The 1st Large-Scale Kinship Recognition Database: To visually recognize and understand families in the wild

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Motivation

- Automatic kinship recognition is a challenging task.
- After lots of focus since 2010, it has yet to transition from research-to-reality:
- Existing datasets do not properly represent true data distributions.
- Complex factors of the problem remain unfound throughout ML community.

Goal: Build large-scale kinship dataset to best support the task of kinship recognition.

Families In The Wild

- Built the largest image dataset for kinship recognition to date [1].
- Collected and annotated over 31,000 facial images (**Table 2**)
- Provided 365k pairs, 11 types, with 4 grandparents-children for 1st time (**Table 1**)
- Developed annotation tool to capture complex family structures (Fig 1)

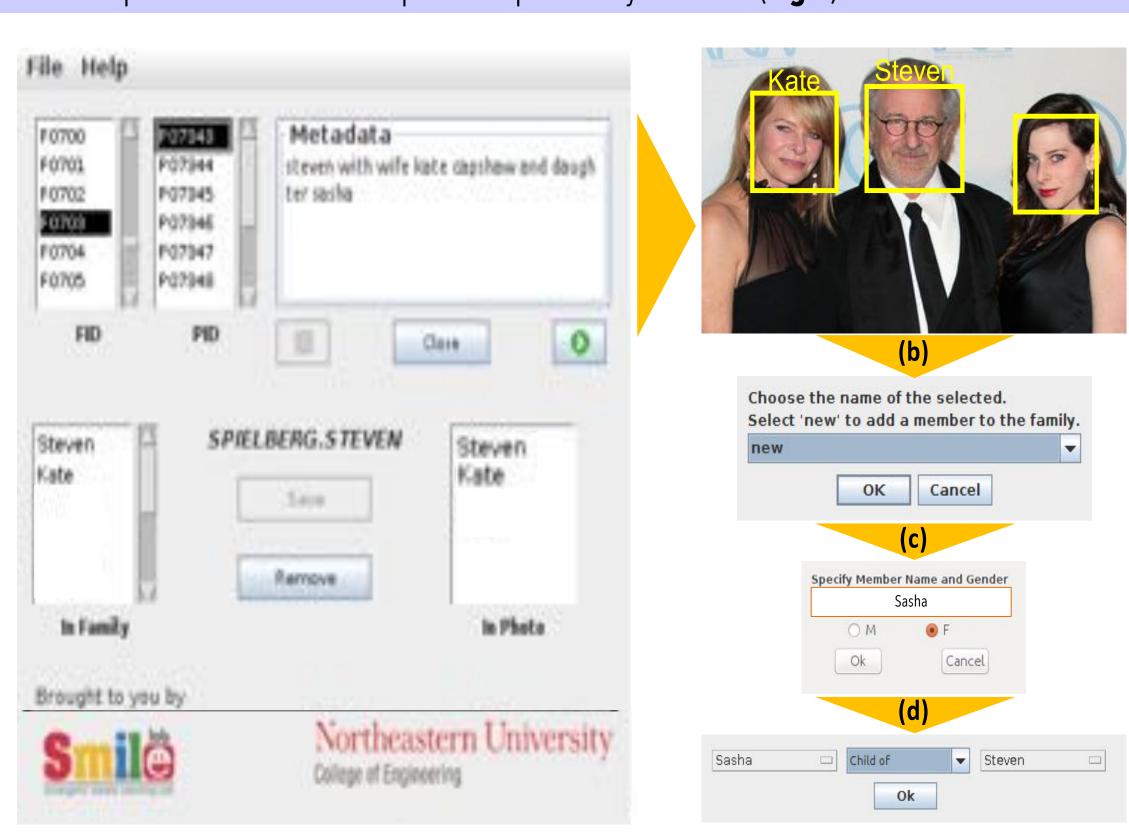


Fig 1 Labeling tool used to build FIW v1.0 (a). Faces are detected and bounded by resizable boxes (b). Existing member names are specified via dropdown menu- if new is selected (c), then name and gender is specified (d), along with relationships to others (e).

Semi-Automatic Annotation

- While initial annotation process worked, it was slower than ideal and prone to human error.
- When finalizing FIW, we optimized this process by proposing labels using k-means clustering with true labels as side information, where our objective function can be expressed in **Eq 1**.

$$\min \sum_{k=1}^K \sum_{\gamma:\in C_k} f_{cos}(x_i, m_k) + \lambda U_c(S, H \otimes S), \tag{1}$$

where f_{cos} is cosine similarity, H is final partition, $H_s = H \otimes S$ is partition of H with instances as side information S, m_k is centroid of C_k , U_c is Categorical Utility Function, and λ is trade-off parameter. The first term is the standard K-means with cosine similarity, and the second term can also be transformed into a K-means problem with squared Euclidian distance.

• A cluster validation tool was developed in JAVA, i.e., cluster id-> true lable (**Fig 2**).





Table 1 No. pairs in FIW and other kinship image collections 130,000 Brother-Brother 86,000 130,000 Father-Daughte Mother-Daughte

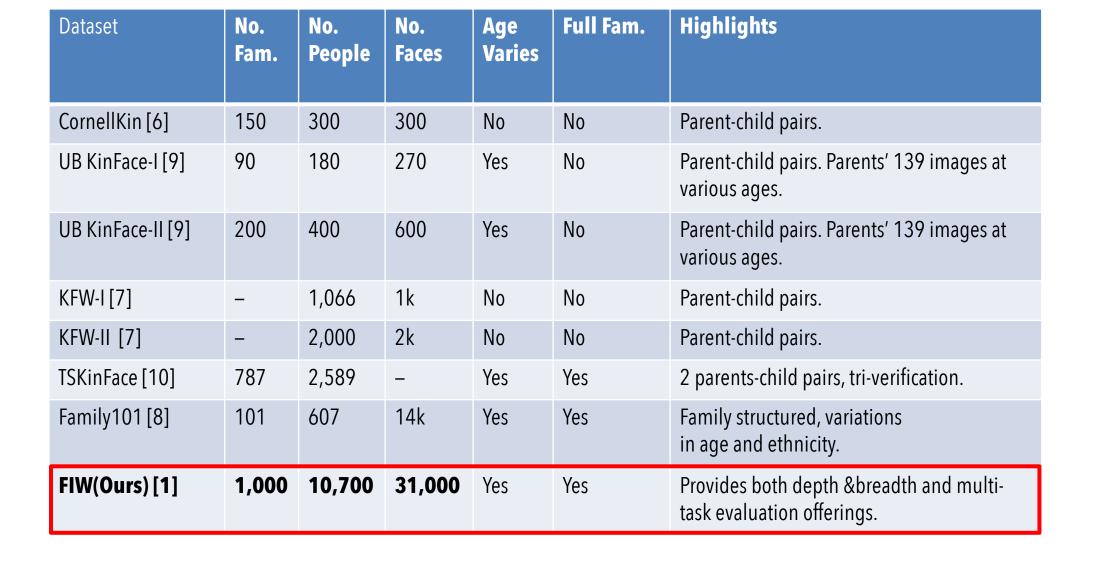
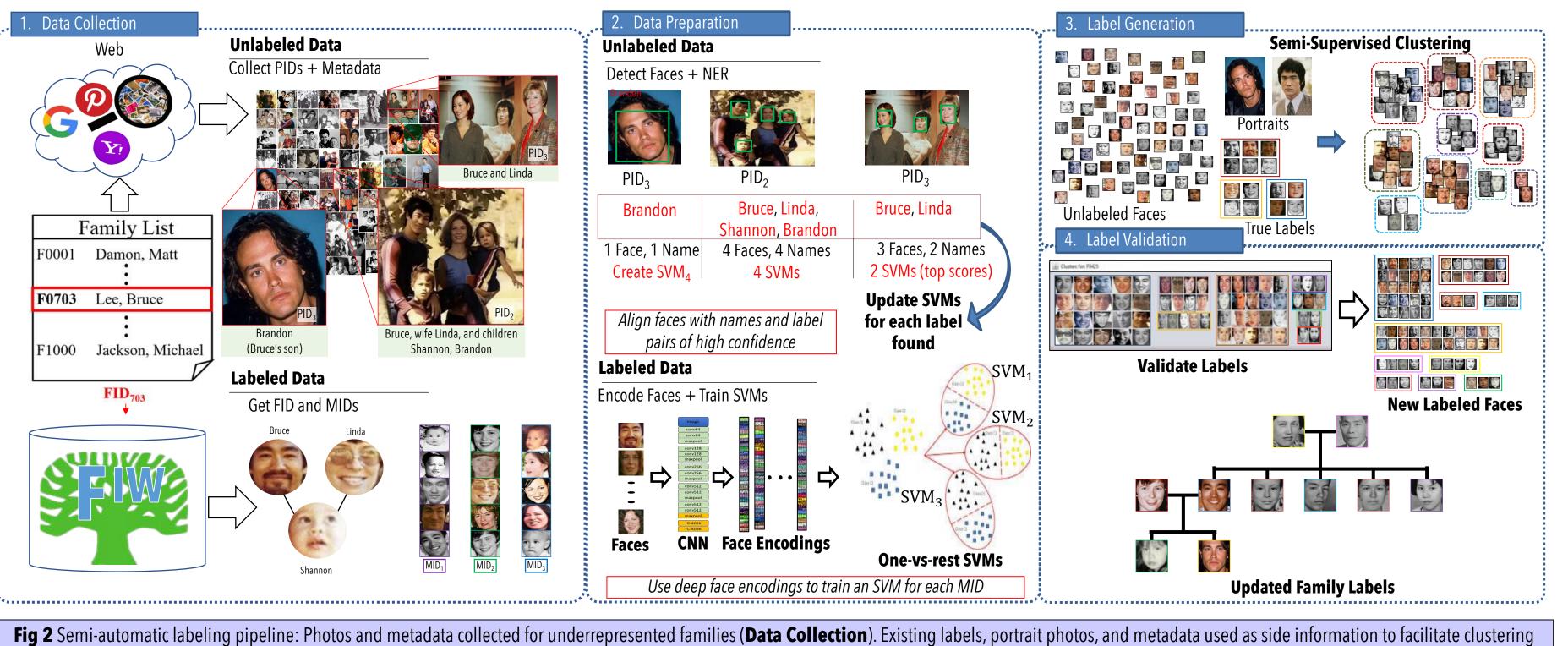
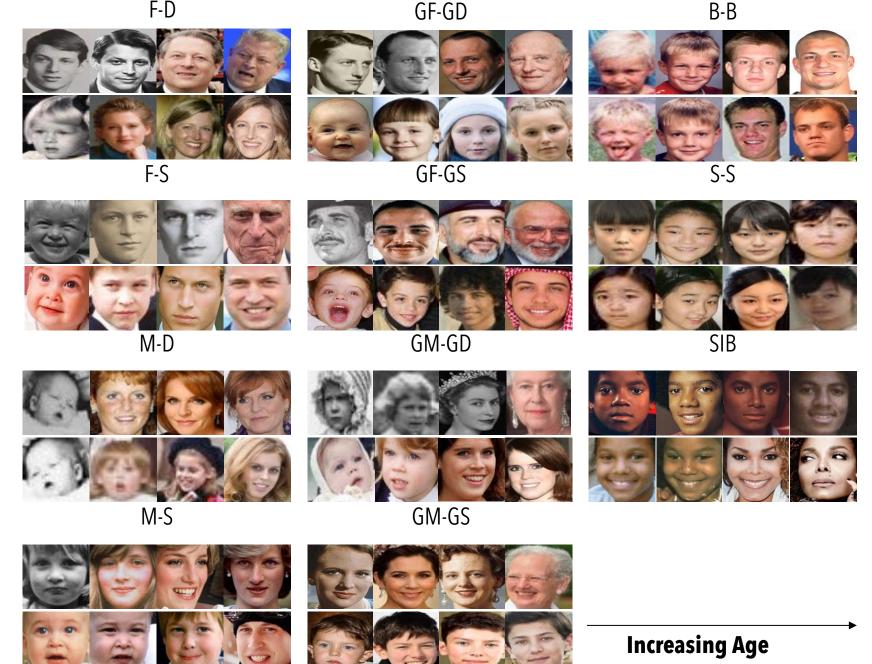


Table 2 Comparison of FIW with related datasets.



(Data Preparation). Then, label proposals generated via semi-supervised model (Label Generation). JAVA tool used to validate labels (Label Validation).

418,060 645,000



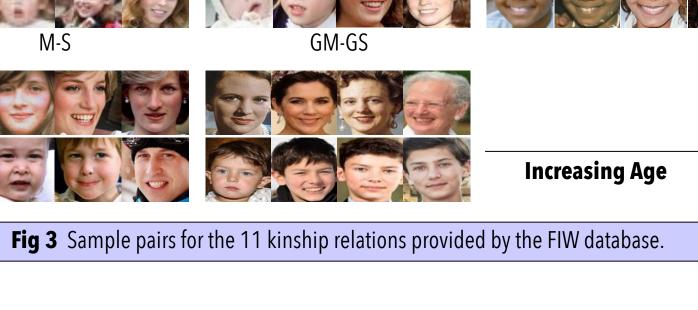


Table 3 Family classification scores on 524 families.

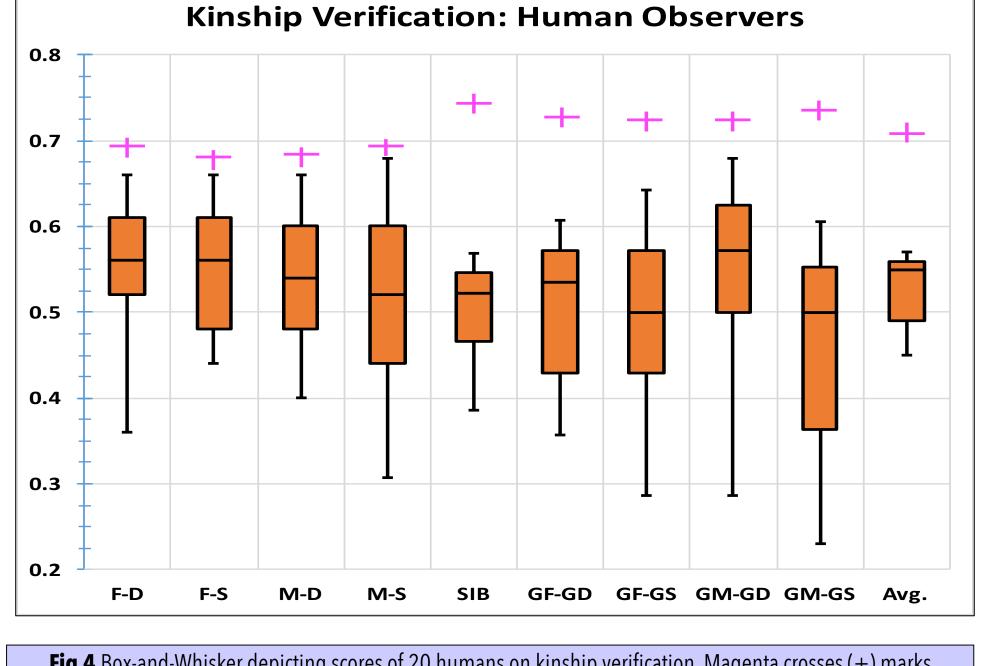


Fig 4 Box-and-Whisker depicting scores of 20 humans on kinship verification. Magenta crosses (+) marks
average score of fine-tuned CNN model, which outperforms humans in every category.

GF-D GF-S GM-D GM-S Avg.

56.4 56.4 54.3 56.9 55.7

56.9 56.1 60.3 58.0 57.1

60.8 63.1 59.9 61.9 64.1

63.9 60.4 63.7 60.2 65.6

71.1 74.7 77.2 70.4 66.8

66.9 69.4 67.8 68.6 71.3

78.1 77.1 78.0 74.8 74.1

Table 4 Verification scores. No family overlap between (5) folds. Top accuracies obtained by fine-tuned (FT) VGG-Face on FIW.

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Network(s) Details	Acc.		F-D	F-S	M-D	M-S	SIBS	B-B	S-S
		LBP	54.8	54.7	55.8	55.3	57.2	57.7	56.4
VGG-f _{c7} + <i>one-vs-all</i> SVMs 4096D	2.87	SIFT	56.1	56.3	56.3	55.4	58.8	57.8	59.0
VGG fine-tuned softmax 524D	10.48	VGG-Face	64.6	64.6	66.0	63.7	73.2	70.1	71.0
		VGG-Face LMNN	65.7	67.1	68.1	67.2	73.9	70.1	72.3
Centerface + SVM	2.15	Centerface (CF)	57.6	58.8	58.7	58.0	68.6	70.3	68.9
Centerface fine-tuned	11.34	FT CF	70.1	71.5	72.0	71.2	72.8	77.4	77.0
		FT + Triplet loss + PCA	68.1	70.1	69.0	68.5	77.2	78.3	75.6

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Experiments

Kinship Verification on FIW.

- Kin relation types and sample sizes (**Table 1** & **Fig 3**).
- Cross-validated on 5-fold (**Table 4**).
- Both fine-tuned VGG-Face and Centerface deep CNN models achieved top scores.

Family Classification.

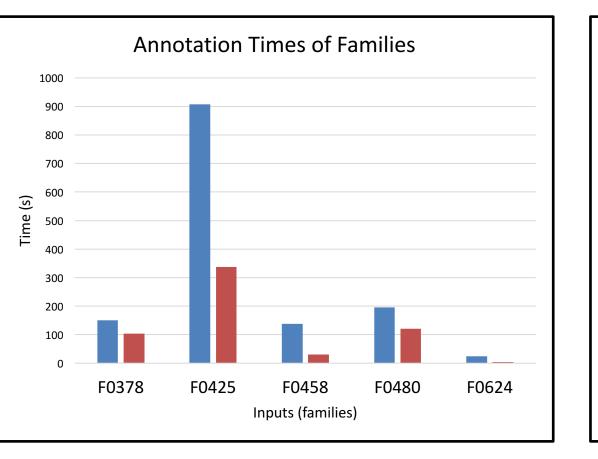
- VGG-Face + *one-vs-rest* SVMs were used as baseline.
- Five members from families which have more than five members were randomly selected, resulting in 524 families with total 12,007 images.
- Fine-tuned Centerface model achieved top score of 11.34% (**Table 3**).

Human Kinship Verification.

 Human performers scored an overall average of 56.6%, which was outscored by fine-tuned CNN by approximately 15% (Fig 4), using 200 pairs of the 11 types.

Semi-Automatic Annotation

 Semi-supervised clustering algorithm reduced time to annotate a family by 52% and clicks to annotate a family by 68% (Fig 3), in comparison to initial annotation process (Fig 1).



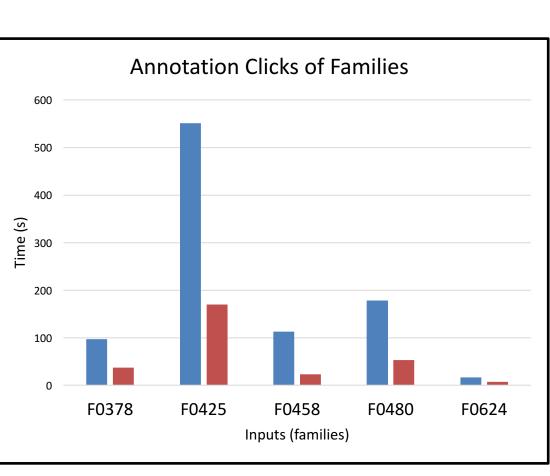


Fig 3 Comparison in time (left) and manual input (right) between old (blue) and new (red) labeling scheme.

Conclusions

- Built the largest and most comprehensive image database for kinship recognition to date, along with the labels, baseline results, and evaluation protocols needed to further and track future progress.
- Finalized database as FIW v2.0 using a semi-automatic labeling pipeline with a verification tool to add new data more efficiently, reducing annotation time and clicks per family by 52% and 68%, respectively, and increasing the number of pairs by \sim 227,000.
- Found pre-trained CNNs yield the best features for our unconstrained dataset.
- Revealed algorithms outperform humans doing the verification tasks.
- Obtained top scores for both kinship verification and family recognition by fine-tuning CNN network on FIW data.

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