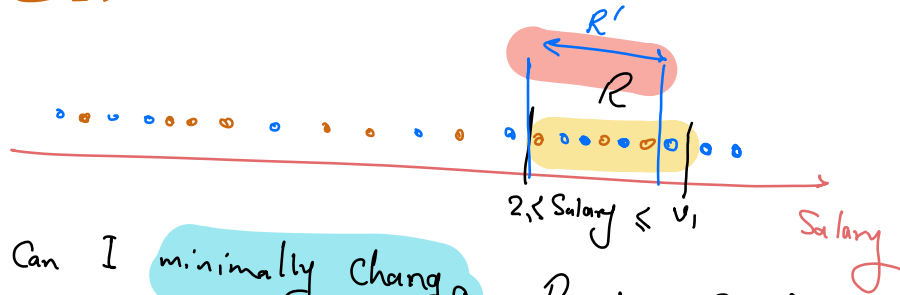


Select * from Employee

← only one condition.

$$|g_1 - g_2| \leq \tau$$
 w_1 w_2

e.g., $\tau = 0$

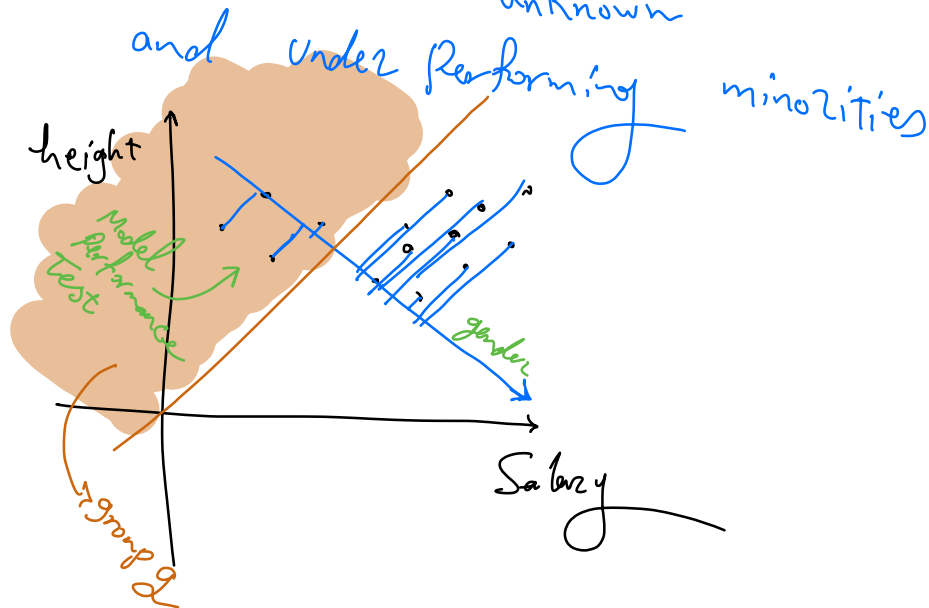


how can I minimally change R to satisfy bias constraint.

$$\text{Sim}(R', R) = \text{Jaccard}(O(R), O(R'))$$

$$= \frac{|O(R) \cap O(R')|}{|O(R) \cup O(R')|}$$

Minority Mining: Identifying underrepresented, ~~sets~~ unknown and underperforming minorities



Find the high-skew projections for which the model is underperforming for the tail (minority)

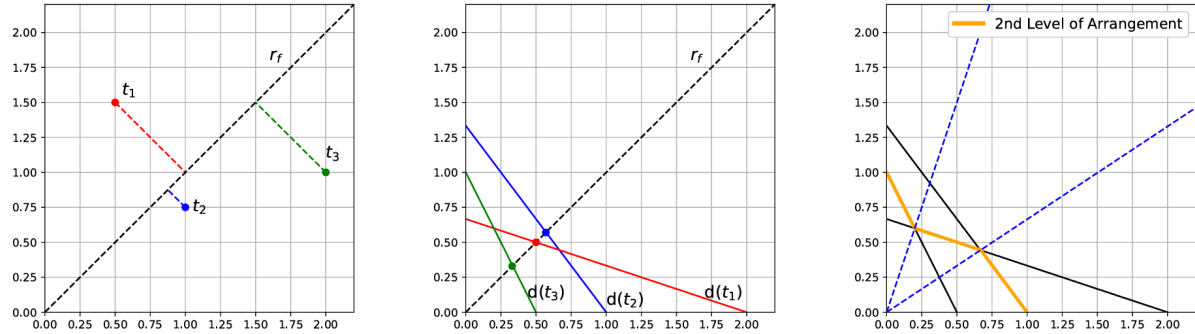
$$S \equiv \frac{3(\overset{\text{mean}}{\mu}(D) - \overset{\text{median}}{\nu}(D))}{\sigma(D)}$$

Standard Deviation

$\langle x_1, x_2 \rangle$

$$\hookrightarrow f_w = \theta_1 x_1 + \theta_2 x_2 = \theta^T x$$

$$f_{\theta}(x) = \sum \theta_i x_i = \theta^T x$$



(a) Primal space: $[t_2, t_1, t_3]$ shown as points, along with their projection on the ray r_f .

(b) Dual space: The intersection of dual hyperplanes of the points with a ray r_f .

(c) 2nd level of arrangements in the dual space highlighted as the orange line segments.

Figure 2: The illustration of the toy dataset $\mathcal{D} = \{t_1\langle .5, 1.5 \rangle, t_2\langle 1, .75 \rangle, t_3\langle 2, 1 \rangle\}$ in the primal space, the dual space, and the 2nd level of the arrangement in the first quadrant. The order of projection in Fig. 2a is the reverse of the intersection of dual hyperplanes with r_f ($[d(t_3), d(t_1), d(t_2)]$) in Fig. 2b. In Fig. 2c, the dotted blue lines indicate the boundaries of the median regions (the change in the line segment indicates a change in the median (2nd point) of \mathcal{D}_f).

$$t = \langle a, b \rangle \xrightarrow{\text{Line}} ax + by = 1$$

Median Region Can be found using
Computational Geometry In $\Theta(n^2 \sqrt[3]{n})$

has at most $\frac{O(n^3 \sqrt[3]{n})}{O(n^{4/3})}$ regions

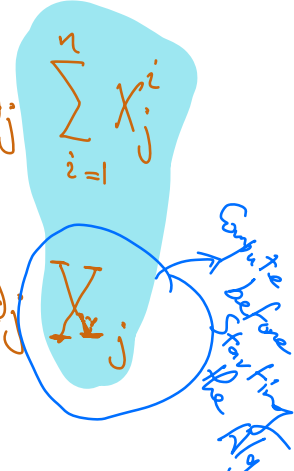
→ Ray-Sweeping for finding the k-th level of Arrangement

$$\mu_{\theta}(D) = \frac{1}{n} \sum_{i=1}^n f_{\theta}(x^i) = \frac{1}{n} \sum_i \sum_j \theta_j x_j^i$$

$$= \frac{1}{n} \sum_j \sum_i \theta_j x_j^i$$

$$= \frac{1}{n} \sum_j \theta_j \sum_{i=1}^n x_j^i$$

$$= \frac{1}{n} \sum_j \theta_j X_j$$


 Sum over i

$$\mu_{\theta}(D) = \theta_1 X_1 + \theta_2 X_2$$