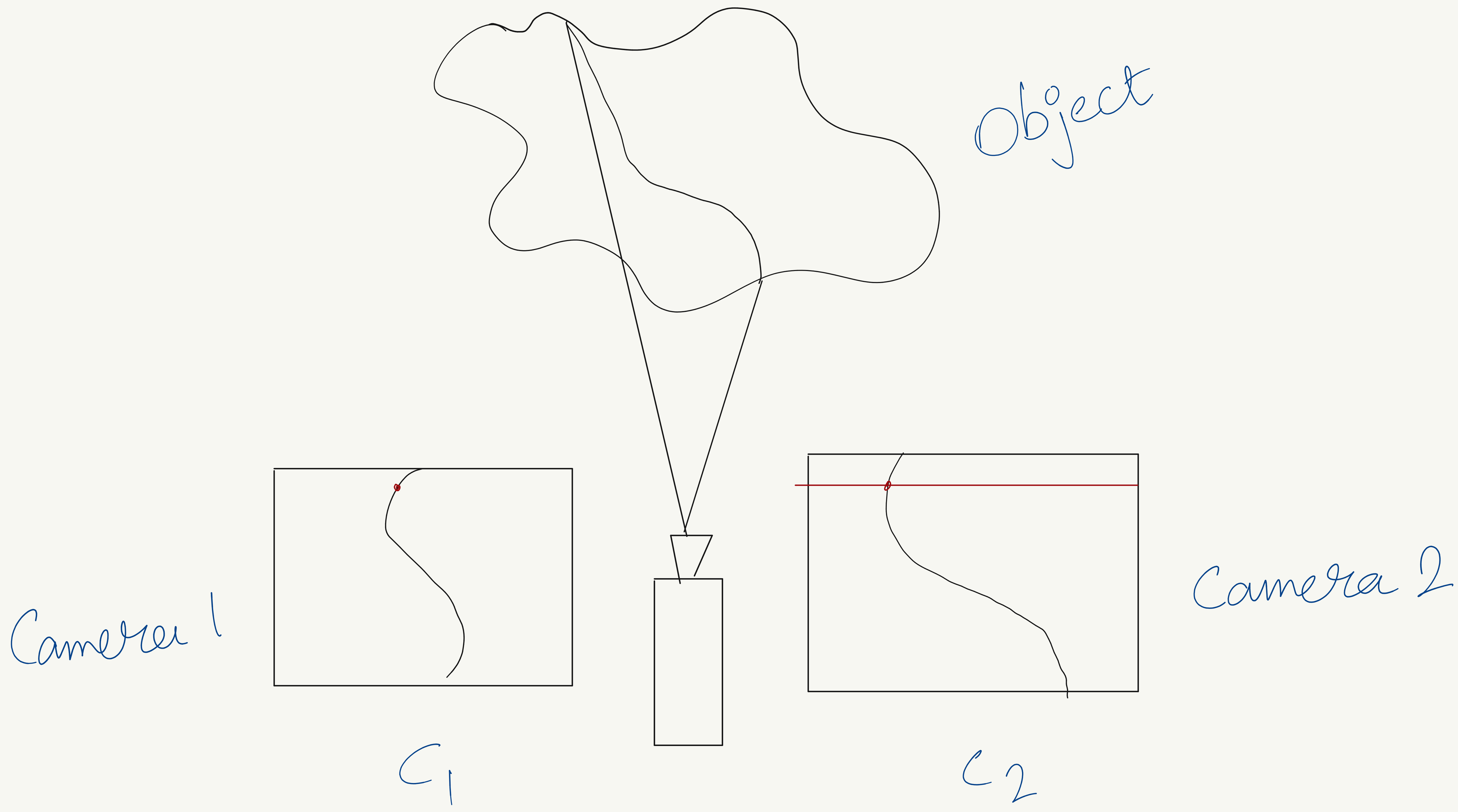


Similarly, we through a laser beam from p_1, that hits P and then reflected through p_2



Corrospondance of the points in 2D





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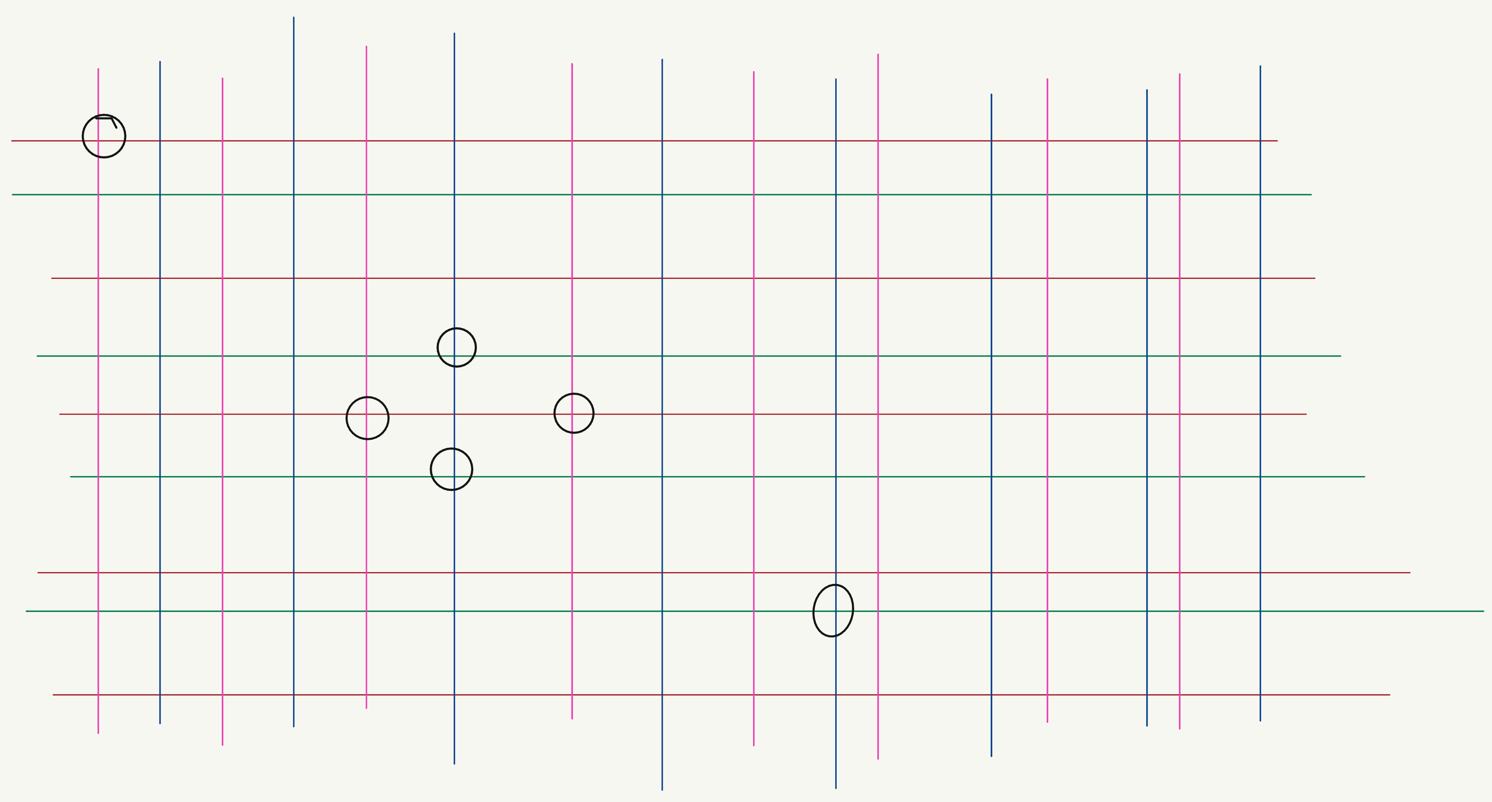
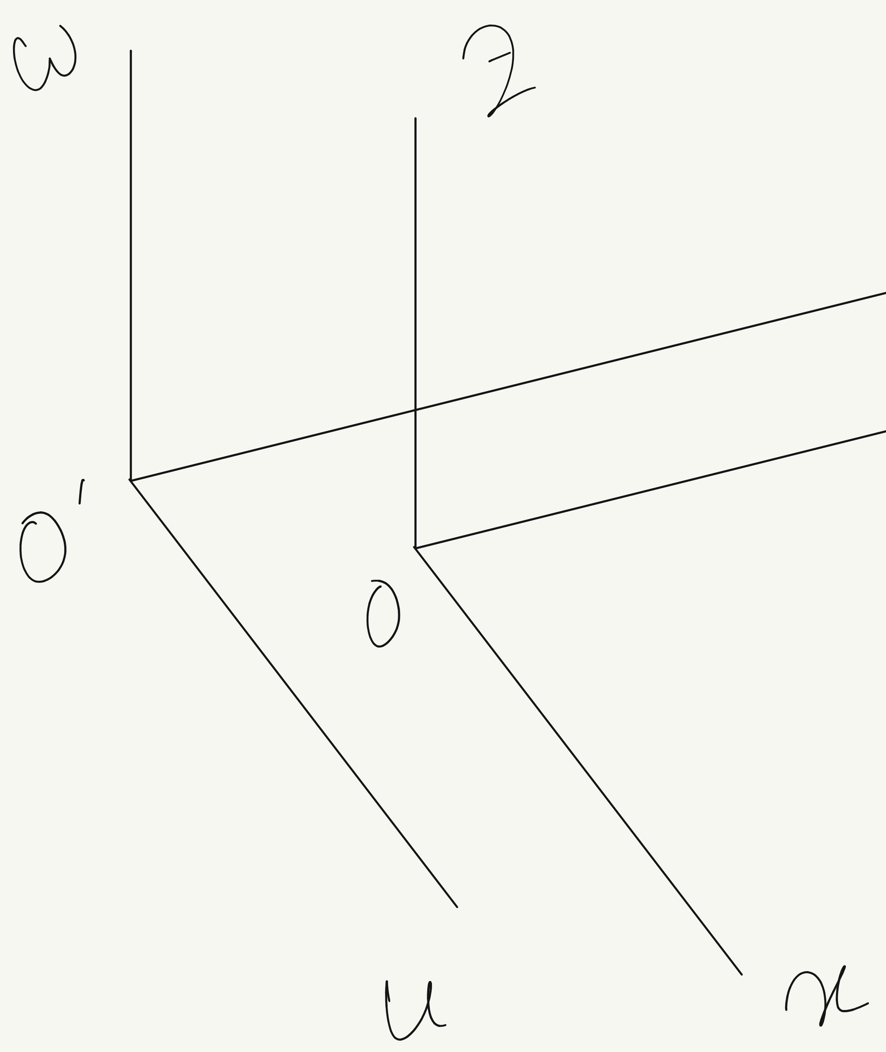
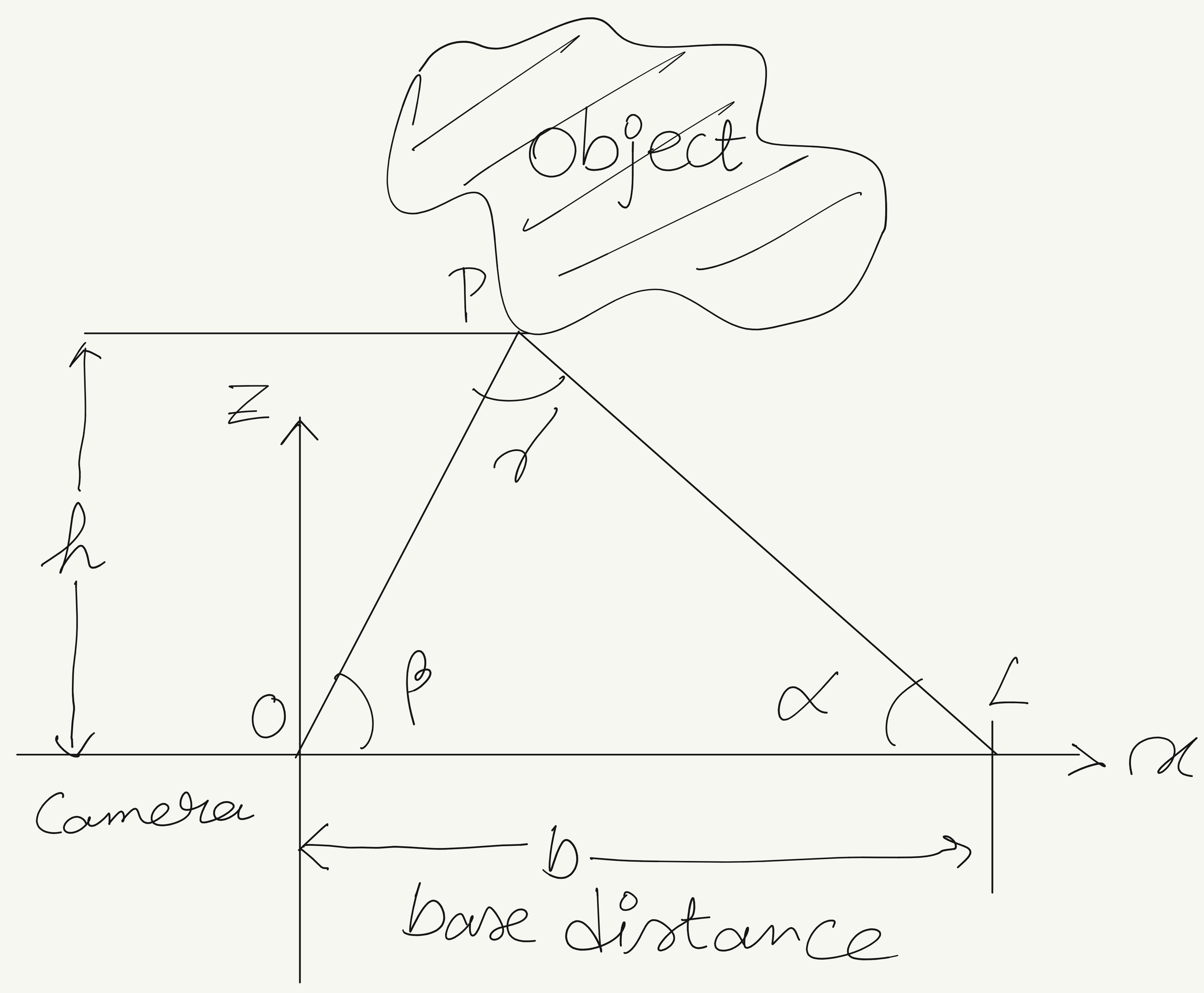
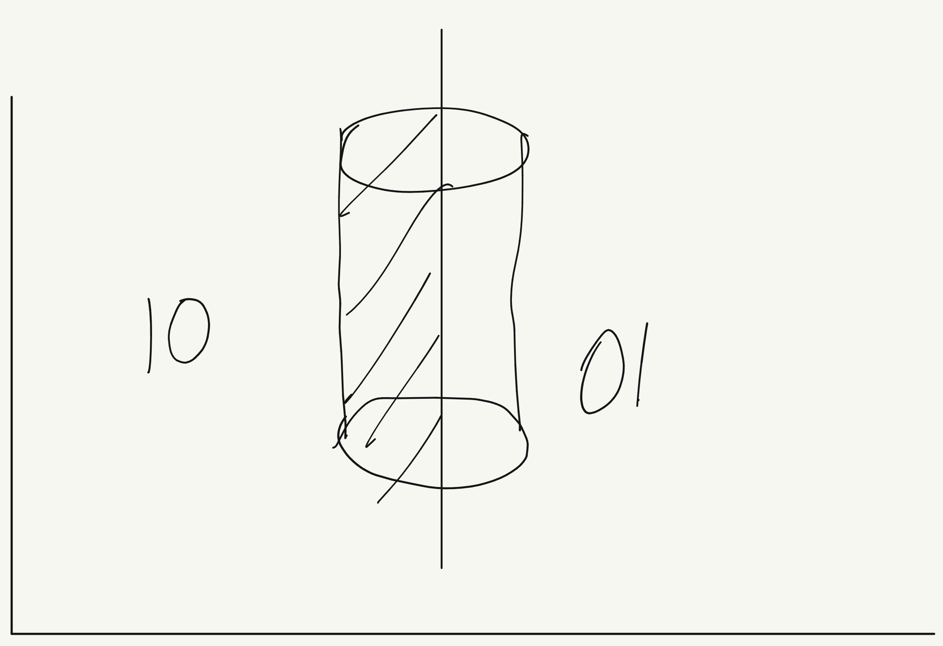


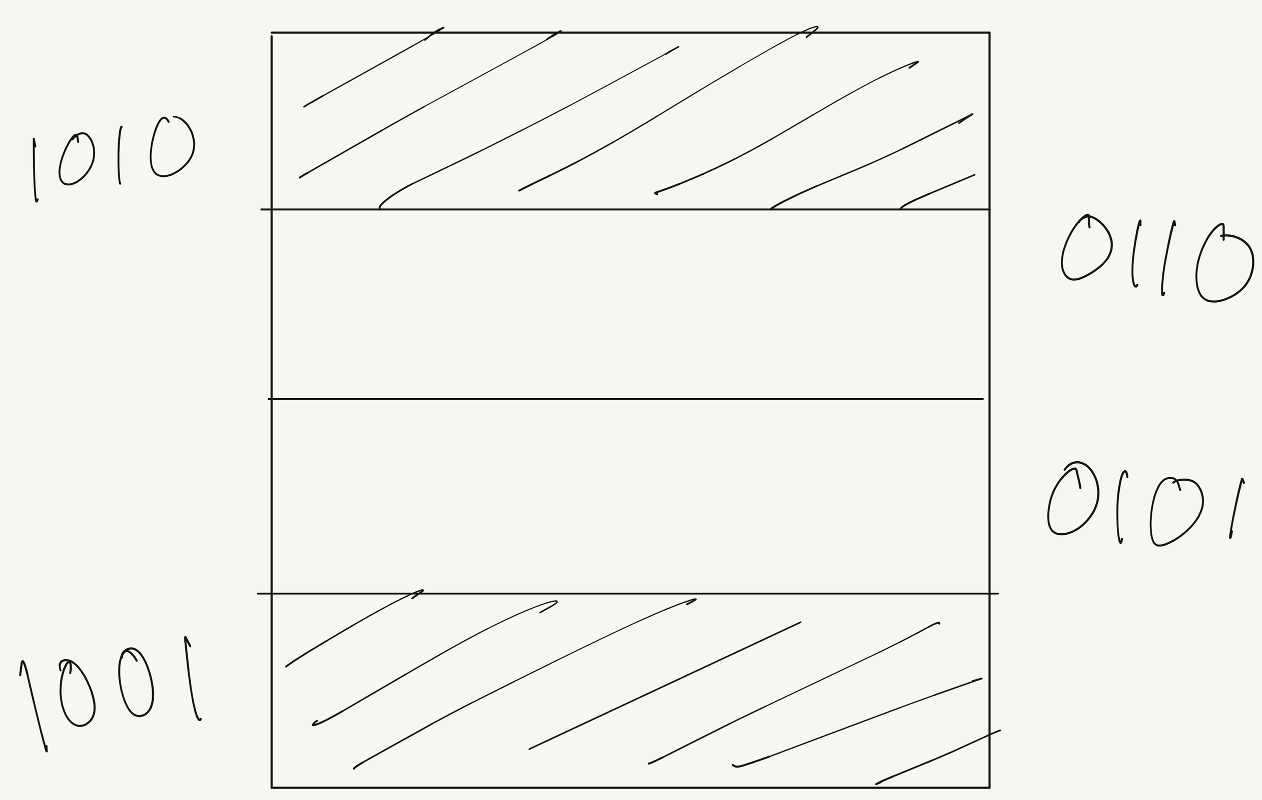
the locations are red-pink cross and green-blue cross

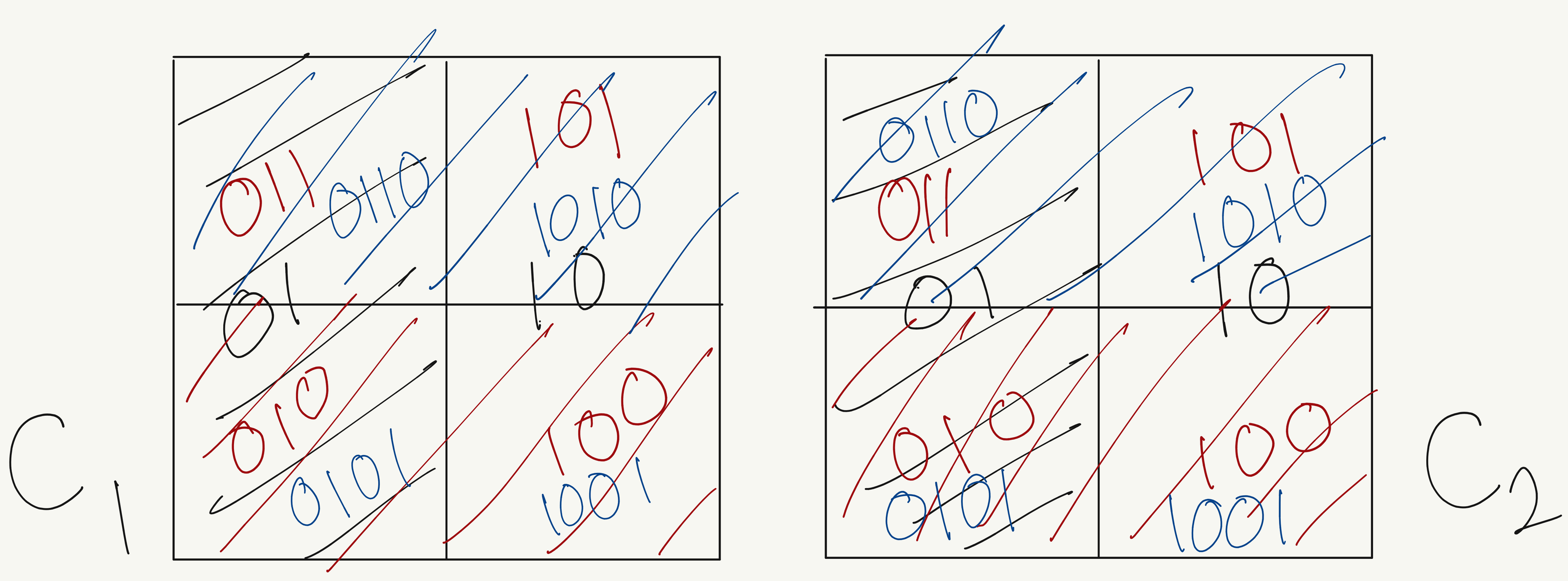






Dark → 0
Bright → 1

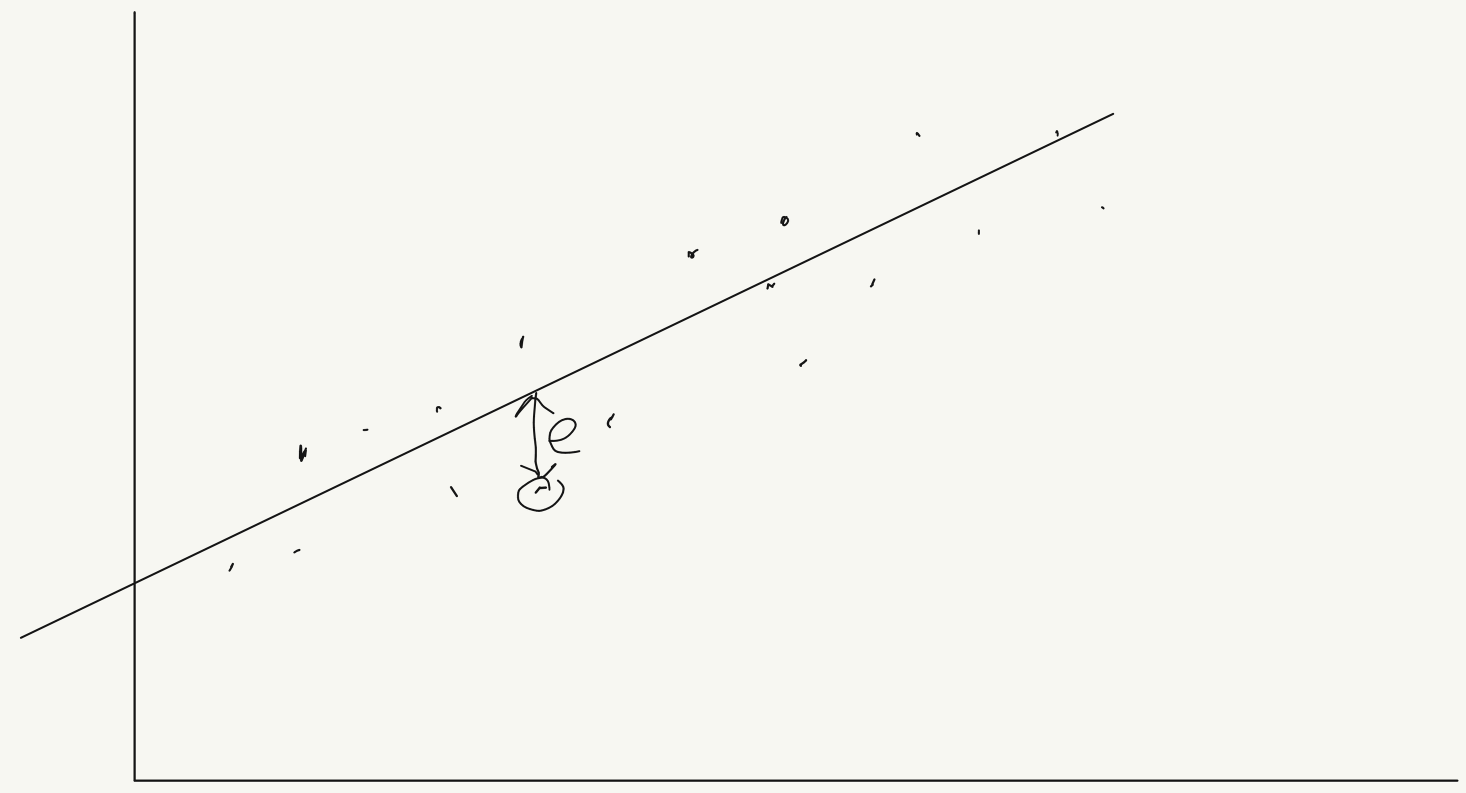




1st and 2nd light pattern
3rd light pattern
4th light pattern

08/05/2023

$(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$



Simple Linear Regression:

$$y_i = m x_i + C - \text{error}$$

$$\therefore e = \sum_i \left(y_i - m x_i - c\right)^2$$

Predicted class

Actual class	P(+)	N(-)
P(+)	Correctly Positive	Falsely Negative
N(-)	Falsely Positive	Correctly Negative

$$\text{Accuracy} = \frac{CP + CN}{CP + CN + FP + FN} \times 100\%$$

$$\text{Failure} = \frac{FP + FN}{CP + CN + FP + FN} \times 100\%$$

$$\text{FP percentage} = \frac{FP}{FP + CN} \times 100\%$$

$$\text{FN percentage} = \frac{FN}{FN + CP} \times 100\%$$

Eg.: $CP = 170$, $FN = 0$, $FP = 30$, $CN = 0$

then,

$$\text{Accuracy} = \frac{170}{200} \times 100\% = 85\%$$

$$\text{Failure} = \frac{30}{200} \times 100\% = 15\%$$

$$\text{FP percentage} = \frac{30}{30} \times 100\% = 100\%$$

$$\text{FN percentage} = \frac{0}{170} \times 100\% = 0\%$$

Predicted

Actual	A	B	C	D
A	CA	Not A		
B	False A			
C				
D				

11/05/2023

dependent $\qquad$ independent

$\omega = f(a)$

Similarly. $P_r = f(x_1, x_2, x_3)$

dependent $\qquad$ independent

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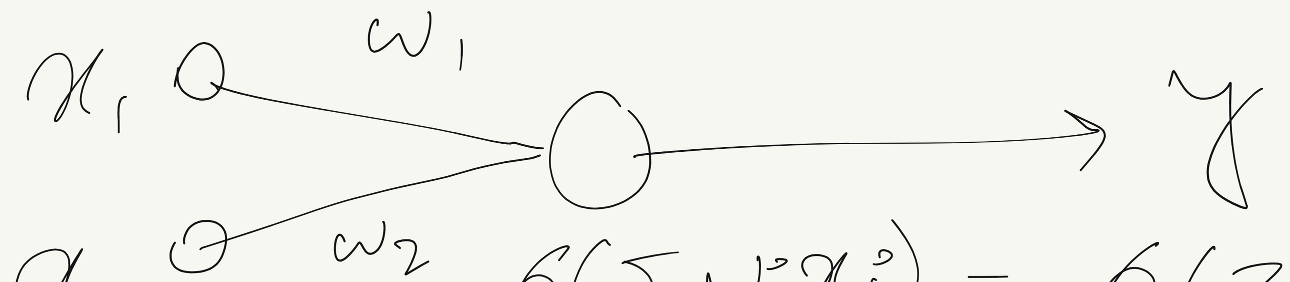
$$\phi = f(x, y, z) = g(a, b, c) = ax + by + cz$$

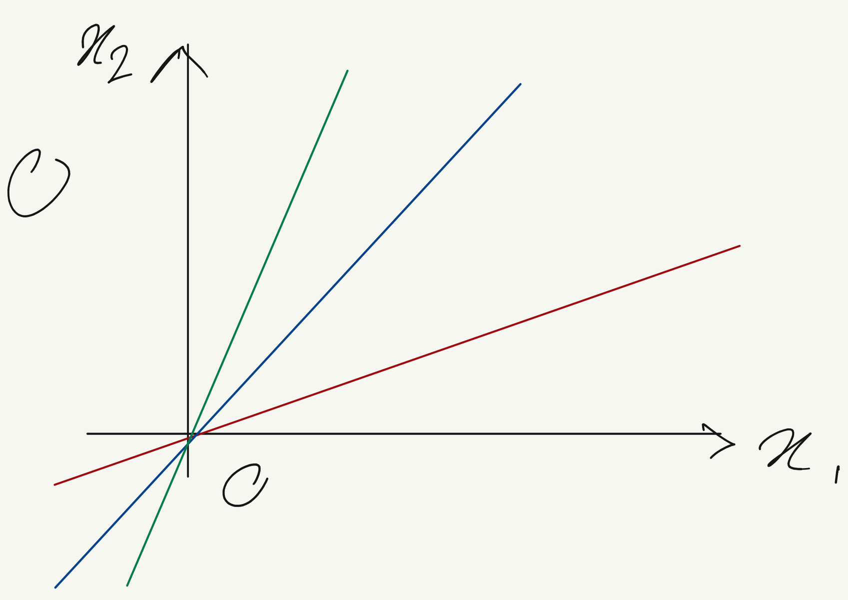


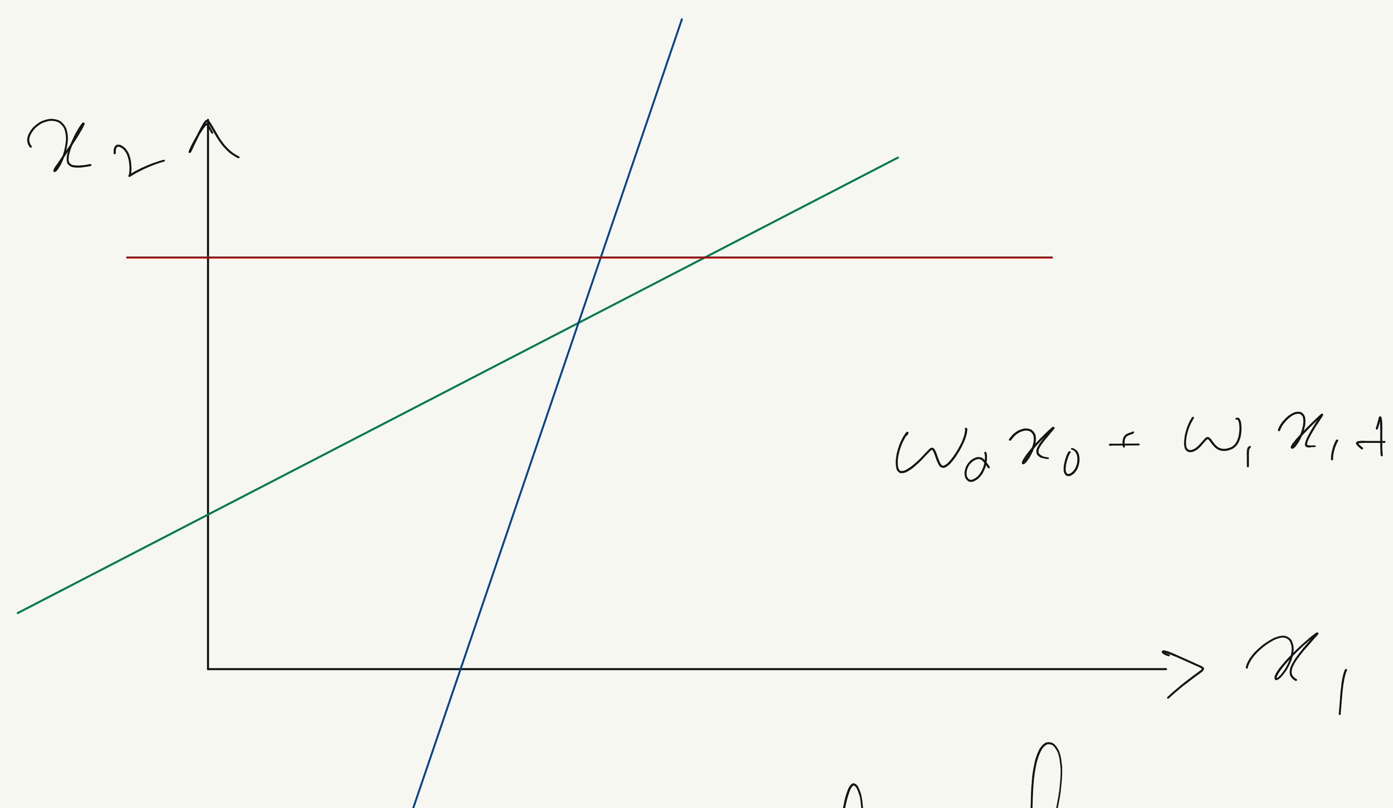
$\sigma(\sum w_i x_i) = \sigma(z)$

Similarly, $y = mx + c$ and $e = \sum_i \|y_i - mx_i - c\|^2$

$z = \sum w_i x_i$

$w_1 x_1 + w_2 x_2 = 0$



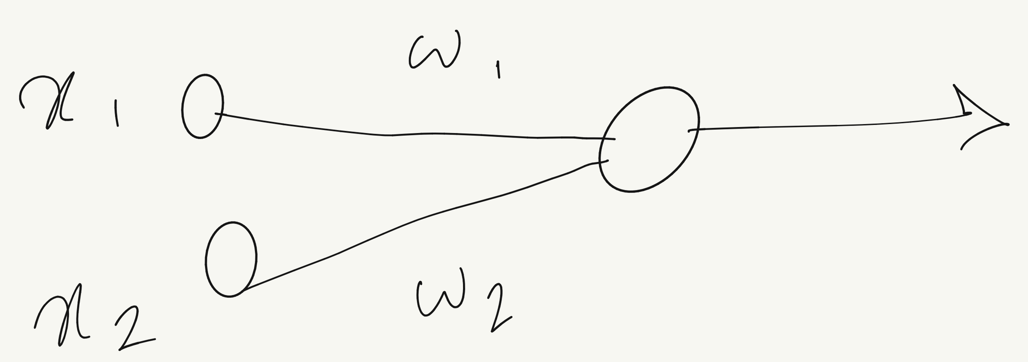


$w_0 x_0 + w_1 x_1 + w_2 x_2 = 0$

Let us consider the linear transformation.

$T(z) = wz$

but, $T(z) = wz + k$ is not a linear transformation.

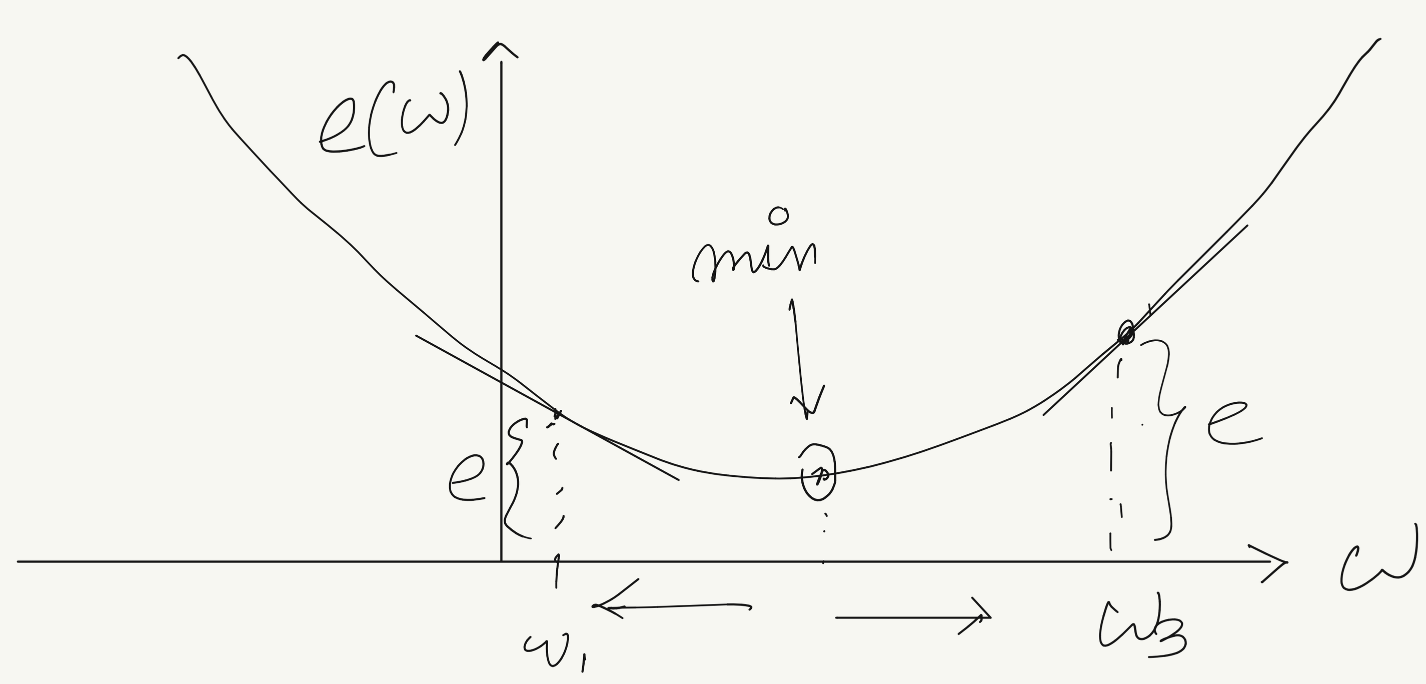


$y = \sigma(w_1 x_1 + w_2 x_2)$ $\quad \hat{y}$

$y = (x, w)$

$e(w_1, w_2) = \|y - \hat{y}\|^2$

If, $e(w) = \|y - \hat{y}\|^2$

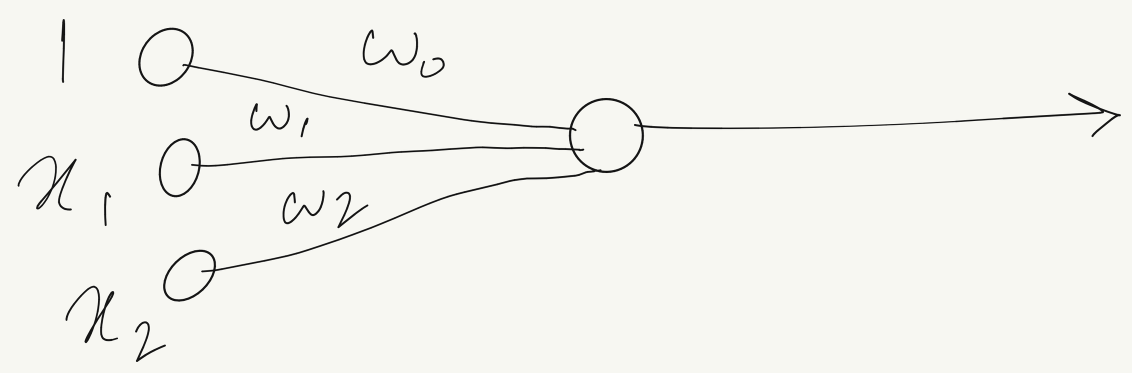


$W_{new} = W_{old} - \left(\frac{de}{dw}\right) \Delta w$

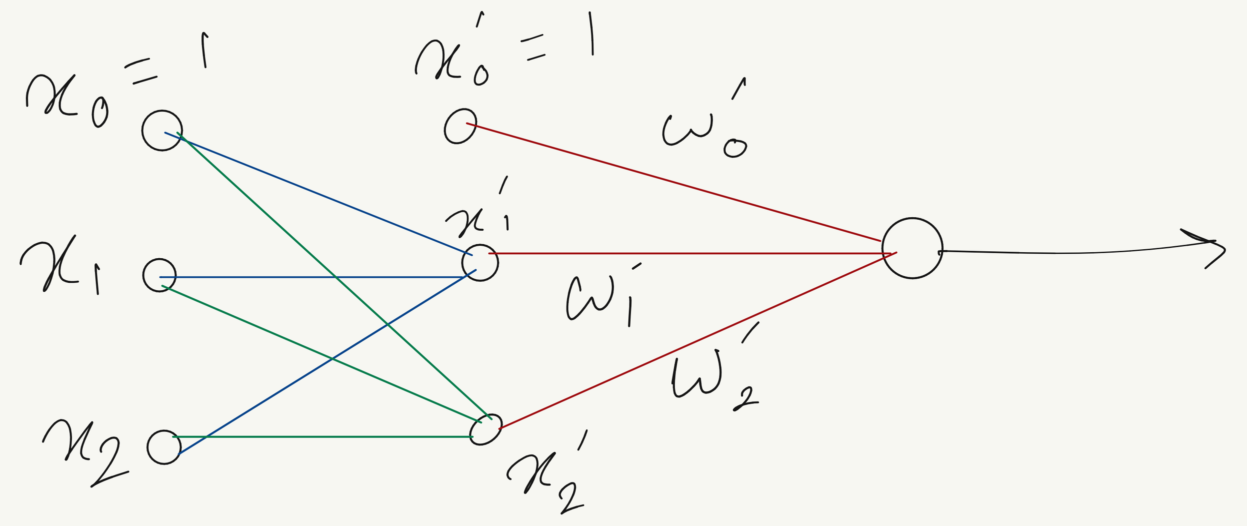
$\Rightarrow \boxed{W_{new} = W_{old} - \eta \frac{de}{dw}}$

For the multiple variables,

$$\boxed{w_{i,new} = w_{i,old} - \eta \frac{\partial e}{\partial w_i}}$$



$$y = \sigma(w_0 + w_1 x_1 + w_2 x_2)$$



$$y = \sigma(w_0' x_0' + w_1' x_1' + w_2' x_2')$$

$\hat{y}$

$$e(w') = \| y - \hat{y} \|^2$$

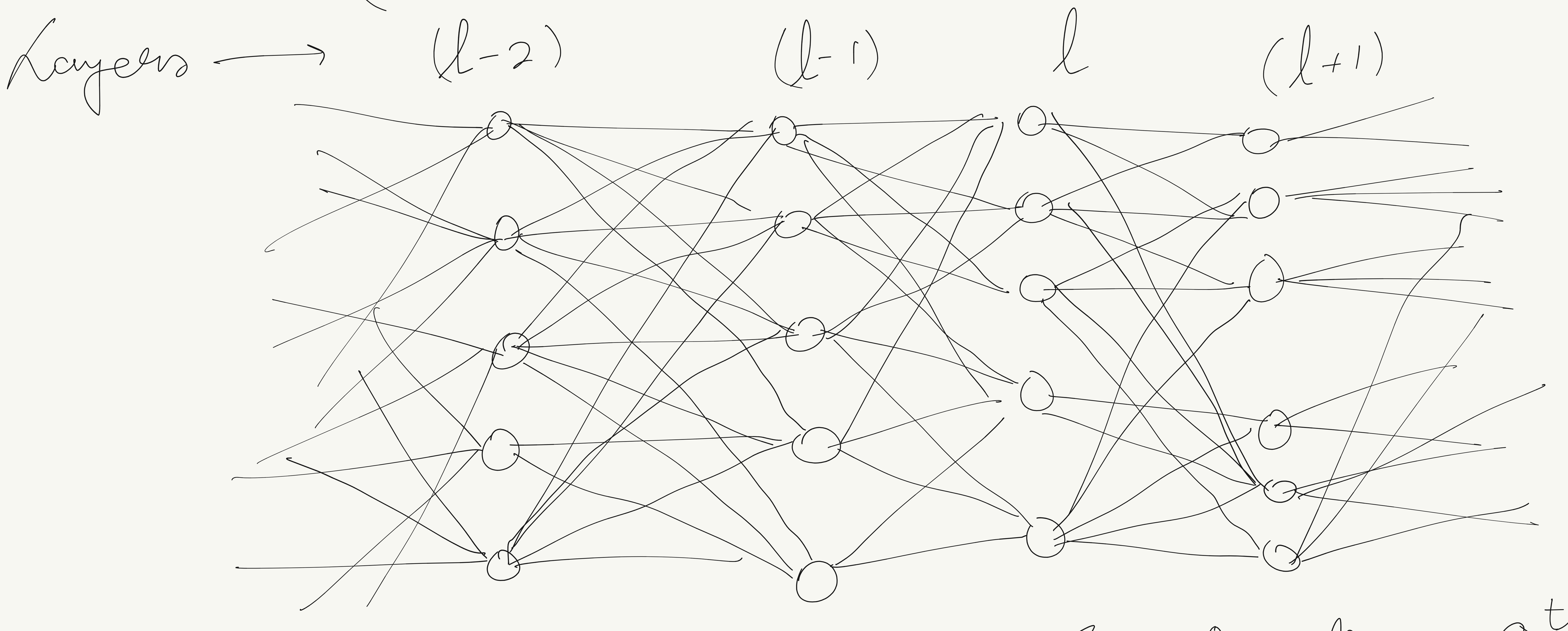
$$y = e^{a \sin(x^3)} \Rightarrow \frac{dy}{dx} = e^{a \sin(x^3)} \cdot a \cos(x^3) \cdot 3x^2$$

$$\Rightarrow \frac{dy}{dx} = 3 a x^2 \cos(x^3)\, e^{a \sin(x^3)}$$

Thus,

$$y = \sigma(w_0' x_0' + w_1' x_1' + w_2' x_2') \quad (\text{for 2 layers})$$

$$= \sigma\left(w_0' + w_1' \sigma(w_{10} + w_{11} x_1 + w_{12} x_2) + w_2' \sigma(w_{20} + w_{21} x_1 + w_{22} x_2) \right)$$



Starting from 0th layer

$$W^{(\text{to layer})}_{(\text{to node})(\text{from node})}$$

$$\boxed{y_i = \sigma(w^{i-1} x^{i-1})}$$

$x^{i-1} \to y_{i-1}$

$$x_i \equiv y_i$$

$\boxed{\text{eg.}}$ $$\boxed{w^2_{33(new)} = w^2_{33(old)} - \eta \left(\frac{\partial E}{\partial w^2_{33}} \right)}$$

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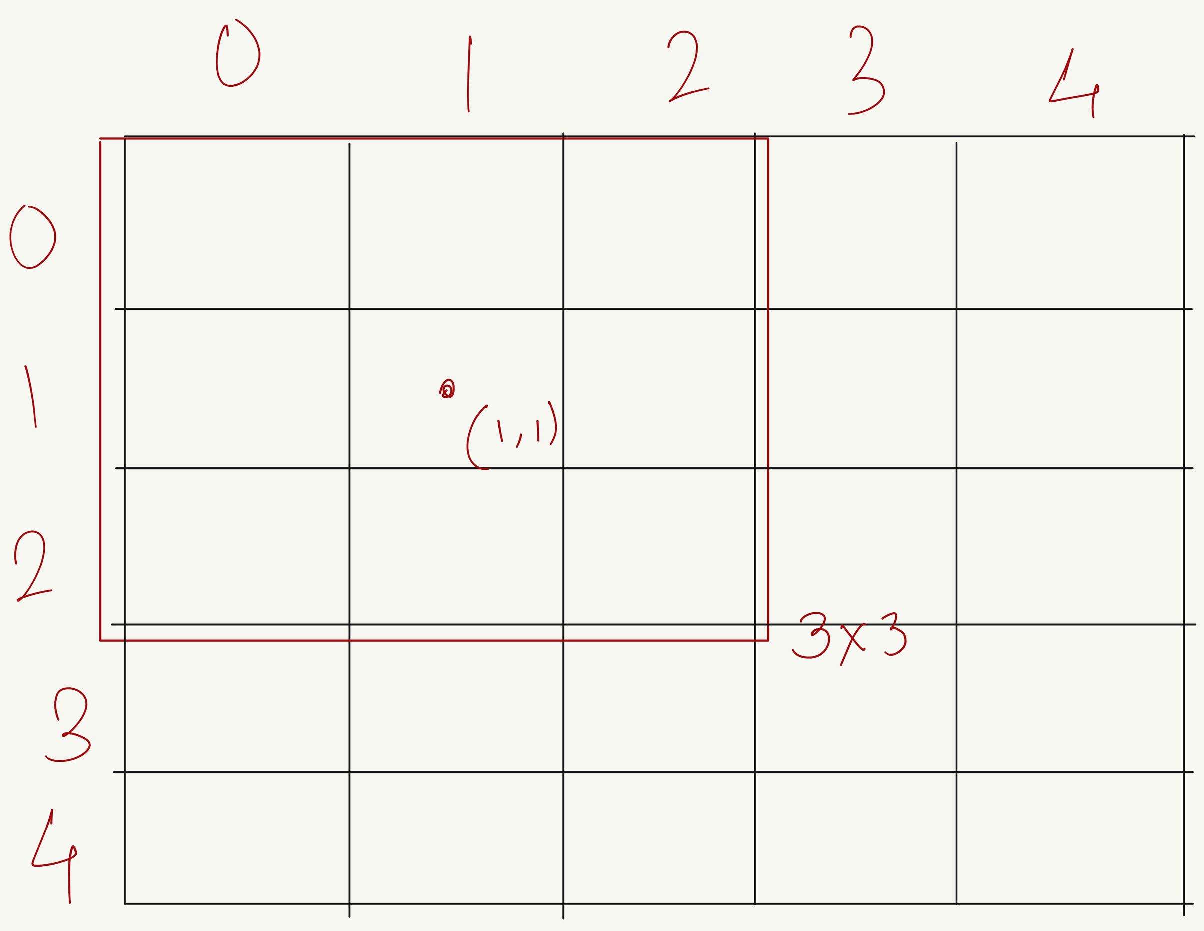
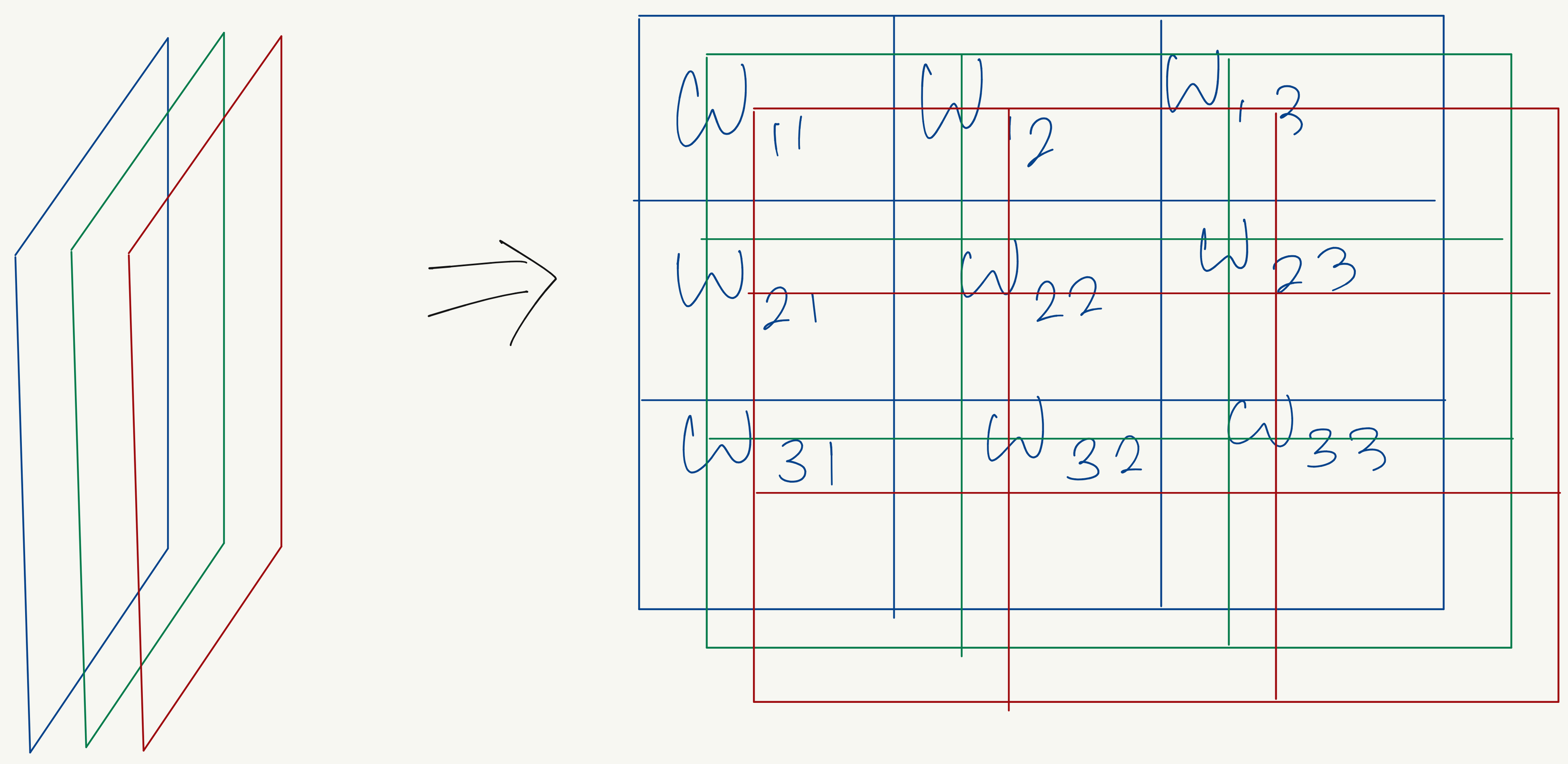


Total kernels we get,

$(4-2+1)\times(4-2+1)$

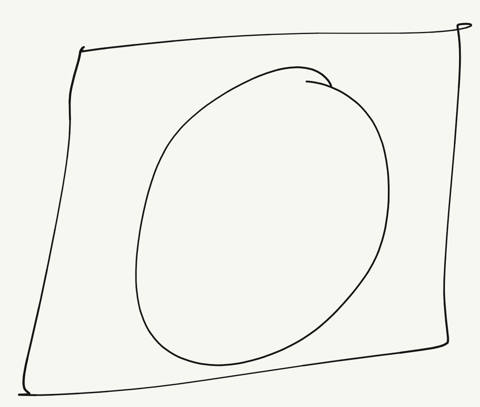
i.e. in general,

$(M+1-3+1)\times(N+1-3+1)$



dimension

$5\times5\times6$



1 feature map has 1 kernel

6 feature maps have 6 kernels