Assignment for Computer Vision 2

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Homework Assignment 1
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Problem 1 Probabilites and Statistics

Problem 1.1

discrete	&	discrete	$\Rightarrow$	exam grade	&	exam date
continuous	&	discrete	$\Rightarrow$	time	&	number of bacteria in a yoghurt
continuous	&	continuous	$\Rightarrow$	location while driving	&	velocity while driving

Problem 1.2

When we marginalize the joint distribution $p(x,y)$ over x we get $\int_x p(x,y)dx$. The solution to this integral is the probability of $p(y)$, this way we do not care about x any more.

Problem 1.3

For this problem we want to find the probability that we have chosen a box which contains a gold coin in each drawer, given we know one of the drawers of that box contains a gold coin.

$p(gold)$ is the probability of seeing gold.
$p(GG), p(GS), p(SS)$ are the probabilities of the different boxes that containing the different combinations of coins. The Problem is to calculate the probability $p(GG|Gold)$ as described. Therefore we can make use of Bayes rule:

$$\begin{aligned} p(SS) = p(GS) = p(GG) &= \frac{1}{3} \\ p(Gold|GG) &= 1 \\ p(Gold|GS) &= \frac{1}{2} \\ p(Gold|SS) &= 0 \\ p(Gold) &= \frac{1}{3}(p(Gold|GG) + p(Gold|GS) + p(Gold|SS)) = \frac{1}{3}(1 + 0.5 + 0) = 0.5 \end{aligned}$$

Therefore we can make use of Bayes rule:

$$p(GG|Gold) = \frac{p(GG) \cdot p(Gold|GG)}{p(Gold)} = \frac{\frac{1}{3} \cdot 1}{0.5} = \frac{2}{3}$$

Problem 1.4

$$\begin{aligned} p(x,y|z) &= \frac{p(x,y,z)}{p(z)} \\ &= \frac{p(x|y,z)p(y,z)}{p(z)} \\ &= \frac{p(x|y,z)p(y|z)p(z)}{p(z)} \\ &= p(x|y,z)p(y|z) && \text{as x and y are indepent given z} \\ &= p(x|z)p(y|z) \end{aligned}$$

Problem 2 Modeling

Problem 2.1

We assume the content of I^1 is nearly the same as in picture I^0, because it only has been translated by the d given at each pixel location. Therefore we assume brightness constancy and no occlusions, if they are violated this doesn't hold.

Problem 2.2

Gaussian distributions are very sensitive to outliers, because they are light tailed. This assumes outliers are less probable and therefore them. In stereo vision these outliers are caused by occlusions and shadows, due to different view angles. Our images are affected by noise because sensors can't be perfect and are affected by the properties of light. Additionally the choice of the coordinate system has an effect on the distributions.

Problem 2.3

In a MRF neighbouring pixels are encoded to have similar disparities because they often belong to the same real world object. Therefore d_1 and d_3 are not independent given d_2 because connections in the MRF model a undirected dependency.

Problem 2.4

This function has it maximum 1 when a and b are the same, else we penalize bigger differences more than smaller ones.

$$\delta = \frac{1}{1+\sqrt{(a-b)^2}}.$$

Problem 2.5

In our probabilistic view we use a prior global state of the depicted real world scene, because of that we don't need to take the local region into account to get our disparities.

Problem 4 Stereo Likelihood

Problem 4.3

For the likelihood we need multiply the probability of each pixel. If we now assume a Gaussian and we are sampling for an almost optimal case. We could assume the following equation(try calculating $0.4^{384\cdot 288}$) :

$$\max \mathcal{N}(0,1)^{384\cdot 288} \approx 0.4^{384\cdot 288} \approx 0$$

This is the reason for using the negative log likelihood.

Problem 4.6

We calculate the negative log likelihoods for the Gaussian and Laplacian without the scaling term. Both Models seem to are not robust at all. But the Laplacian seems to be less effected by outliers than the Gaussian.

Noise	Gaussian	Laplacian	L / G
0 %	128.20	1482.75	11.56
10 %	865.19	4239.03	4.89
30 %	2701.06	11074.46	4.10