A Flatter Loss for Bias Mitigation in Cross-dataset Facial Age Estimation

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25th International Conference on Pattern Recognition
January, 2021

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Outline

1. Age estimation Algorithms
2. The proposed Method
3. Numerical Results
4. Conclusion and Future Work

Outline

Age Estimation Problem

Age estimation is the prediction of a persons age based on biometric features extracted from the face.

Semantic Similarity

There is semantic similarity between features of adjacent ages. This semantic information should be reflected into the training algorithm.

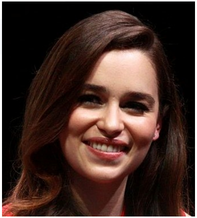
Age estimation methods:

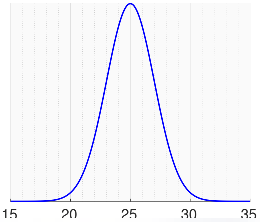
- **Regression:** Scalar labels
- **Classification:** 0/1 labels
- **Ranking:** Ensemble of binary classifiers
- **Label Distribution Learning:** Label distribution

Outline

Age estimation problem as distribution learning problem

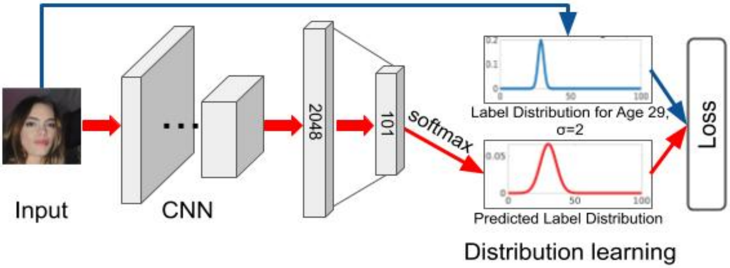
- Due to the similarity between neighbouring ages, a scalar age label is encoded as a label distribution (a set of description degrees) .
- Sum of all description degrees equal to 1.
- The maximum degree is assigned to the corresponding age.





Label distribution for a facial image at the age of 25

LDL based Age estimation System



Existing Loss Function

Kullback-Leibler divergence (KL)

$$L(\mathbf{p}, \mathbf{q}) = \sum_{k=1}^{L} q_k \log(\frac{q_k}{p_k})$$

Distribution Cognisant Loss (DC-v1)

$$L(\mathbf{p}, \mathbf{q}) = \log(1 - \alpha(1 - \sum_{k=1}^{L} \sqrt{p_k q_k})) / \log(1 - \alpha) \quad 0 < \alpha < 1$$

Distribution Cognisant Loss (DC-v2)

$$L(\mathbf{p}, \mathbf{q}) = \sum_{k=1}^{L} |q_k^\alpha - p_k^\alpha|^{\frac{1}{\alpha}} = \sum_{k=1}^{L} q^k \left|1 - (\frac{p_k}{q_k})^\alpha\right|^{\frac{1}{\alpha}} \quad 0 \leq \alpha \leq 1$$

Main Property

The smoother loss surface provides a better generalisation for the output model trained by that loss function.

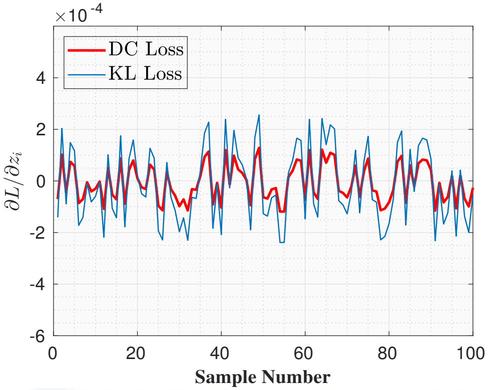
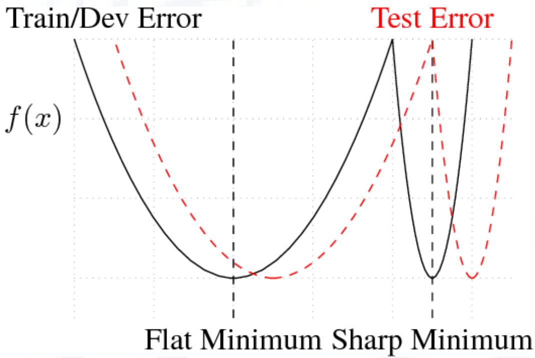


Figure: Behaviour of gradient of the KL loss and the proposed DC loss.

A Conceptual Sketch of Flat and Sharp Minima.



Main Result

It is well known that the flat minimum could help to improve the generalisation capability.

Outline

Evaluation Settings

Train Database

- **Our BAG:** $200,123$ images, crawled from Internet

Test Databases

- **FGNET:** Images with different lighting condition
- **MORPH:** Four ethnicities
- **FACES:** Six expressions
- **SC-ROT:** Images with different pose
- **SC-SUR:** Images with different quality

Architecture

- VGG16

Evaluation

- Cross database evaluation

Cross-database Evaluation (MAE & CS) on the Target Databases

	FG-NET		MORPH		FACES		SC-FACE		Average	
Method	MAE	CS(%)	MAE	CS(%)	MAE	CS(%)	MAE	CS(%)	MAE	CS(%)
Human	4.70	69.5	6.30	51.0	NA	NA	NA	NA	5.50	60.25
Microsoft	6.20	53.80	6.59	46.00	-	-	-	-	6.39	49.90
DEX	3.57	78.94	6.54	53.38	6.59	50.83	6.19	65.05	5.86	59.50
AGEn	3.53	79.78	6.40	53.97	6.34	52.40	6.12	65.21	5.72	60.60
DLDL	3.24	81.54	6.01	57.36	6.11	55.60	6.52	60.64	5.55	61.98
CE-MV	3.34	80.44	6.22	55.60	6.25	54.63	6.23	64.38	5.62	61.84
DLDL-v2	3.35	81.44	5.80	57.30	5.92	56.68	6.52	61.61	5.48	62.77
Proposed	**3.26**	**81.57**	**5.69**	**58.83**	**5.92**	**57.45**	**5.41**	**67.90**	**5.07**	**66.43**

Effect of Ethnicity on Age Estimation

MAEs and CS Scores with Respect to Ethnicity

	Microsoft		KL		DC	
Ethnicity	**MAE**	**CS (%)**	**MAE**	**CS (%)**	**MAE**	**CS (%)**
European	6.59	46.22	4.59	68.44	**4.60**	**68.64**
African	7.21	42.32	5.45	58.92	**4.96**	**64.80**
Indian	8.40	36.89	7.60	46.35	**6.95**	**48.91**
Chinese	10.12	33.56	8.56	43.35	**7.50**	**47.81**

Outline

Conclusion

- The effect of loss function on the generalisation performance of a DNN model
- The smoother loss surface provides a better generalisation for the output model
- Age estimation problem

Future work

1. Extending our framework to other applications, pose estimation and segmentation

Thank You!