

An Accurate Evaluation of MSD Log-likelihood and its Application in Human Action Recognition

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Objectives

1. To propose a new parameterization of the **Multinomial Scaled Dirichlet** (MSD) [1] log-likelihood function based on a truncated series consisting of Bernoulli polynomials.
2. To adopt the **mesh algorithm** for computing this log-likelihood used for parameters estimation within the mixture model framework.
3. To propose a **model selection** approach which is seamlessly integrated with the parameters estimation and avoids several drawbacks of the standard Expectation-Maximization algorithm.

Approximating the Paired Log-Gamma Difference

- ▶ The MSD likelihood function is given by:

$$\mathcal{L}(p, \psi, \beta; \mathbf{X}) = -\left(\ln \Gamma(1/\psi + N) - \ln \Gamma(1/\psi)\right) - \sum_{w=1}^W x_w \ln(\beta_w) + \sum_{w=1}^W \left(\ln \Gamma\left(1/\frac{\psi}{\rho_w} + x_w\right) - \ln \Gamma\left(1/\frac{\psi}{\rho_w}\right)\right) \quad (1)$$

where $N = \sum_{w=1}^W x_w$, $\psi = 1/A$ is the overdispersion parameter, and $\rho_w = \psi \alpha_w$.

- ▶ We use the approximation of the paired log-gamma difference method

$$\ln \Gamma(1/x + y) - \ln \Gamma(1/x) \approx -y \ln x + D_m(x, y) \quad (2)$$

when y is an integer, $|x|, \min(|y-1|, |y|) < 1$, $xy \leq \delta$ and:

$$D_m(x, y) = \sum_{n=2}^m \frac{(-1)^n \phi_n(y)}{n(n-1)} x^{(n-1)}$$

where $\phi_n(y) = B_n(y) - B_n$ is the old type Bernoulli polynomial, $B_n(y)$ and B_n indicate the n th Bernoulli polynomial, and n th Bernoulli number ($B_n = B_n(0)$), respectively.

The Mesh Algorithm for Evaluating the Log-likelihood

- ▶ First, generate the mesh using:

$$x_w^{(l)} = \lfloor \alpha_w^{(l-1)} \delta \rfloor \quad (3)$$

- ▶ Then, we select the level of the mesh L , so it would be the smallest integer satisfying:

$$\sum_{l=1}^L x_w^{(l)} \geq x_w \quad \text{for all } w = 1, \dots, W$$

- ▶ Afterwards, we adjust $x_w^{L'}$ such that $\sum_{l=1}^{L'} x_w^{(l)} = x_w$, and all the remaining $x_w^{(l)} (l > L')$ will be set to zero.

- ▶ With this adjusted mesh, we can use the approximation in (Eq.2) to compute the MSD log-likelihood as the sum of each $\mathbf{X}^{(l)}$ log-likelihood, as:

$$\mathcal{L}(p, \psi, \beta; \mathbf{X}^+) = \sum_{l=1}^L \mathcal{L}(p^{(l-1)+}, \psi^{(l-1)}, \beta^{(l-1)+}; \mathbf{X}^{(l)+}) \quad (4)$$

where \mathbf{X}^+ is the vector of non-zero elements in \mathbf{X} .

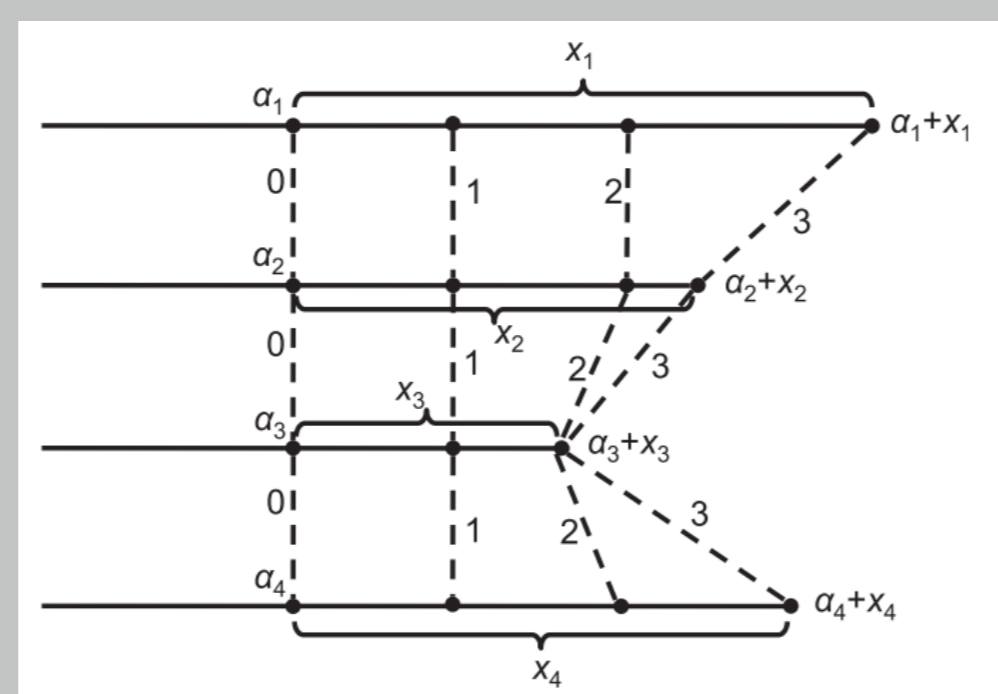


Figure 1: A graphical depiction of the mesh algorithm [2].

The Estimation and Selection Framework

- ▶ The algorithm starts with a large number of components and iteratively deletes components as they become irrelevant.
- ▶ The model selection is based on the minimum message length (MML) criterion, defined as:

$$\Theta_{MML} = \arg \min_{\Theta} \left\{ -\ln P(\Theta) - \mathcal{L}(\mathcal{X}, \mathcal{Z}|\Theta) + \frac{1}{2} \ln |\mathbf{I}(\Theta)| + \frac{\mathcal{D}(\Theta)}{2} \left(1 + \ln \frac{1}{12}\right) \right\} \quad (5)$$

where $\mathcal{L}(\mathcal{X}, \mathcal{Z}|\Theta)$ the complete-data log-likelihood, $P(\Theta)$ is the prior distribution, $\mathbf{I}(\Theta)$ is the expected Fisher information matrix, and $\mathcal{D}(\Theta)$ denotes the model dimensionality.

- ▶ We use the component-wise EM procedure (CEM), and any weak component will be annihilated.
- ▶ MML criterion is re-evaluated for non-zero components only until the message length difference becomes insignificant.

Results-Frame Level

- ▶ Frames extracted from the UCF sports dataset.
- ▶ Each extracted frame is treated as an image from which a set of interest points are detected and described using Scale-Invariant Feature Transform (SIFT), then represented as count vectors using Bag of Features (BoF) approach.

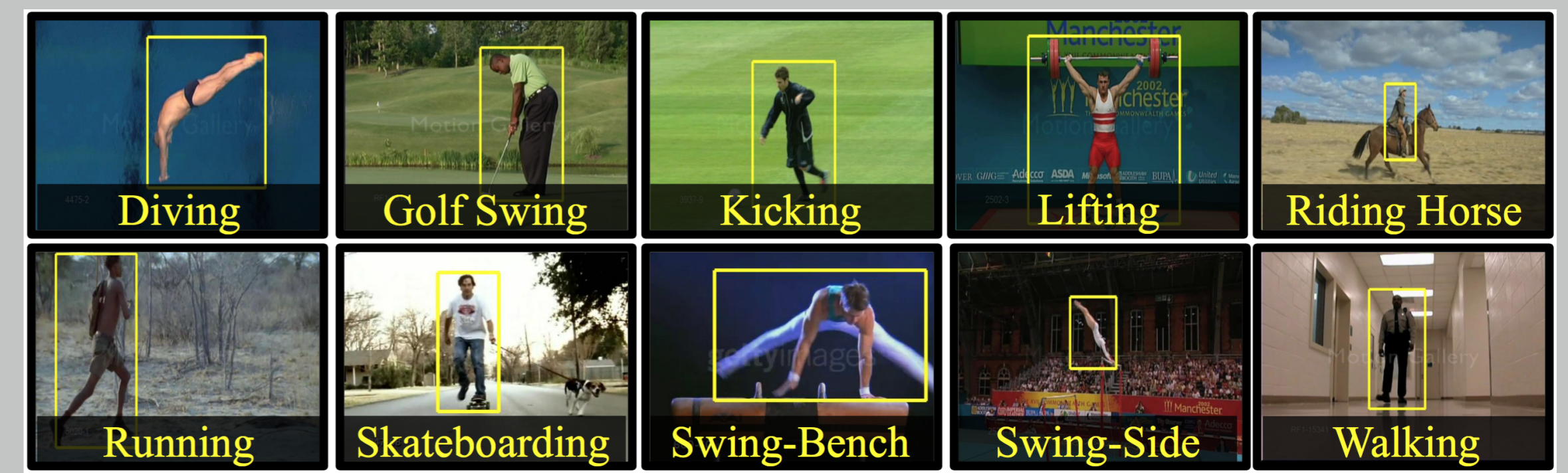


Figure 2: Sample frames from UCF sports dataset.

MM	DMN	MSD	MSD Mesh
61.72%	66.97%	66.97%	78.60%

Table 1: The average recognition accuracy for UCF sports dataset.

*MM: Mixture of Multinomials, DMN: Mixture of Dirichlet-Multinomial, MSD: Mixture of MSD as in [1], MSD.Mesh: the proposed framework.

Results-Video Sequences

- ▶ Each video is represented as a vector of count data using the extension of Bag of words paradigm to videos.
- ▶ Detection of the local neighborhood with a significant variations is via Spatio Temporal Interest Points (STIP), then 3D SIFT descriptor is used.

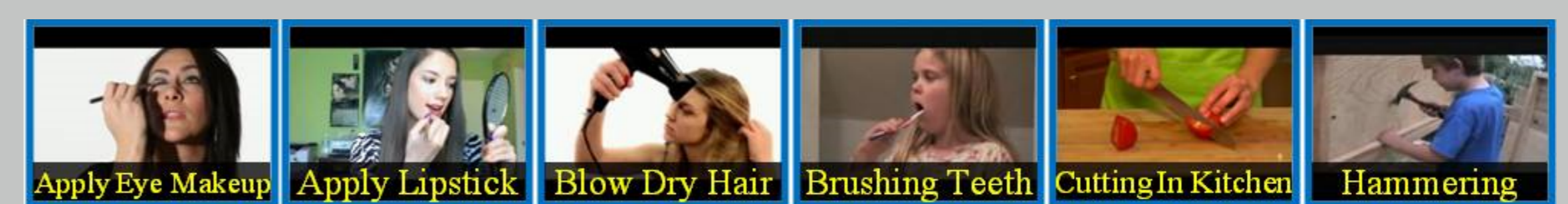


Figure 3: Sample Human-Object Interaction frames from UCF101.

MM	DMN	MSD	MSD Mesh
81.77%	82.29%	84.90%	87.76%

Table 2: The average recognition accuracy for Human-Object Interaction subset.



Figure 4: Sample Playing Musical Instruments frames from UCF101.

MM	DMN	MSD	MSD Mesh
81.89%	82.65%	89.54%	92.60%

Table 3: The average recognition accuracy for Playing Musical Instruments subset.

Conclusion

- ▶ The mesh method is generally more stable and provides an accurate computation of the log-likelihood function leads to a significant improvement in the clustering accuracy.
- ▶ The proposed algorithm successfully selected the optimal number of components, that agrees with the prespecified ones for different datasets.

References

- [1] Nuha Zamzami and Nizar Bouguila. Text modeling using multinomial scaled dirichlet distributions. *In Recent Trends and Future Technology in Applied Intelligence. IEA/AIE 2018. Lecture Notes in Computer Science, vol 10868*, pages 69–80. Springer, 2018.
- [2] Peng Yu and Chad A Shaw. An efficient algorithm for accurate computation of the dirichlet-multinomial log-likelihood function. *Bioinformatics*, 30(11):1547–1554, 2014.
- [3] Mario A. T. Figueiredo and Anil K. Jain. Unsupervised learning of finite mixture models. *IEEE Transactions on Pattern Analysis & Machine Intelligence*, (3):381–396, 2002.

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