

Results for Assignment 1 - Group xx

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1 Task 1

Information which was deduced from the text:

$$P(D = 0) = P(H) = 0.95,$$

$$P(D = 1) = P(A) = 0.04,$$

$$P(D = 2) = P(C) = 0.01,$$

$$P(T = 1|C) = 0.98; P(T = 0|C) = 1 - P(T = 1|C) = 0.02,$$

$$P(T = 1|H) = 0.01; P(T = 0|H) = 1 - P(T = 1|H) = 0.99,$$

$$P(T = 1|A) = 0.20; P(T = 0|A) = 1 - P(T = 1|A) = 0.80.$$

Table 1: Probability table.

T/D	H (D = 0)	A (D = 1)	C (D = 2)	p(T _i)
T = 1	0.0259	0.0011	0.0003	0.0273
T = 0	0.9241	0.0389	0.0097	0.9727
p(D _i)	0.95	0.04	0.01	1

At first calculate the marginal probability.

$$P(T = 1) = 0.01 * 0.95 + 0.2 * 0.04 + 0.98 * 0.01 = 0.0273$$

$$P(T = 0) = 0.99 * 0.95 + 0.8 * 0.04 + 0.02 * 0.01 = 0.9727$$

Then calculate all joint probabilities.

$$P(H, T = 1) = P(H) * P(T = 1) = 0.95 * 0.0273 = 0.0259$$

$$P(A, T = 1) = P(A) * P(T = 1) = 0.04 * 0.0273 = 0.0011$$

$$P(C, T = 1) = P(C) * P(T = 1) = 0.01 * 0.0273 = 0.0003$$

$$P(H, T = 0) = P(H) * P(T = 0) = 0.95 * 0.9727 = 0.9241$$

$$P(A, T = 0) = P(A) * P(T = 0) = 0.04 * 0.9727 = 0.0389$$

$$P(C, T = 0) = P(C) * P(T = 0) = 0.01 * 0.9727 = 0.0097$$

2 Task 2

Blabla explanation.
Blabla.

3 Task 3

Blabla explanation.
Blabla.

4 Task 4

4.1 Verify conditional mean.

$$\begin{aligned}
E_Y[Y|X=x] &= \sum_{n=1}^N y_n * p(Y=y_n|X=x) \\
&= \sum_{n=1}^N y_n * \frac{p(X=x|Y=y_n)*p(Y=y_n)}{p(X=x)},
\end{aligned}$$

where $p(X=x)$ is a constant and can be neglected and $p(Y=y_n) = 1$ because of the uniform distribution. Which brings the following equation:

$$= \sum_{n=1}^N y_n * p(X=x|Y=y_n),$$

however, the equation needs to be normalized. Which is why the formular needs to be divided by $\sum_{n=1}^N p(X=x|Y=y_n)$, which brings following equation:

$$E_Y[Y|X=x] = \frac{\sum_{n=1}^N y_n * p(X=x|Y=y_n)}{\sum_{n=1}^N p(X=x|Y=y_n)}$$

4.2 Verify MAP.

$$P(Y|X=x) = \frac{P(X=x|Y)*p(Y)}{p(X=x)}$$

We seek value $y_n \in Y$ that maximises the posterior.

$$\begin{aligned}
\hat{y}_{MAX} &= \operatorname{argmax} p(Y=y_n|X=x) \\
&= \operatorname{argmax} \frac{p(X=x|Y=y_n)*p(Y=y_n)}{p(X=x)},
\end{aligned}$$

where $p(X=x)$ is a constant and can be neglected and $p(Y=y_n) = 1$ because of the uniform distribution. Which brings the following equation:

$$\hat{y}_{MAX} = \operatorname{argmax} p(X=x|Y=y_n)$$

4.3 Plot results.

Here the plot containing all result images can be seen. (Sorry for the mess, latex is doing what it wants...)

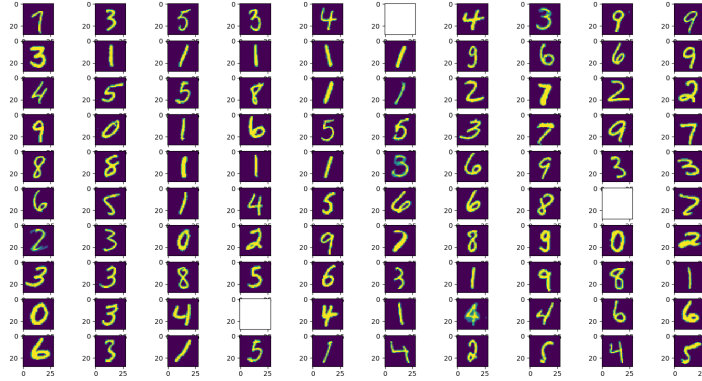


Figure 1: Result of CM algo with sigma 0.25.

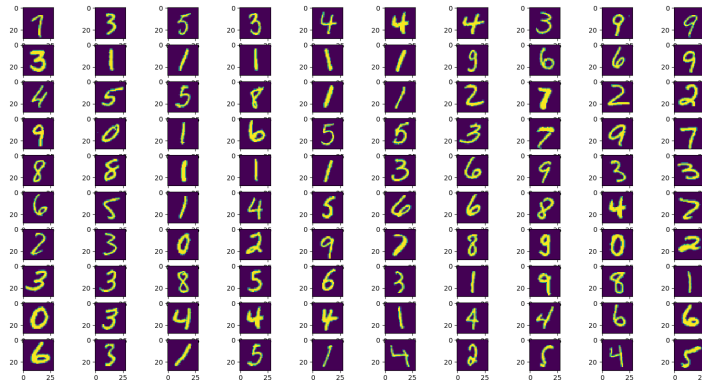


Figure 2: Result of MAP algo with sigma 0.25.

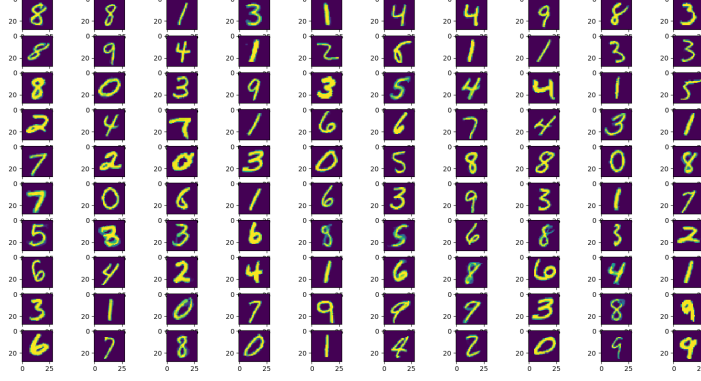


Figure 3: Result of CM algo with sigma 0.50.

4.4 Discuss results.

In our experiments we used three different values for σ : 0.25, 0.5, 1. The smaller the sigma, the smaller the amount of noise added to the testing images. The bigger the sigma, the bigger the amount of added noise. Generally speaking: the more noise an image has, the harder it is for an algorithm to remove the noise.

4.4.1 Sigma with 0.25

As can be seen in figure 1 the CM algorithm did a pretty good job at removing the noise. There are only a few images, where the noise was not removed completely (e.g. the 3 at position $x=6, y=5$, where the algorithm almost made an 8 out of the 3) The MAP algorithm, however, did an excellent job, as can be seen in figure 2

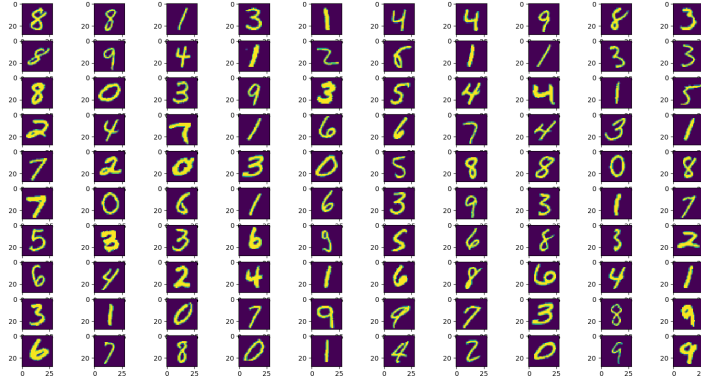


Figure 4: Result of MAP algo with sigma 0.50.

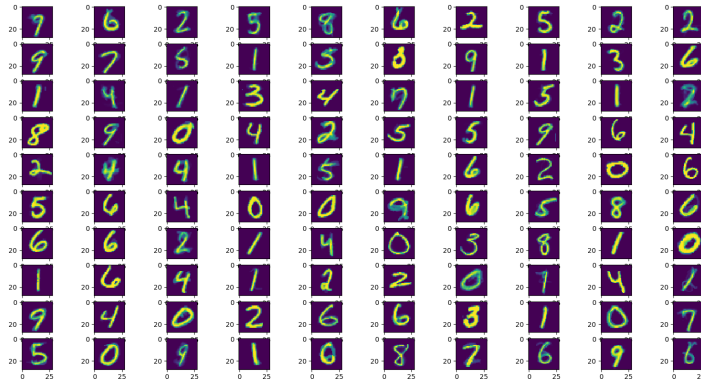


Figure 5: Result of CM algo with sigma 0.50.

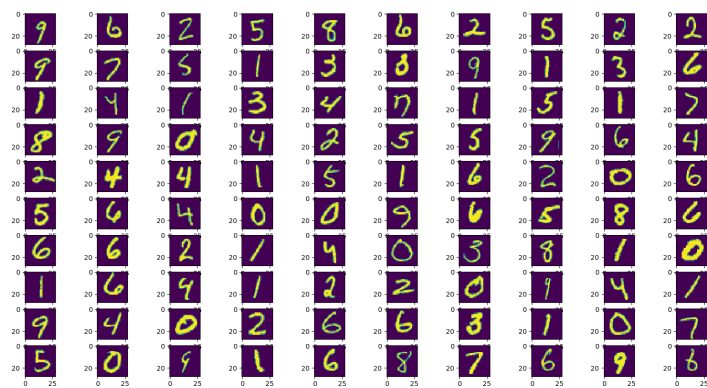


Figure 6: Result of MAP algo with sigma 1.0.