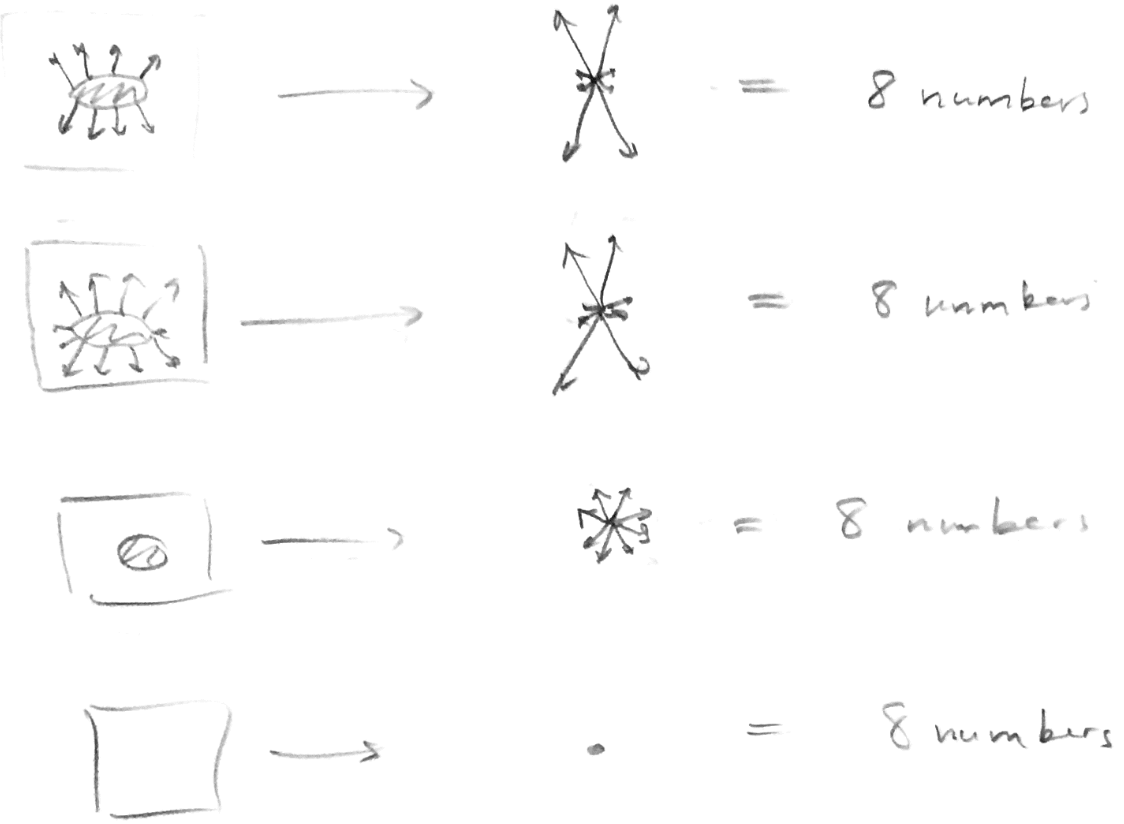
1a) 32 elements

b)



The descriptor is a normalized 32-vector with these numbers.

c) A has the same descriptor as Q

B has the same 8-bin histograms but the values in the "lower left" histogram are relatively larger than in Q. This relative difference is preserved when the 32-vector is normalized.

2a) $\theta^{(k+1)} = \theta^{(k)} - \mu \cdot \nabla L_i(\theta^{(k)})$

b) Computational speed. If n is large then computing ∇L_i is much faster than computing $\nabla L = \sum_{i=1}^{n} \nabla L_i$.

c) Check your lab.

3 a) See older exams.

b) The minimal solver uses 3 correspondences. (Unless the resulting matrix M in a is singular), these 3 correspondences will be inliers, so 3 inliers means practically nothing

Ans: very uncertain.

c) Much better than b: 3 corr will lock a unique solution. The risk that a fourth correspondence is consistent with this solution by chance is rather low.

d) Every other row and column would contain only zeros. Not what we want.

4) See older exams.

5a) We have 12 unknowns. Each correspondence yields 3 equations so the minimal case is 4 correspondences.

$\alpha = P(\text{picking an outlier-free subset}) = (1-p)^4$

$P(\text{not picking an outlier-free subset } K \text{ times}) =$

$(1-\alpha)^K$

We want $(1-\alpha)^K \approx 0.0001 \Rightarrow$

$$K = \frac{\ln(0.0001)}{\ln(1-\alpha)}$$

5b) Rule of thumb:

$$K_{th} = \frac{100}{\alpha}$$

If $p \approx 1$, then $\alpha \approx 0$ and

$\ln(1-\alpha) \approx -\alpha$ (First order Maclaurin)

so $$\frac{\ln(0.0001)}{\ln(1-\alpha)} \approx \frac{-9}{-\alpha} \approx \frac{10}{\alpha}$$

Ans: $K_{th} \approx 0.1 \cdot K$

6 a) See lecture notes

b) Let $f_i(\theta) = r_i^2(\theta)$, and let θ^* be the value of θ when IRLS has converged. At convergence the w_i's has stopped changing so $w_i = h'(f_i(\theta^*))$. $*$ Furthermore, $\nabla L_w(\theta^*) = 0$ as we solve the weighted least squares problem in each iteration.

But

$$\nabla L_h(\theta^*) = \sum_{i=1}^{n} h'(f_i(\theta^*)) \nabla f_i(\theta^*) = / * /$$

$$= \sum_{i=1}^{n} w_i \nabla f_i(\theta^*) = \nabla L_w(\theta^*) = 0$$

$\square$