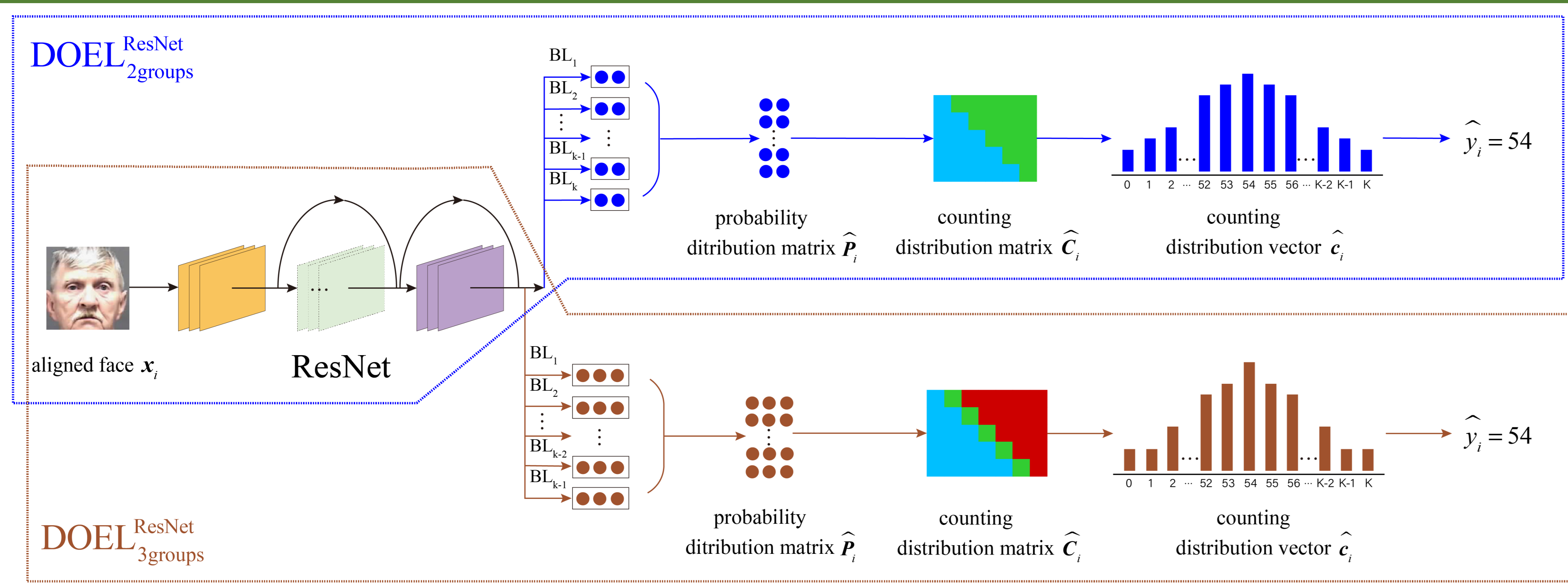


Framework of Two DOELs



Evaluation Results

Methods	Validation Set		Test Set		Num. of Networks
	MAE	ϵ -error	MAE	ϵ -error	
DEX [53]	3.25	0.28	-	0.265	20
Tan et al. [46]	3.21	0.28	2.94	0.264	8
DHAA [61]	3.052	0.265	-	0.252	1
BridgeNet [62]	2.98	0.26	2.87	0.255	1
DOEL ^{ResNet101} _{2groups}	2.933	0.258	2.713	0.247	1
DOEL ^{ResNet101} _{3groups}	2.965	0.259	2.726	0.249	1

Table 1. Evaluation Results on Chalearn LAP 2015 database

[Link](https://github.com/Xiejiu/second_age_estimation)
[codes] https://github.com/Xiejiu/second_age_estimation

Methods	MAE	CS($l=5$)	CS($l=10$)
DEX [53]	4.63	-	-
Liu et al. [57]	3.93	76.0%	91.0%
LSDML [58]	3.92	75.0%	89.0%
ODFL [42]	3.89	80.0%	91.0%
Tan et al. [46]	4.34	76.0%	86.0%
Shen et al. [47]	3.85	80.6%	-
Pan et al. [40]	4.10	78.0%	88.0%
Xie et al. [32]	3.58	78.3%	92.3%
ODL [59]	3.71	81.0%	96.0%
SADAL [60]	3.68	-	-
DHAA [61]	3.72	-	-
DOEL ^{ResNet101} _{2groups}	3.52	81.1%	92.6%
DOEL ^{ResNet101} _{3groups}	3.44	82.7%	93.0%

Table 2. Evaluation Results on FG-NET database.

Highlights

- We modify the ordinal ranking method for age prediction from the perspective of **ensemble learning**.
- Our modification named DOEL_{2groups} has **better interpretability and lower prediction errors theoretically**.
- We present a further modification called DOEL_{3groups}.
- Extensive evaluations validate the efficacy of our two approaches.

Limitations of OR_{2groups} [1,2]

Binary classifier	Age group 1	Age group 2	Output
BC ₁	0	1,2,...,K	$\hat{r}_1(x) = 0$ if $x \in g_1^1$ else 1
BC ₂	0,1	2,3,...,K	$\hat{r}_2(x) = 0$ if $x \in g_2^1$ else 1
⋮	⋮	⋮	⋮
BC _k	0,1,...,k-1	k,k+1,...,K	$\hat{r}_{k-1}(x) = 0$ if $x \in g_{k-1}^1$ else 1
⋮	⋮	⋮	⋮
BC _{K-1}	0,1,...,K-2	K-1, K	$\hat{r}_{K-1}(x) = 0$ if $x \in g_{K-1}^1$ else 1
BC _K	0,1,...,k-1	K	$\hat{r}_K(x) = 0$ if $x \in g_K^1$ else 1

Predicted age: $\hat{y} = \sum_{k=1}^K \hat{r}_k(x)$ (1)

- Eq. (1) is **logical only when** we get the ranking predictions as the follows: $\hat{r}_1 = \hat{r}_2 = \dots = \hat{r}_m = 1$, and $\hat{r}_{m+1} = \hat{r}_{m+2} = \dots = \hat{r}_K = 0$
- The **Conflicts may emerge in practice**, such as $\hat{r}_m = 0$ whereas $\hat{r}_{m+1} = 1$.

DOEL_{2groups}

Base learner	Age group 1	Age group 2	Output
BL _k	0,1,...,k	k+1,k+2,...,K	$\hat{c}_k(x) = \begin{cases} (1,1, \dots, 1, 0,0, \dots, 0) & \text{if } x \in g_k^1 \\ (0,0, \dots, 0, 1,1, \dots, 1) & \text{if } x \in g_k^2 \end{cases}$

- Counting distribution matrix: $\hat{C}(x) = [\hat{c}_1; \hat{c}_2; \dots; \hat{c}_K]$
- Counting distribution vector: $\hat{c}(x) = [\sum_{k=1}^K \hat{c}_{k,1}, \sum_{k=1}^K \hat{c}_{k,2}, \dots, \sum_{k=1}^K \hat{c}_{k,K+1}]$
- Estimated age: $\hat{y} = \text{index}(\max \hat{c}(x))$

DOEL_{3groups}

Base learner	Age group 1	Age group 2	Age group 3	Output
BL _k	0,1,...,k-1	k	k+1,k+2,...,K	$\hat{c}_k(x) = \begin{cases} (1,1, \dots, 1, 0,0,0, \dots, 0) & \text{if } x \in g_k^1 \\ (0,0, \dots, 0, 1,0,0, \dots, 0) & \text{if } x \in g_k^2 \\ (0,0, \dots, 0, 0,1,1, \dots, 1) & \text{if } x \in g_k^3 \end{cases}$

- Counting distribution matrix: $\hat{C}(x) = [\hat{c}_1; \hat{c}_2; \dots; \hat{c}_{K-1}]$
- Counting distribution vector: $\hat{c}(x) = [\sum_{k=1}^{K-1} \hat{c}_{k,1}, \sum_{k=1}^{K-1} \hat{c}_{k,2}, \dots, \sum_{k=1}^{K-1} \hat{c}_{k,K+1}]$
- Estimated age: $\hat{y} = \text{index}(\max \hat{c}(x))$

OR_{2groups} vs. DOEL_{2groups} vs. DOEL_{3groups}

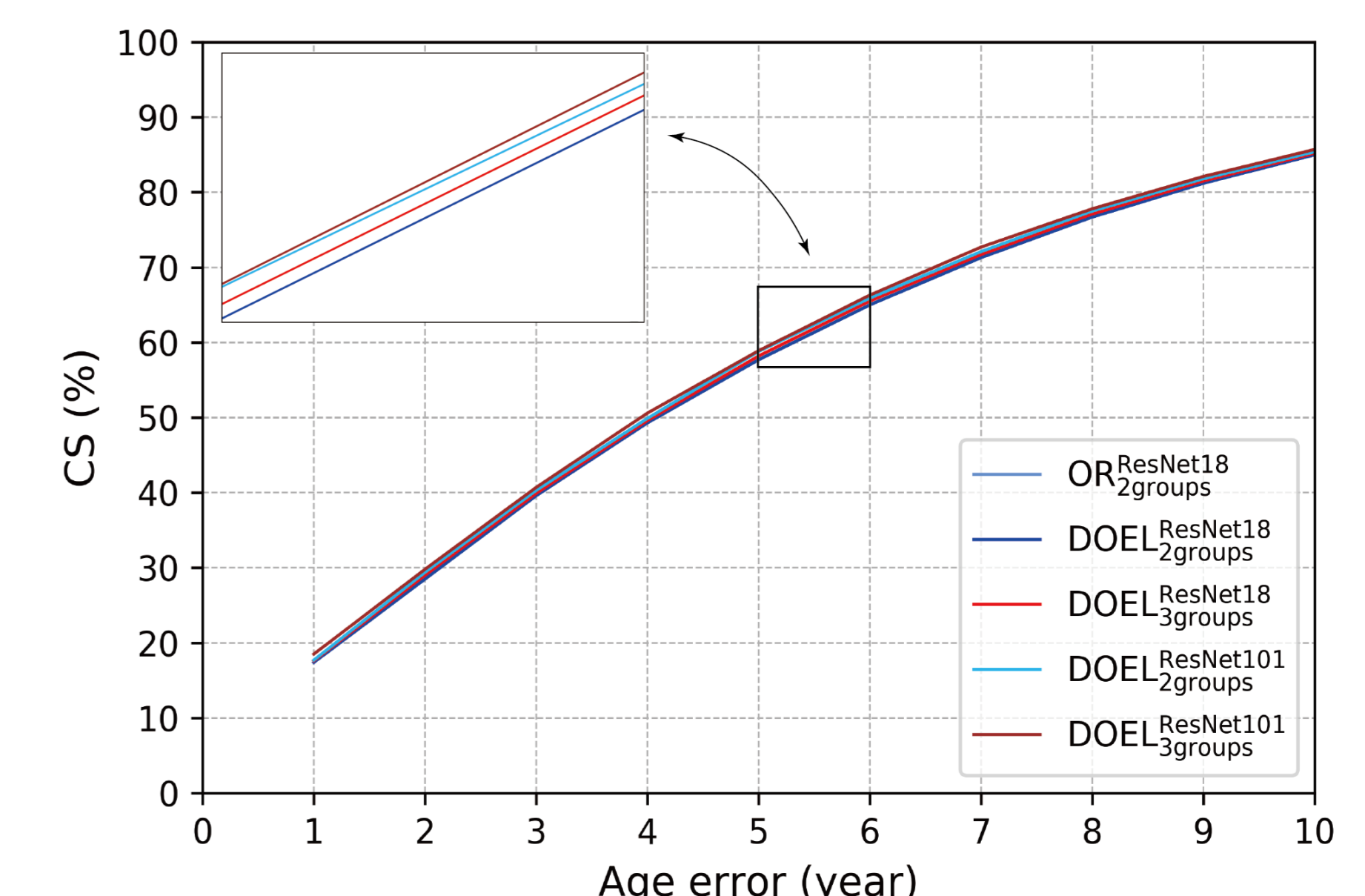


Figure 1. CS curves of different ordinal regression modellings.

Methods	on AgeDB	
	MAE	IR
OR ^{ResNet18} _{2groups}	5.83422	30/16488
DOEL ^{ResNet18} _{2groups}	5.83408	-
DOEL ^{ResNet18} _{3groups}	5.79756	-
DOEL ^{ResNet101} _{2groups}	5.73700	-
DOEL ^{ResNet101} _{3groups}	5.69204	-

Table 3. Comparisons among different ordinal regression modellings.

References

[1] Z. Niu, M. Zhou, L. Wang, X. Gao, and G. Hua. Ordinal regression with multiple output CNN for age estimation. *CVPR*, 2016.
 [2] S. Chen, C. Zhang, M. Dong, J. Le, and M. Rao. Using ranking-CNN for age estimation. *CVPR*, 2017.