# Using Ranking-CNN for Age Estimation[1]

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# Agenda

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# Introduction

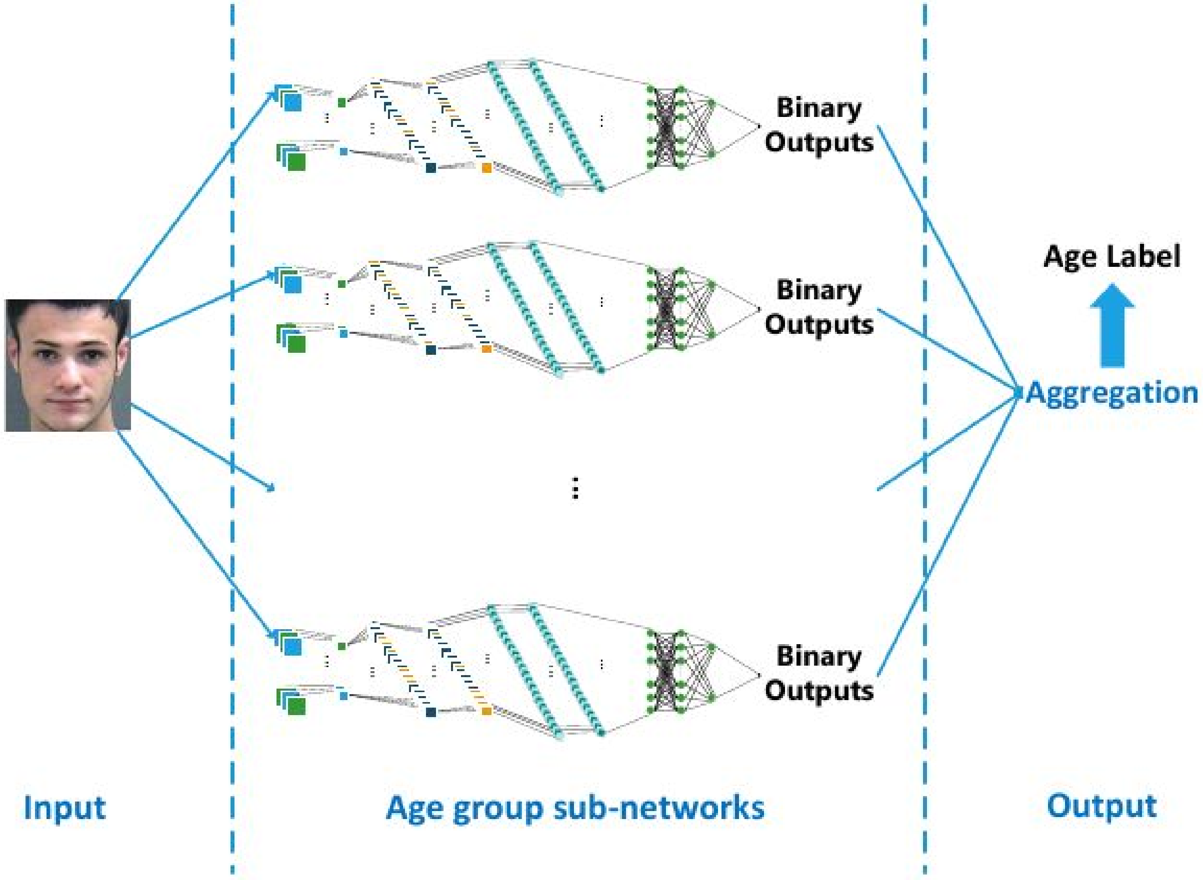
- Age estimation importance
- Many feature extraction techniques
- Estimation models

# Motivations

- Performance improvements using deep learning
- Existing approaches ignore age-related ordinal information (multi-class classification) or over-simplify the problem to a linear model (regression)

# Overview and Contributions

- A Ranking-CNN model that contains a series of basic CNNs to estimate age based on face images



## Overview and Contributions

The main contributions are:

- Each basic CNN is trained for an age group independently, leading to better performance and preventing overfitting
- Takes the ordinal relation between ages: more likely to get smaller estimation errors when compared with multi-class classification approaches

## Related Works

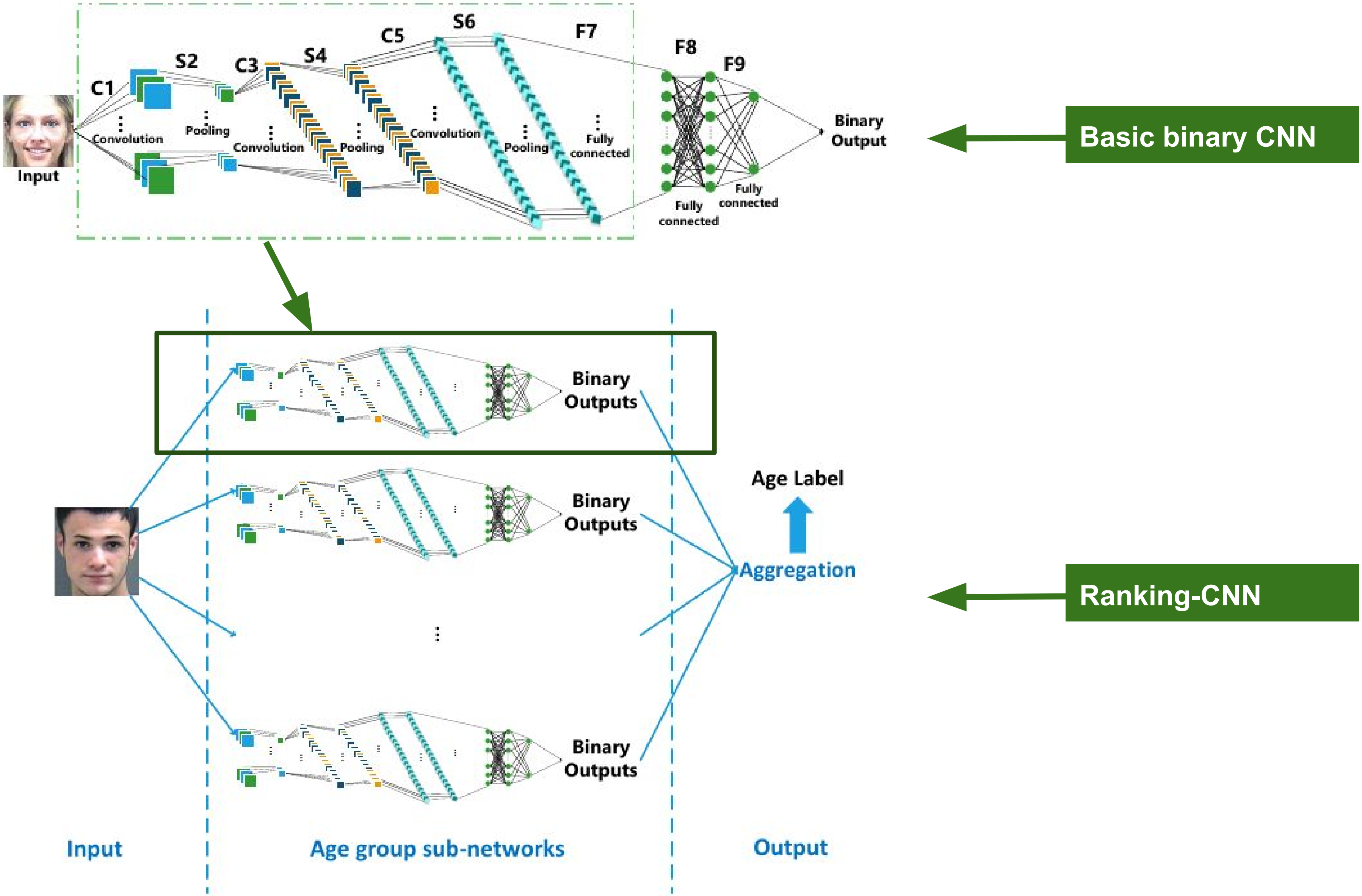
- Early estimation models (handcrafted feature extraction techniques)
  - Active Appearance Model (AAM)
  - AGing pattErn Subspace (AGES)
  - Bio Inspired Features (BIF)
  - General purpose features, such as LBP or HOG.
- More recently: CNN-based methods
- Ranking based approach with scattering transform (ST) proposed by Chang et al.[2]

# Approach

Ranking-CNN for Age Estimation

- Uses a series of basic binary CNNs with ordinal age labels.
- Each basic binary CNN categorizes samples into two groups: either higher or lower than a certain age
- The binary outputs of all basic CNNs are aggregated to make the final age prediction.

# Architecture



# Training

Consists of two stages:

- A base network is pre-trained with unconstrained facial images.
- From the base network, a series of basic binary CNNs with ordinal age labels is trained.
- Assuming k age groups, k-1 basic binary CNNs are trained from the base one.
- To train the k-th binary CNN, the entire dataset D is split into two subsets, with ages higher or lower (or equal to) than max(ages(k)).

# Ranking-CNN

- Given an unknown input $x_i$, the basic binary CNNs output a set of binary decisions
- The binary decisions are aggregated to make the final prediction $r(x_i)$

$$r(x_i) = 1 + \sum_{k=1}^{K-1} [f_k(x_i) > 0].$$

$f_k(x_i)$ is the output of the basic CNN
[ v ] - truth operator: 1, if v is true
0, otherwise.

- The final ranking error is bounded by the maximum error of the binary rankers.

# Experiments

- Dataset: MORPH Album 2

  Samples selected in the range between 16 and 66 years old: 51 age groups - 50 binary rankers are needed.

The age and gender information of the 54,362 samples randomly selected from MORPH Album 2.

| | <20 | 20-29 | 30-39 | 40-49 | >50 | Total |
|---|---|---|---|---|---|---|
| Male | 6543 | 13849 | 12322 | 9905 | 3321 | 45940 |
| Female | 829 | 2291 | 2886 | 1975 | 441 | 8422 |
| Total | 7372 | 16140 | 15208 | 11880 | 3762 | 54362 |

# Experiments

- Baselines
  - ❑ BIF+OLPP
  - ❑ ST
  - ❑ Multi-class CNN techniques

# Experiments

- ## Results

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** |

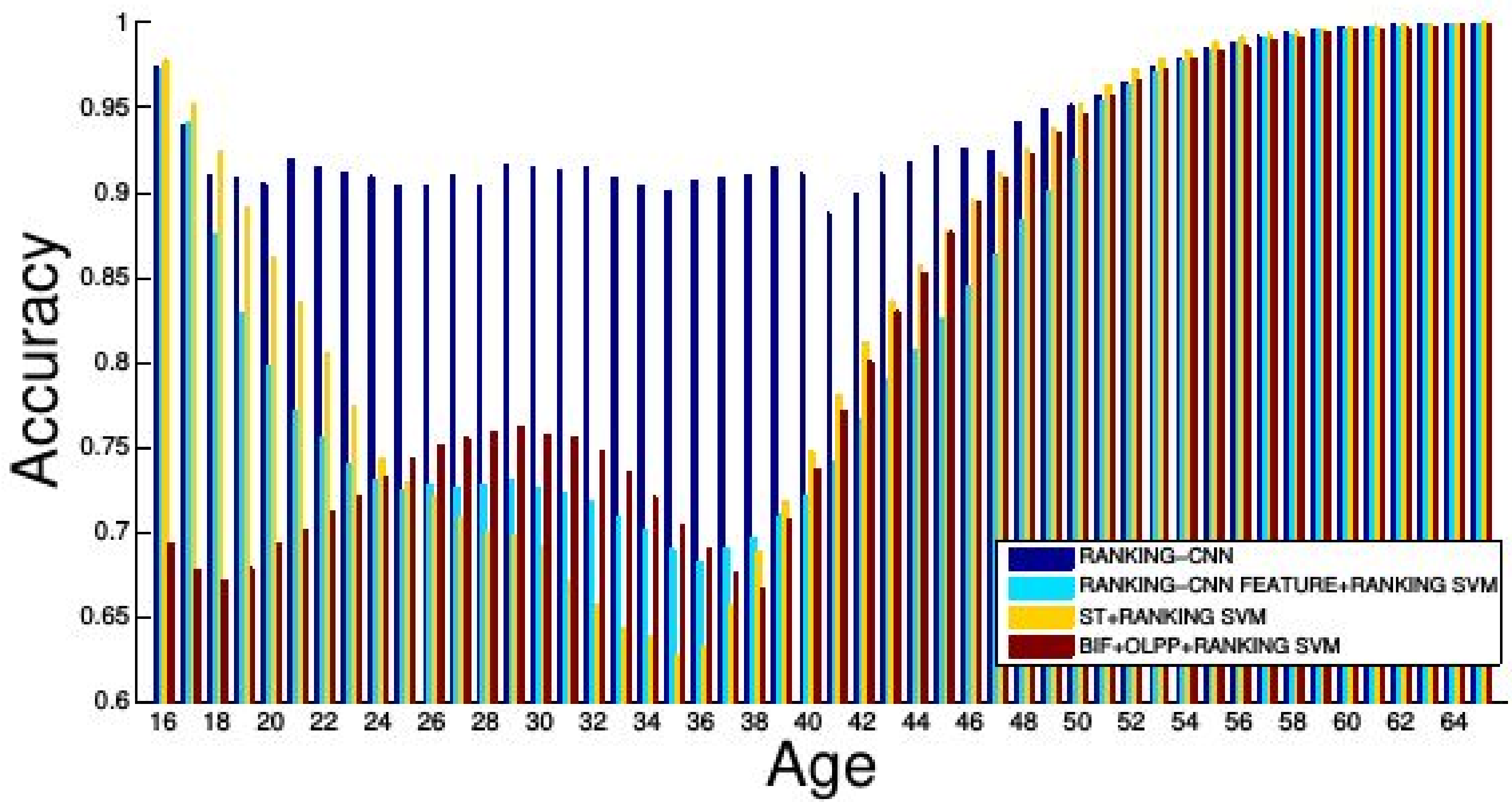
MAE among different CNN-based techniques

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

Ordinal Regression with CNN (OR-CNN)
Metric Regression with CNN (MR-CNN) [3]
Deep EXpectation (DEX) [4]

# Experiments

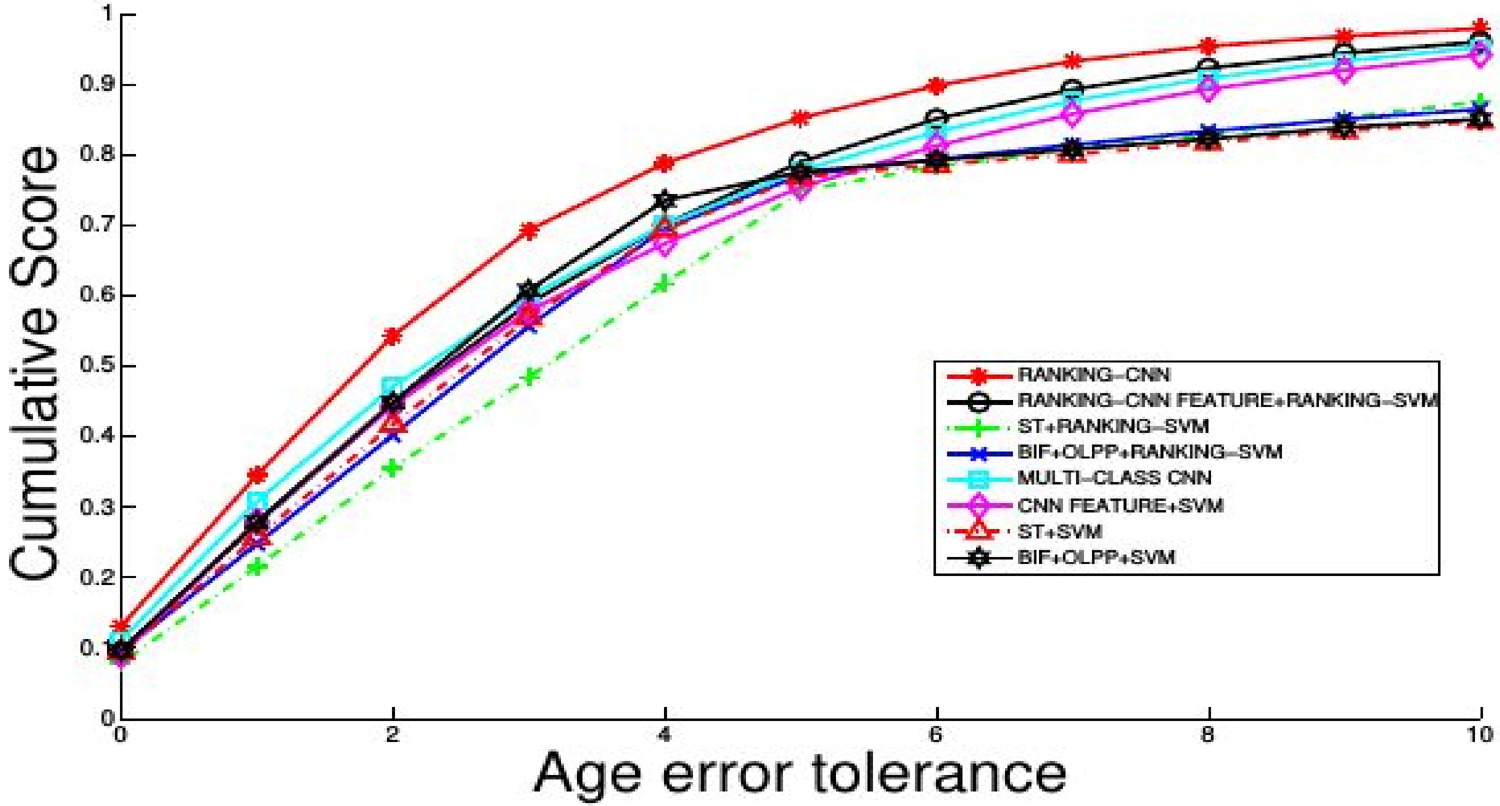
- Results




Accuracy of each binary ranker in ranking models.

# Experiments

- Results




Comparison on Cumulative Score with $L$ in $[0, 10]$.

$L$ (age error tolerance range) from 0 to 10

# Conclusion

- The proposed method outperforms state-of-the-art age estimation methods
- Taking ordinal relation between ages into consideration seems to be a good strategy to approach the age estimation task

# References

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