Using Ranking-CNN for Age Estimation

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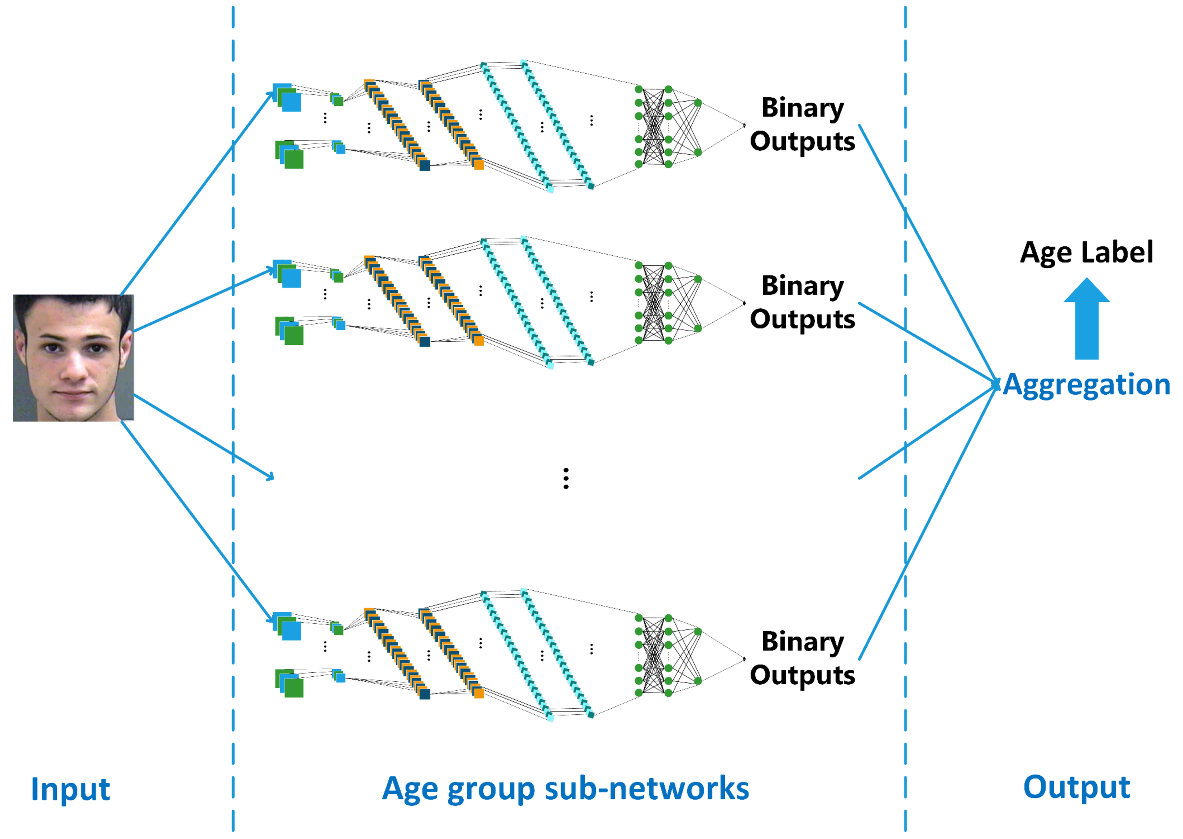
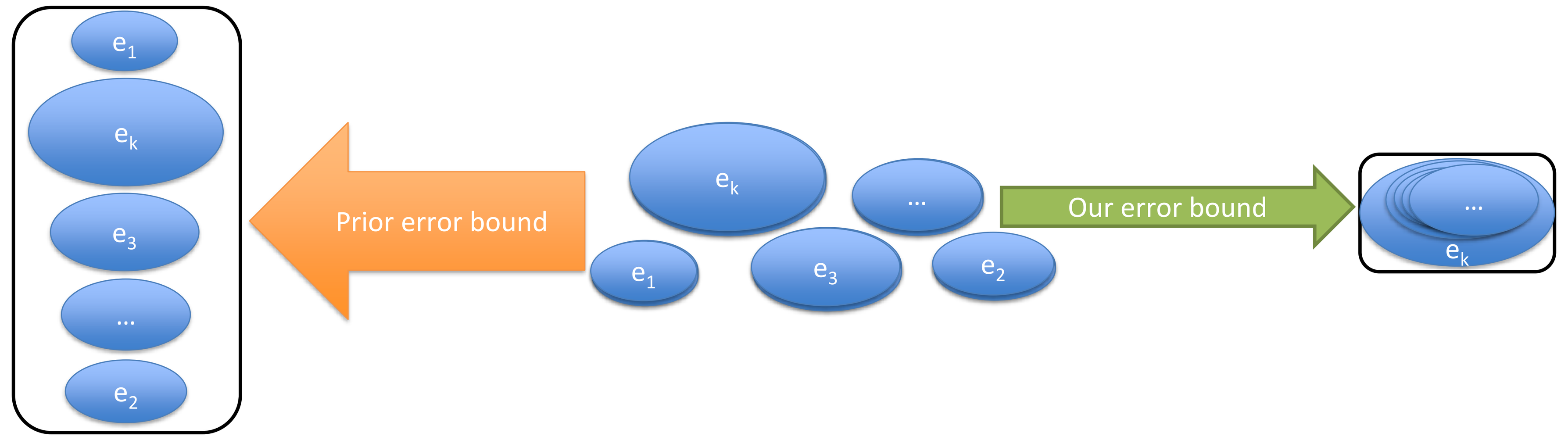
Introduction:

- Existing Techniques in Human Facial Image-base Age Estimation :
  - Feature extraction: geometry features, engineered features.
  - Estimators: classification (SVM), regression (SVR), ranking.
  - Deep learning: multi-class CNN, multi-scale CNN, MR-CNN, DEX.
- Ranking-CNN
  - Contains a series of basic CNNs.
  - Initialized with a pre-trained base CNN, fine-tuned with ordinal age labels.
  - The binary outputs are aggregated to make the final age prediction.



Theoretical Analysis:

- A new error bound for ranking

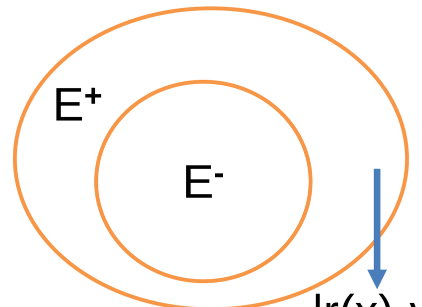


Theorem *For any observation (x, y), in which $y > 0$ is the actual label (integer), then the following inequality holds:*

$$|r(x) - y| \le \max_k e_k(x),$$

where $r(x)$ is the estimated rank of age, $k = 1, \cdots, K-1$. That is, we can diminish the final ranking error by minimizing the greatest binary error.

- Step I
  - Input x, output y, aggregated rank r(x),
  - E^+: the number of misclassifications when y≤k,
  - E^-: the number misclassification when y>k.



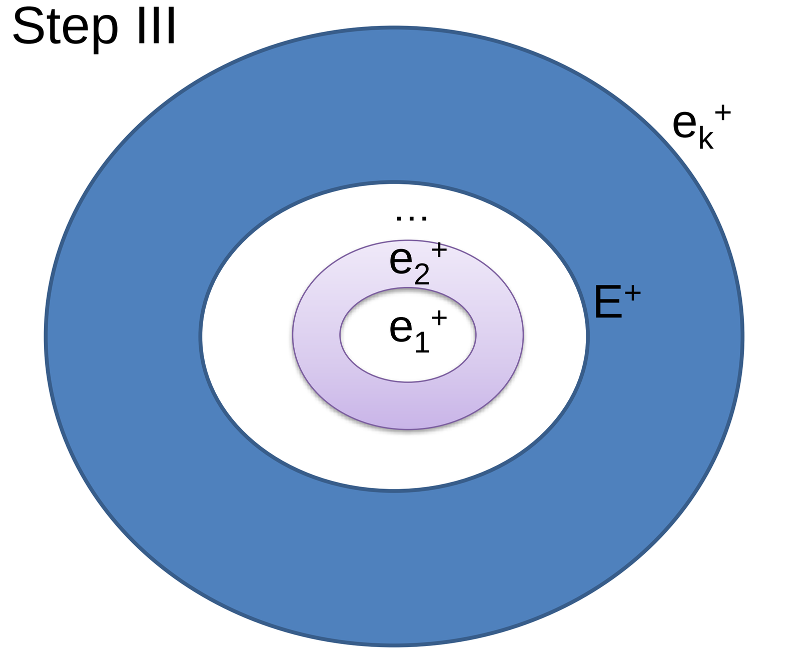
$|r(x)-y| = E^+ - E^- \le E^+$

- Step II
  - Denote the error produced by each binary ranker as e_i, i =1,…k.
  - Sort the sub errors of E^+ in an increasing order and find out the ordinal relation:

$$1 \le e_1^+ < e_2^+ < \dots < e_k^+$$

$$|e_2^+ - e_1^+| \ge 1, \dots, |e_k^+ - e_{k-1}^+| \ge 1$$

- Step III



Finally, $|r(x)-y| \le E^+ \le e_k^+$.

Explanatory example:
When y = 3, the binary outputs are supposed to be 11000.
If we get 00101:
e_1^+ =3-3+1=1, e_2^+ =5-3+1=3,
|r(x)-y| = 0,
E^+ = 2,
$e_k^+ = e_2^+$ =3.

- Ranking vs. Softmax
  - The expected error for ranking-CNN is bounded by the maximum training error of basic CNNs adding a term associated with VC dimension.
  - Given the same training samples, **ranking-CNN is more likely to attain a smaller testing error than multi-class CNN with softmax output.**
- Advantages of Ranking-CNN
  - Can be seen as an ensemble of CNNs, fused with aggregation.
  - Features are learned independently to depict variant aging patterns
    - more discriminating power
    - in prior work, the same set of features were used for all age groups (rankers)
  - Technical consideration with the new error bound
    - Derive the expectation of prediction error
    - Solve inconsistency issue of sub-models
    - Helpful guidance for the training of an ensemble of deep learning models

Experiments:

- Experiment setup
  - Pre-train with 26,580 image samples from the unfiltered faces dataset.
  - Fine-tune on the age estimation benchmark MORPH dataset.
  - Randomly select 54,362 samples in the age range between 16 and 66.

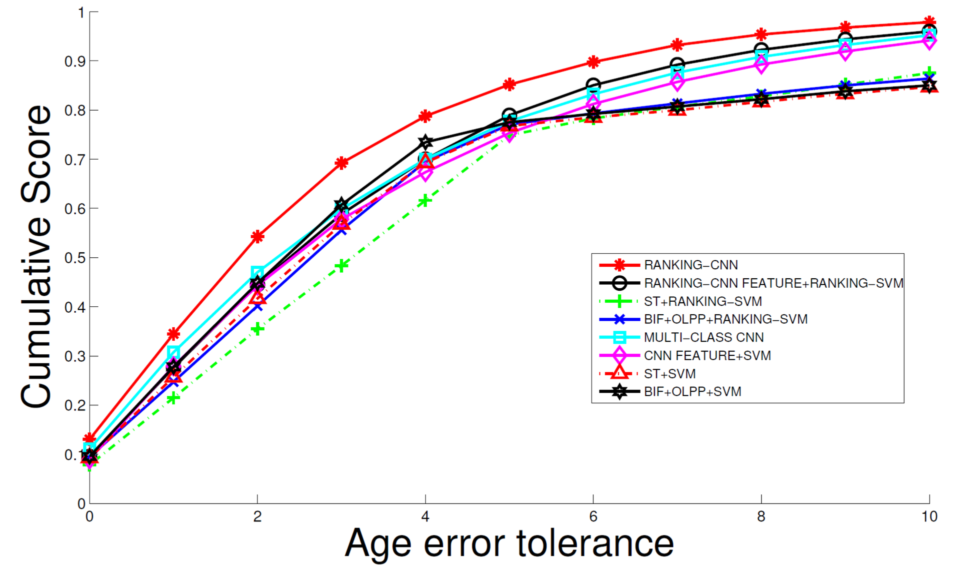
Comparison of MAE among different combinations of features and estimators.

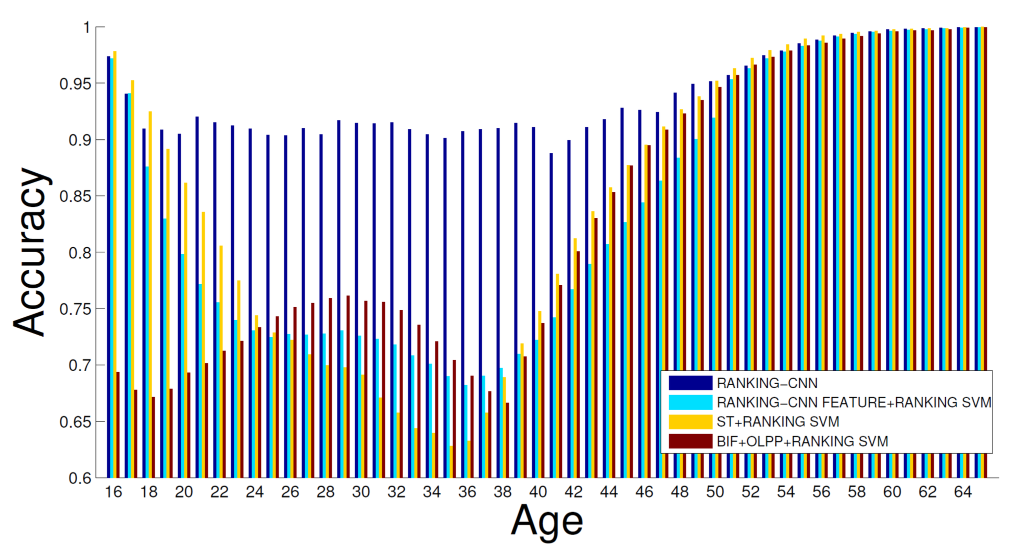
		Engineered Features		Learned Features	
		BIF+OLPP	ST	CNN Feature	Ranking-CNN Feature
Classification Model	SVM	4.99	5.15	3.95	-
	Multi-class CNN	-	-	3.65	-
Ranking Model	Ranking-SVM	5.03	4.88	-	3.63
	ranking-CNN	-	-	-	**2.96**

Comparison with state-of-the-art models: MR-CNN, OR-CNN and DEX.

	Ranking-CNN	MR-CNN	OR-CNN	DEX
MAE	**2.96**	3.27	3.34	3.25

Comparison on Cumulative Score and binary accuracy.





T test outcomes of all eight combinations of features and estimators.

	#1	#2	#3	#4	#5	#6	#7	#8
#1 Ranking-CNN	NaN	1	1	1	1	1	1	1
#2 Ranking-CNN Feature +Ranking-SVM	$6.36e^{-148}$	NaN	1	1	0.85	1	1	1
#3 ST+Ranking-SVM	0	0	NaN	1	0	0	1	1
#4 BIF+OLPP+Ranking-SVM	0	0	$1.79e^{-135}$	NaN	0	0	0.99	0.81
#5 Multi-class CNN	0	0.14	1	1	NaN	1	1	1
#6 CNN Feature+SVM	$4.12e^{-276}$	$8.90e^{-184}$	1	1	$5.43e^{-24}$	NaN	1	1
#7 ST+SVM	0	0	$1.94e^{-121}$	$2.00e^{-4}$	0	0	NaN	$3.66e^{-6}$
#8 BIF+OLPP+SVM	0	0	$4.56e^{-90}$	0.18	0	0	0.99	NaN

- Acknowledgement
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https://github.com/RankingCNN
http://www.cs.wayne.edu/~mdong