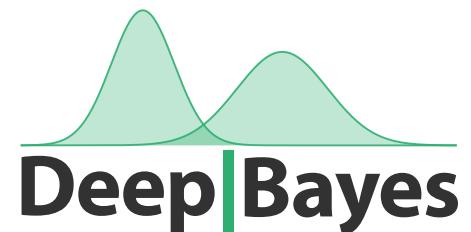


# EM algorithm for the investigation

*Ekaterina Lobacheva*

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# EM algorithm in one slide

$X$  — observed

$$\log p(X \mid \theta) \rightarrow \max_{\theta}$$

$Z$  — latent

$\vee|$

$\theta$  — parameters

$$\mathcal{L}(q, \theta) = \mathbb{E}_{q(Z)} \log p(X, Z \mid \theta) - \mathbb{E}_{q(Z)} \log q(Z) \rightarrow \max_{q, \theta}$$

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$$\mathcal{L}(q, \theta) = \mathbb{E}_{q(Z)} \log p(X, Z \mid \theta) - \mathbb{E}_{q(Z)} \log q(Z) \rightarrow \max_{q, \theta}$$

## Iterations:



E-step:

$$q(Z) = \arg \max_q \mathcal{L}(q, \theta) = \arg \min_q KL(q||p) = p(Z \mid X, \theta)$$

M-step:

$$\theta = \arg \max_{\theta} \mathcal{L}(q, \theta) = \arg \max_{\theta} \mathbb{E}_{q(Z)} \log p(X, Z \mid \theta)$$

Stopping criteria:

$$\mathcal{L}(q^{(t+1)}, \theta^{(t+1)}) - \mathcal{L}(q^{(t)}, \theta^{(t)}) < tol$$

# Story time

One of the school organisers decided to prank us and hid all games for our Thursday Game Night somewhere. Let's investigate!

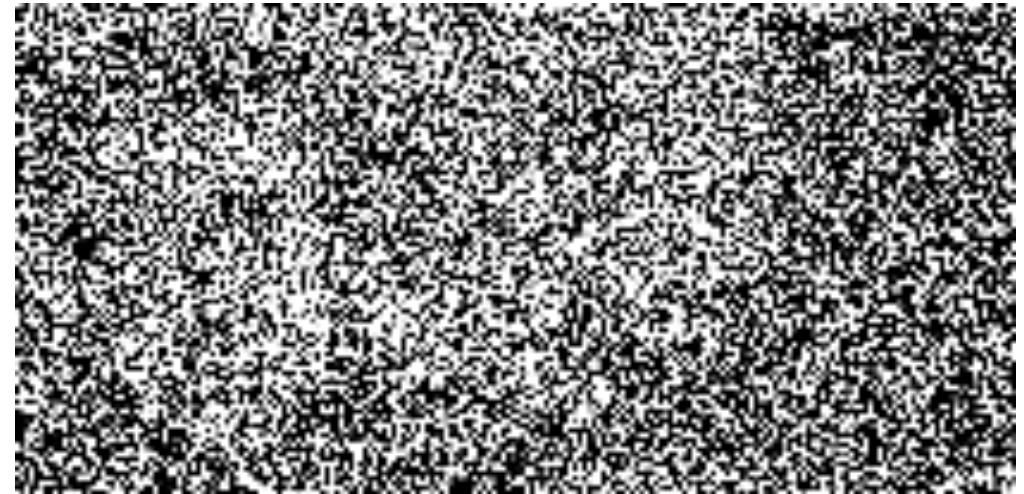


# Story time

One of the school organisers decided to prank us and hid all games for our Thursday Game Night somewhere. Let's investigate!

We've obtained a set of  $K$  photographs of the suspect, but all of them are corrupted by a directed electromagnetic noise.

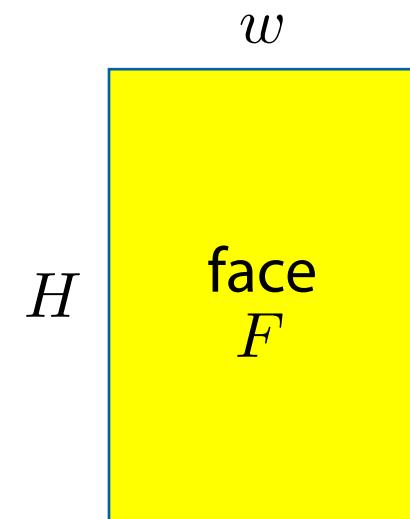
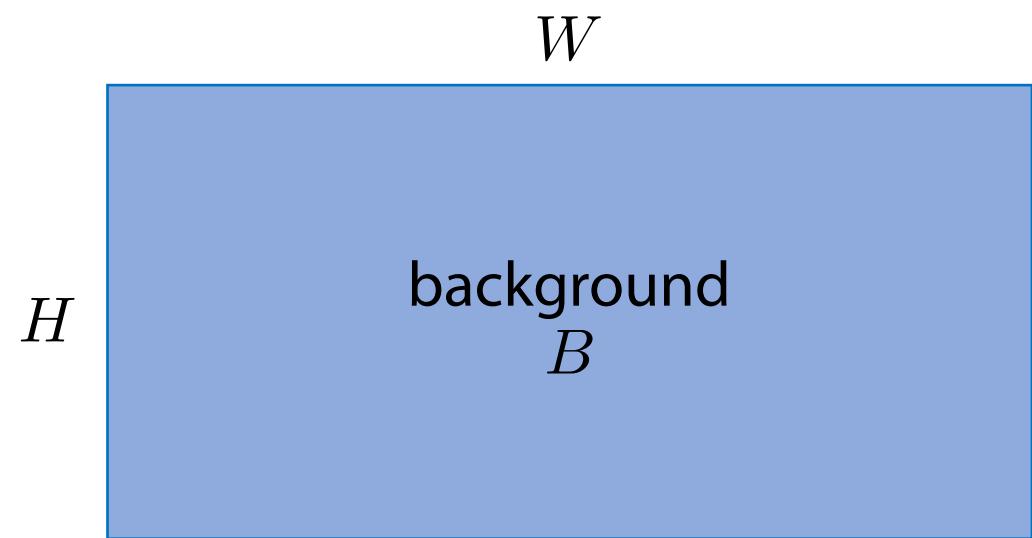
Maybe Bayesian algorithms may help us to expose the prankster?



# Data and Notation

$B \in \mathbb{R}^{H \times W}$  — clean background image

$F \in \mathbb{R}^{H \times w}$  — clean face image



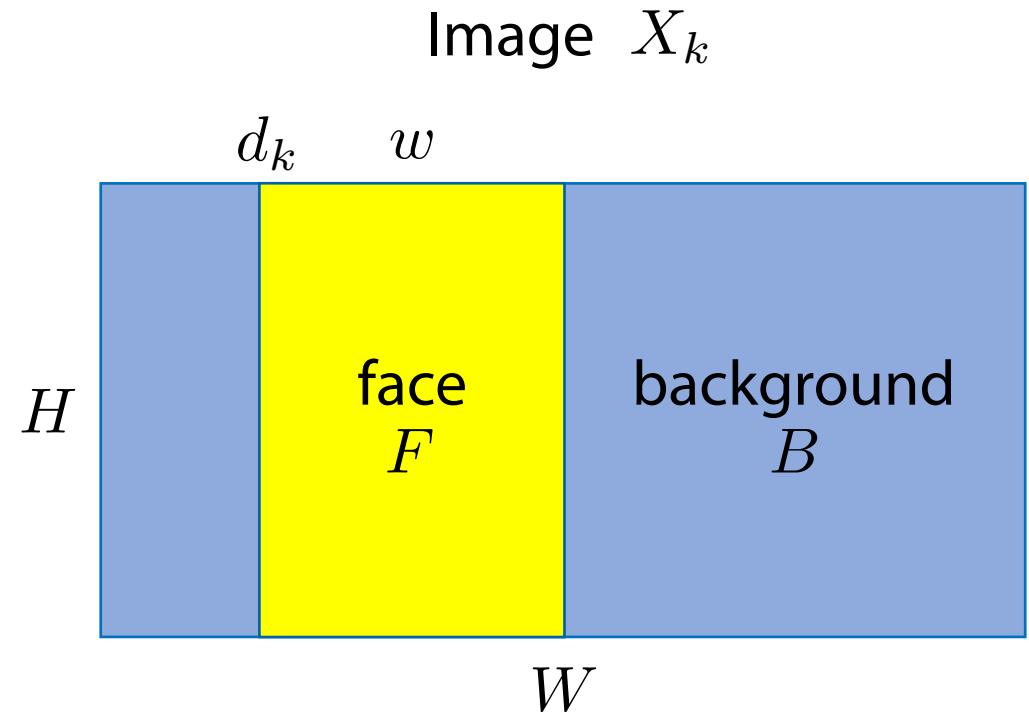
# Data and Notation

$B \in \mathbb{R}^{H \times W}$  — clean background image

$F \in \mathbb{R}^{H \times w}$  — clean face image

$X_k$  — k-th image from the dataset

$d_k$  — coordinate of the upper-left corner of the face on the k-th image



All images contain the whole face!

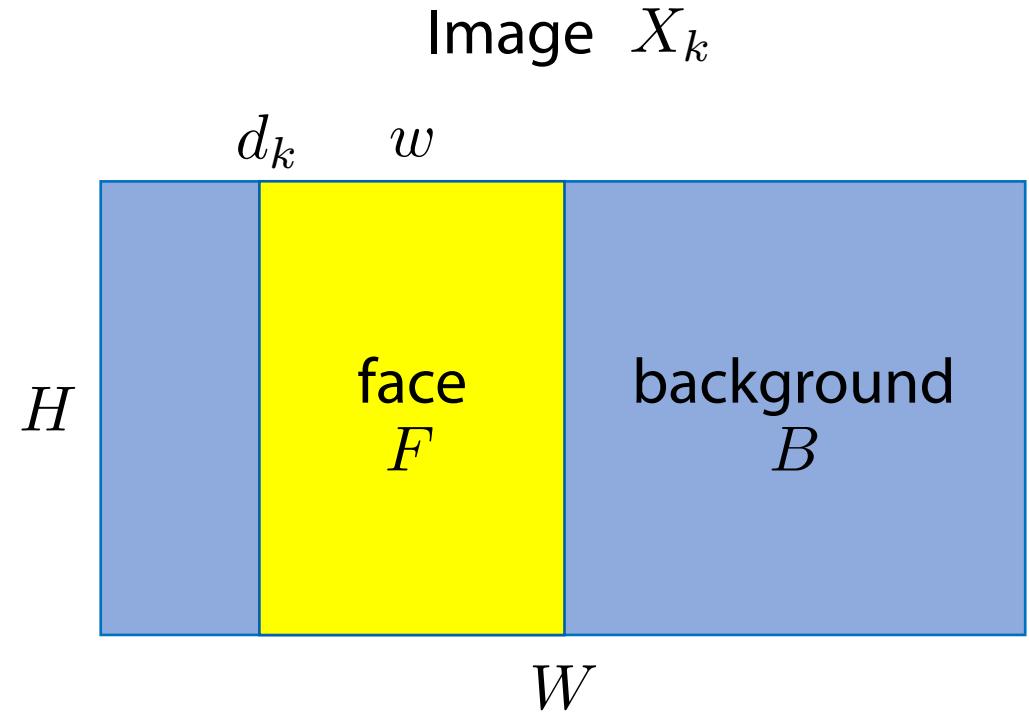
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+ noise from  $\mathcal{N}(0, s^2)$

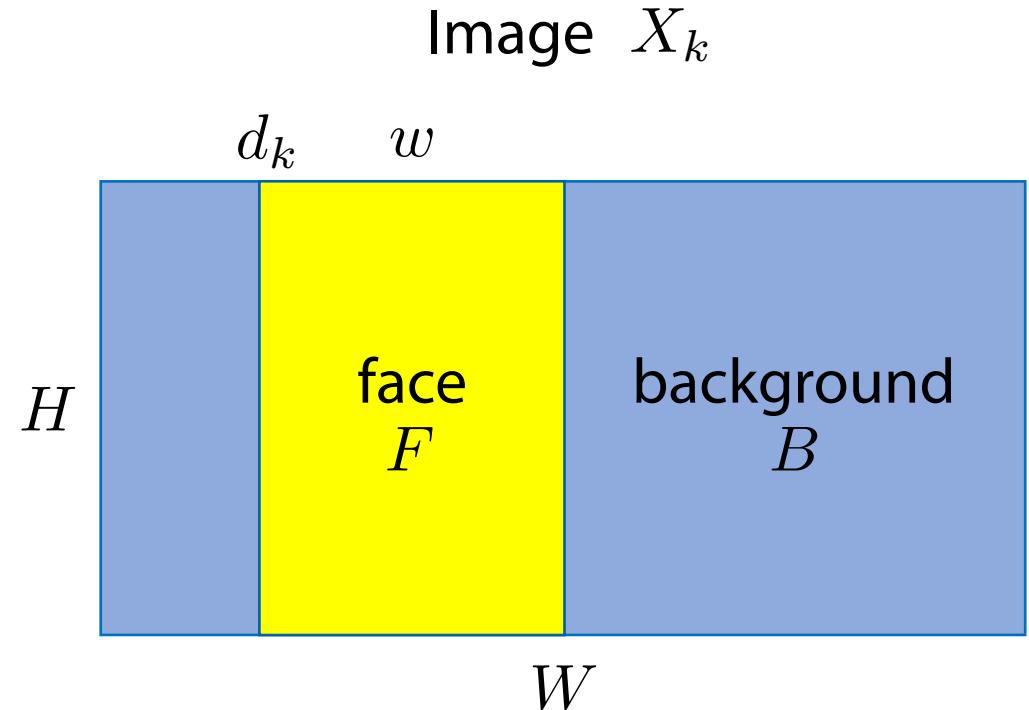
All images contain the whole face!

# Probabilistic Model

Observed: ?

Latent: ?

Parameters: ?



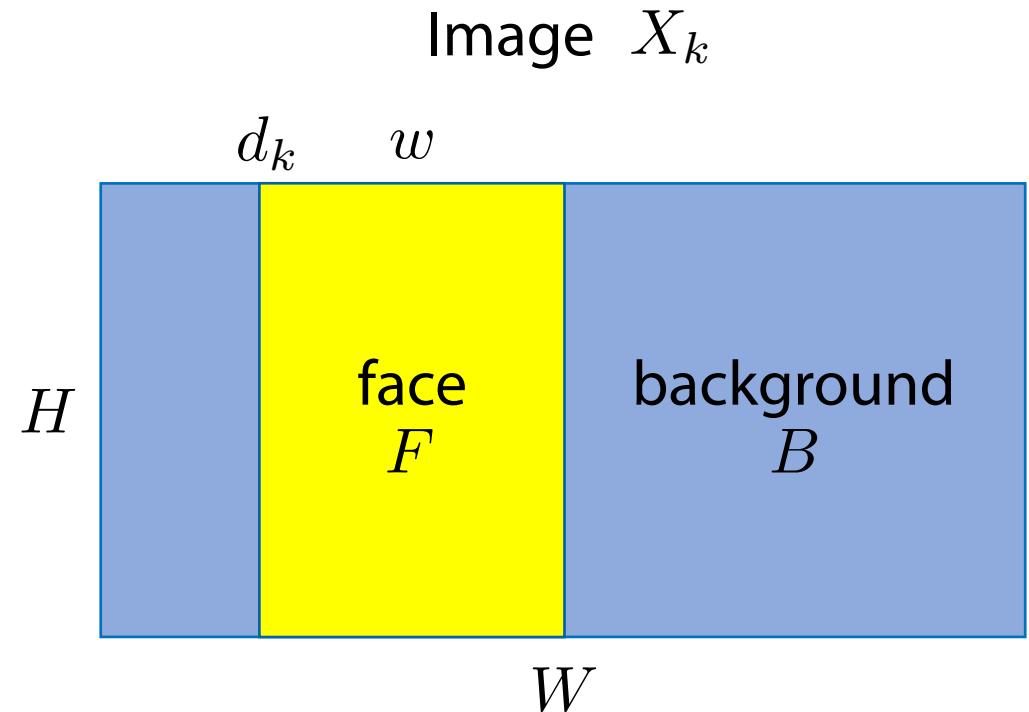
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# Probabilistic Model

Observed:  $X = \{X_1, \dots, X_K\}$

Latent: ?

Parameters: ?



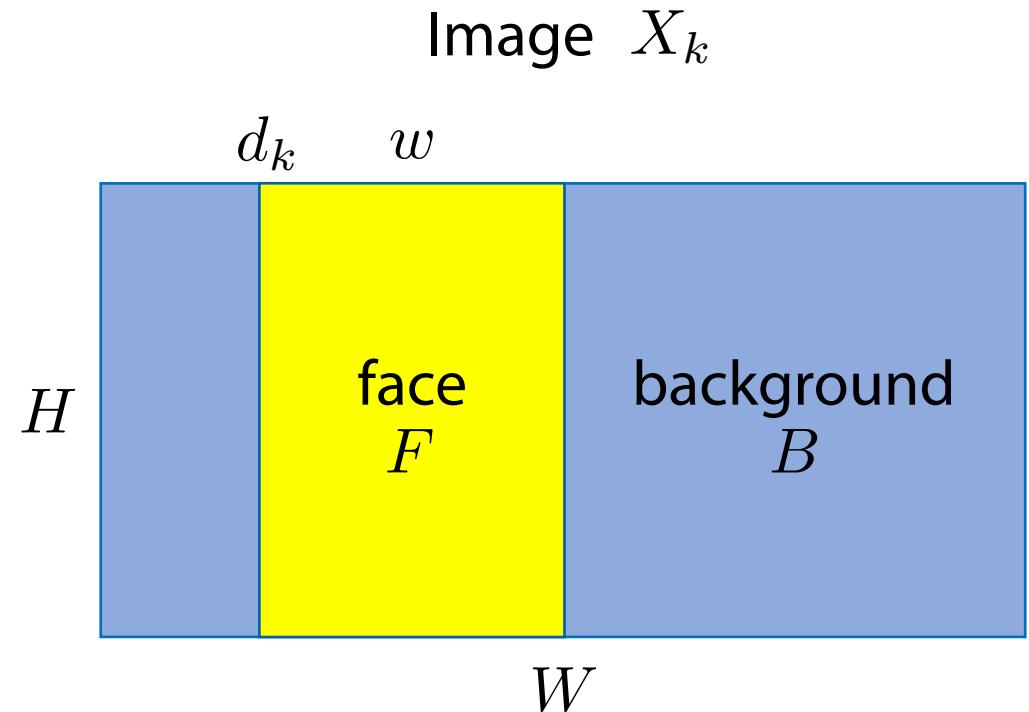
+ noise from  $\mathcal{N}(0, s^2)$

# Probabilistic Model

Observed:  $X = \{X_1, \dots, X_K\}$

Latent:  $d = \{d_1, \dots, d_K\}$

Parameters: ?



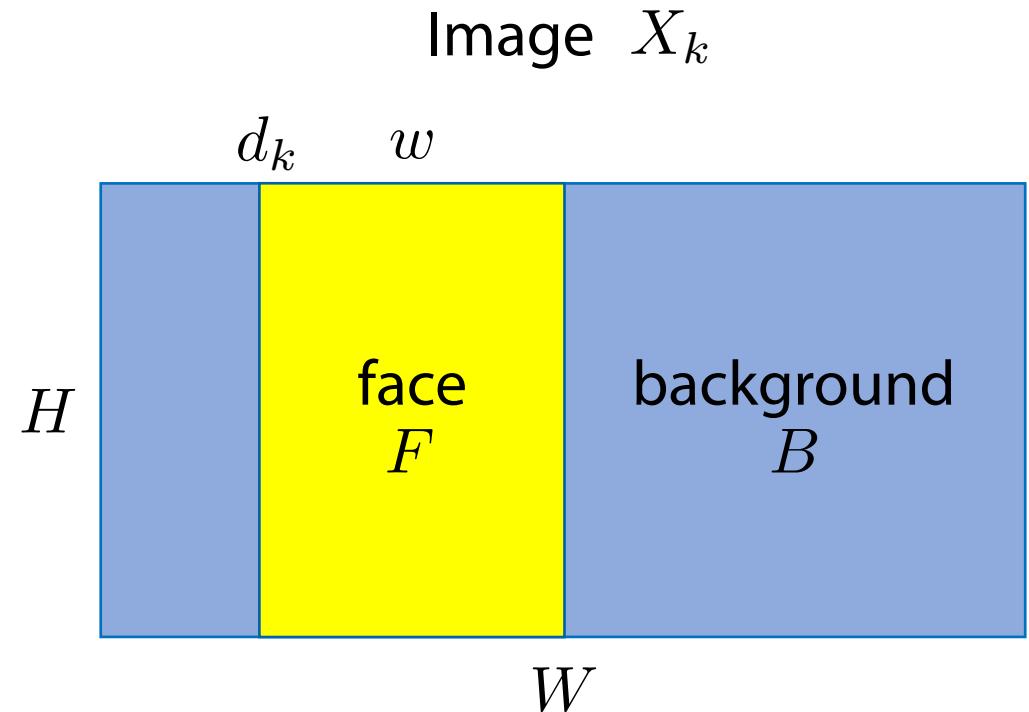
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# Probabilistic Model

Observed:  $X = \{X_1, \dots, X_K\}$

Latent:  $d = \{d_1, \dots, d_K\}$

Parameters:  $\theta = \{B, F, s^2\}$



+ noise from  $\mathcal{N}(0, s^2)$

# Probabilistic Model

Generation of one image:

$$p(X_k \mid d_k, \theta) = ?$$

# Probabilistic Model

Generation of one image:

$$p(X_k \mid d_k, \theta) = \prod_{ij} \begin{cases} \mathcal{N}(X_k[i, j] \mid F[i, j - d_k], s^2), & \text{if } [i, j] \in faceArea(d_k) \\ \mathcal{N}(X_k[i, j] \mid B[i, j], s^2), & \text{otherwise} \end{cases}$$

What else do we need?

# Probabilistic Model

Generation of one image:

$$p(X_k \mid d_k, \theta) = \prod_{ij} \begin{cases} \mathcal{N}(X_k[i, j] \mid F[i, j - d_k], s^2), & \text{if } [i, j] \in faceArea(d_k) \\ \mathcal{N}(X_k[i, j] \mid B[i, j], s^2), & \text{otherwise} \end{cases}$$

Prior on face positions:

$$p(d_k \mid a) = a[d_k], \quad \sum_j a[j] = 1, \quad a \in \mathbb{R}^{W-w+1}$$

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Prior on face positions:

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Joint probabilistic model:

$$p(X, d \mid \theta, a) = \prod_k p(X_k \mid d_k, \theta)p(d_k \mid a)$$

# Task overview

$X$  — observed

$$\log p(X \mid \theta, a) \rightarrow \max_{\theta, a}$$

$d$  — latent

VI

$\theta, a$  — parameters

$$\mathcal{L}(q, \theta, a) = \mathbb{E}_{q(d)} \log p(X, d \mid \theta, a) - \mathbb{E}_{q(d)} \log q(d) \rightarrow \max_{q, \theta, a}$$

## Iterations:



E-step:

$$q(d) = p(d \mid X, \theta, a)$$

M-step:

$$\mathbb{E}_{q(d)} \log p(X, d \mid \theta, a) \rightarrow \max_{\theta, a}$$

Stopping criteria:

$$\mathcal{L}(q^{(t+1)}, \theta^{(t+1)}, a^{(t+1)}) - \mathcal{L}(q^{(t)}, \theta^{(t)}, a^{(t)}) < tol$$

# E-step



$$q(d) = p(d \mid X, \theta, a) = ?$$



# E-step

$$q(d) = p(d \mid X, \theta, a) = \prod_k p(d_k \mid X_k, \theta, a)$$



# E-step

$$\begin{aligned} q(d) &= p(d \mid X, \theta, a) = \prod_k p(d_k \mid X_k, \theta, a) \\ &= \prod_k \frac{p(X_k, d_k \mid \theta, a)}{\sum_{d'_k} p(X_k, d'_k \mid \theta, a)} \end{aligned}$$



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$p(X_k \mid d_k, \theta), \quad p(d_k \mid a)$  — we know from the probabilistic model



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$p(X_k \mid d_k, \theta), \quad p(d_k \mid a)$  — we know from the probabilistic model

**In practice for each object k:**

$$q(d_k) \propto p(X_k \mid d_k, \theta)p(d_k \mid a) \in \mathbb{R}^{W-w+1}, \quad \sum_j q(d_k = j) = 1$$



# M-step: function

$$Q(\theta, a) = \mathbb{E}_{q(d)} \log p(X, d \mid \theta, a) \rightarrow \max_{\theta, a}$$

Let's first simplify Q and rewrite it as a function of individual parameters:

$$\mathbb{E}_{q(d)} \rightarrow \mathbb{E}_{q(d_k)} \quad \theta, a \rightarrow F, B, s^2, a$$



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$$\begin{aligned} Q(\theta, a) &= \mathbb{E}_{q(d)} \log \prod_k p(X_k \mid d_k, \theta) p(d_k \mid a) = \mathbb{E}_{q(d)} \sum_k \left( \log p(X_k \mid d_k, \theta) + \log p(d_k \mid a) \right) \\ &= \sum_k \mathbb{E}_{q(d)} \left( \log p(X_k \mid d_k, \theta) + \log p(d_k \mid a) \right) = \sum_k \mathbb{E}_{q(d_k)} \left( \log p(X_k \mid d_k, \theta) + \log p(d_k \mid a) \right) \end{aligned}$$



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$$\log p(X_k \mid d_k, \theta) = \sum_{i,j} \left( -\log(\sqrt{2\pi}s) - \frac{1}{2s^2} \left[ (X_k[i, j] - B[i, j])^2 I_{ijd_k}^B + (X_k[i, j] - F[i, j - d_k])^2 I_{ijd_k}^F \right] \right)$$

$$I_{ijd_k}^F = \mathbb{I}([i, j] \in faceArea(d_k)), \quad I_{ijd_k}^B = \mathbb{I}([i, j] \notin faceArea(d_k)) = 1 - I_{ijd_k}^F$$



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$$\log p(d_k \mid a) = \log a[d_k]$$



# M-step: maximisation w.r.t. $a$

$$\left\{ \begin{array}{l} Q(F, B, s^2, a) = \sum_k \mathbb{E}_{q(d_k)} \left[ \log a[d_k] + \sum_{i,j} \left( -\log(\sqrt{2\pi}s) - \right. \right. \\ \left. \left. - \frac{1}{2s^2} \left[ (X_k[i, j] - B[i, j])^2 I_{ijd_k}^B + (X_k[i, j] - F[i, j - d_k])^2 I_{ijd_k}^F \right] \right) \right] \rightarrow \max_a \\ \sum_j a[j] = 1 \end{array} \right.$$



# M-step: maximisation w.r.t. $a$

$$\left\{ \begin{array}{l} Q(F, B, s^2, a) = \sum_k \mathbb{E}_{q(d_k)} [\log a[d_k]] + \sum_{i,j} \left( -\log(\sqrt{2\pi}s) - \right. \\ \left. - \frac{1}{2s^2} [(X_k[i, j] - B[i, j])^2 I_{ijd_k}^B + (X_k[i, j] - F[i, j - d_k])^2 I_{ijd_k}^F] \right) \rightarrow \max_a \\ \sum_j a[j] = 1 \end{array} \right.$$



# M-step: maximisation w.r.t. $a$

$$\begin{cases} Q(a) = \sum_k \mathbb{E}_{q(d_k)} \log a[d_k] \rightarrow \max_a \\ \sum_j a[j] = 1 \end{cases}$$



# M-step: maximisation w.r.t. $a$

$$\begin{cases} Q(a) = \sum_k \mathbb{E}_{q(d_k)} \log a[d_k] \rightarrow \max_a \\ \sum_j a[j] = 1 \end{cases}$$

The Lagrangian has form:

$$L(a, \lambda) = Q(a) - \lambda(\sum_j a[j] - 1)$$



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$$0 = \frac{\partial L(a, \lambda)}{\partial a[j]} = \sum_k \frac{q(d_k = j)}{a[j]} - \lambda \quad \Rightarrow \quad a[j] = \frac{\sum_k q(d_k = j)}{\lambda}$$

$$0 = \frac{\partial L(a, \lambda)}{\partial \lambda} = \sum_j a[j] - 1 \quad \Rightarrow \quad \lambda = \sum_{j,k} q(d_k = j)$$



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$$0 = \frac{\partial L(a, \lambda)}{\partial \lambda} = \sum_j a[j] - 1 \quad \Rightarrow \quad \lambda = \sum_{j,k} q(d_k = j)$$

In practice:

$$a[j] \propto \sum_k q(d_k = j), \quad \sum_j a[j] = 1$$



# M-step: maximisation w.r.t. $F$

$$Q(F, B, s^2, a) = \sum_k \mathbb{E}_{q(d_k)} \left[ \log a[d_k] + \sum_{i,j} \left( -\log(\sqrt{2\pi}s) - \frac{1}{2s^2} [(X_k[i,j] - B[i,j])^2 I_{ijd_k}^B + (X_k[i,j] - F[i,j-d_k])^2 I_{ijd_k}^F] \right) \right] \rightarrow \max_F$$



# M-step: maximisation w.r.t. $F$

$$Q(F, B, s^2, a) = \sum_k \mathbb{E}_{q(d_k)} \left[ \log a[d_k] + \sum_{i,j} \left( -\log(\sqrt{2\pi}s) - \right. \right.$$
$$\left. \left. - \frac{1}{2s^2} \left[ (X_k[i, j] - B[i, j])^2 I_{ijd_k}^B + (X_k[i, j] - F[i, j - d_k])^2 I_{ijd_k}^F \right] \right) \right] \rightarrow \max_F$$



# M-step: maximisation w.r.t. $F$

$$Q(F) = \sum_k \mathbb{E}_{q(d_k)} \left[ \sum_{i,j} \left( -\frac{1}{2s^2} (X_k[i, j] - F[i, j - d_k])^2 I_{ijd_k}^F \right) \right] \rightarrow \max_F$$



# M-step: maximisation w.r.t. $F$

$$\begin{aligned} Q(F) &= \sum_k \mathbb{E}_{q(d_k)} \left[ \sum_{i,j} \left( -\frac{1}{2s^2} (X_k[i, j] - F[i, j - d_k])^2 I_{ijd_k}^F \right) \right] \\ &= \sum_k \mathbb{E}_{q(d_k)} \left[ \sum_{i=0, m=0}^{H-1, w-1} \left( -\frac{1}{2s^2} (X_k[i, m + d_k] - F[i, m])^2 \right) \right] \rightarrow \max_F \end{aligned}$$



# M-step: maximisation w.r.t. $F$

$$\begin{aligned} Q(F) &= \sum_k \mathbb{E}_{q(d_k)} \left[ \sum_{i,j} \left( -\frac{1}{2s^2} (X_k[i,j] - F[i,j-d_k])^2 I_{ijd_k}^F \right) \right] \\ &= \sum_k \mathbb{E}_{q(d_k)} \left[ \sum_{i=0, m=0}^{H-1, w-1} \left( -\frac{1}{2s^2} (X_k[i, m+d_k] - F[i, m])^2 \right) \right] \rightarrow \max_F \end{aligned}$$

$$0 = \frac{\partial Q(F)}{\partial F[i, m]} = \sum_{k, d_k} \frac{q(d_k)}{s^2} \left( X_k[i, m+d_k] - F[i, m] \right)$$

$$F[i, m] = \frac{\sum_{k, d_k} q(d_k) X_k[i, m+d_k]}{\sum_{k, d_k} q(d_k)} = \frac{\sum_{k, d_k} q(d_k) X_k[i, m+d_k]}{K}$$



# M-step: maximisation w.r.t. $B$

$$Q(F, B, s^2, a) = \sum_k \mathbb{E}_{q(d_k)} \left[ \log a[d_k] + \sum_{i,j} \left( -\log(\sqrt{2\pi}s) - \right. \right.$$
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# M-step: maximisation w.r.t. $B$

$$Q(F, B, s^2, a) = \sum_k \mathbb{E}_{q(d_k)} \left[ \log a[d_k] + \sum_{i,j} \left( -\log(\sqrt{2\pi}s) - \right. \right.$$
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# M-step: maximisation w.r.t. $B$

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$$0 = \frac{\partial Q(B)}{\partial B[i,j]} = \sum_{k,d_k} \frac{q(d_k) I_{ijd_k}^B}{s^2} (X_k[i,j] - B[i,j])$$

$$B[i,j] = \frac{\sum_{k,d_k} q(d_k) I_{ijd_k}^B X_k[i,j]}{\sum_{k,d_k} q(d_k) I_{ijd_k}^B}$$



# M-step: maximisation w.r.t. $s^2$

$$Q(F, B, s^2, a) = \sum_k \mathbb{E}_{q(d_k)} \left[ \log a[d_k] + \sum_{i,j} \left( -\log(\sqrt{2\pi}s) - \right. \right.$$
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# M-step: maximisation w.r.t. $s^2$

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# M-step: maximisation w.r.t. $s^2$

$$Q(s^2) = \sum_k \mathbb{E}_{q(d_k)} \left[ \sum_{i,j} \left( -\frac{1}{2} \log(s^2) - \right. \right.$$
$$\left. \left. - \frac{1}{2s^2} [(X_k[i,j] - B[i,j])^2 I_{ijd_k}^B + (X_k[i,j] - F[i,j-d_k])^2 I_{ijd_k}^F] \right) \right] \rightarrow \max_{s^2}$$



# M-step: maximisation w.r.t. $s^2$

$$Q(s^2) = \sum_k \mathbb{E}_{q(d_k)} \left[ \sum_{i,j} \left( -\frac{1}{2} \log(s^2) - \right. \right. \\ \left. \left. - \frac{1}{2s^2} [(X_k[i,j] - B[i,j])^2 I_{ijd_k}^B + (X_k[i,j] - F[i,j-d_k])^2 I_{ijd_k}^F] \right) \right] \rightarrow \max_{s^2}$$

$$0 = \frac{\partial Q(s^2)}{\partial s^2} = \sum_{k,d_k,i,j} q(d_k) \left( -\frac{1}{2s^2} + \frac{1}{2s^4} [(X_k[i,j] - B[i,j])^2 I_{ijd_k}^B + (X_k[i,j] - F[i,j-d_k])^2 I_{ijd_k}^F] \right)$$

$$s^2 = \frac{1}{\sum_{k,d_k,i,j} q(d_k)} \sum_{k,d_k,i,j} q(d_k) [(X_k[i,j] - B[i,j])^2 I_{ijd_k}^B + (X_k[i,j] - F[i,j-d_k])^2 I_{ijd_k}^F] \\ = \frac{1}{NWH} \sum_{k,d_k,i,j} q(d_k) [(X_k[i,j] - B[i,j])^2 I_{ijd_k}^B + (X_k[i,j] - F[i,j-d_k])^2 I_{ijd_k}^F]$$



# Stopping criteria

$$\mathcal{L}(q^{(t+1)}, \theta^{(t+1)}, a^{(t+1)}) - \mathcal{L}(q^{(t)}, \theta^{(t)}, a^{(t)}) < tol$$

$$\mathcal{L}(q, \theta, a) = ?$$



# Stopping criteria

$$\mathcal{L}(q^{(t+1)}, \theta^{(t+1)}, a^{(t+1)}) - \mathcal{L}(q^{(t)}, \theta^{(t)}, a^{(t)}) < tol$$

$$\mathcal{L}(q, \theta, a) = \mathbb{E}_{q(d)} \left[ \log p(X, d \mid \theta, a) - \log q(d) \right]$$



# Stopping criteria

$$\mathcal{L}(q^{(t+1)}, \theta^{(t+1)}, a^{(t+1)}) - \mathcal{L}(q^{(t)}, \theta^{(t)}, a^{(t)}) < tol$$

$$\begin{aligned}\mathcal{L}(q, \theta, a) &= \mathbb{E}_{q(d)} \left[ \log p(X, d \mid \theta, a) - \log q(d) \right] \\ &= \mathbb{E}_{q(d)} \left[ \log \prod_k p(X_k \mid d_k, \theta) p(d_k \mid a) - \log \prod_k q(d_k) \right] \\ &= \mathbb{E}_{q(d)} \sum_k \left[ \log p(X_k \mid d_k, \theta) + \log p(d_k \mid a) - \log q(d_k) \right]\end{aligned}$$



# Stopping criteria

$$\mathcal{L}(q^{(t+1)}, \theta^{(t+1)}, a^{(t+1)}) - \mathcal{L}(q^{(t)}, \theta^{(t)}, a^{(t)}) < tol$$

$$\begin{aligned}\mathcal{L}(q, \theta, a) &= \mathbb{E}_{q(d)} \left[ \log p(X, d \mid \theta, a) - \log q(d) \right] \\ &= \mathbb{E}_{q(d)} \left[ \log \prod_k p(X_k \mid d_k, \theta) p(d_k \mid a) - \log \prod_k q(d_k) \right] \\ &= \mathbb{E}_{q(d)} \sum_k \left[ \log p(X_k \mid d_k, \theta) + \log p(d_k \mid a) - \log q(d_k) \right] \\ &= \sum_k \mathbb{E}_{q(d)} \left[ \log p(X_k \mid d_k, \theta) + \log p(d_k \mid a) - \log q(d_k) \right] \\ &= \sum_k \mathbb{E}_{q(d_k)} \left[ \log p(X_k \mid d_k, \theta) + \log p(d_k \mid a) - \log q(d_k) \right]\end{aligned}$$

# Task overview



$$q(d_k) \propto p(X_k \mid d_k, \theta)p(d_k \mid a), \quad \sum_j q(d_k = j) = 1$$

$$a[j] \propto \sum_k q(d_k = j), \quad \sum_j a[j] = 1$$

$$F[i, m] = \frac{\sum_{k, d_k} q(d_k) X_k[i, m + d_k]}{K}$$

$$B[i, j] = \frac{\sum_{k, d_k} q(d_k) I_{ijd_k}^B X_k[i, j]}{\sum_{k, d_k} q(d_k) I_{ijd_k}^B}$$

$$s^2 = \frac{1}{NWH} \sum_{k, d_k, i, j} q(d_k) \left[ (X_k[i, j] - B[i, j])^2 I_{ijd_k}^B + (X_k[i, j] - F[i, j - d_k])^2 I_{ijd_k}^F \right]$$

**Stopping criteria:**

$$\mathcal{L}(q^{(t+1)}, \theta^{(t+1)}, a^{(t+1)}) - \mathcal{L}(q^{(t)}, \theta^{(t)}, a^{(t)}) < tol$$

$$\mathcal{L}(q, \theta, a) = \sum_k \mathbb{E}_{q(d_k)} \left[ \log p(X_k \mid d_k, \theta) + \log p(d_k \mid a) - \log q(d_k) \right]$$