Discriminative Invariant Kernel Features:
A Bells-and-Whistles-Free Approach to Unsupervised Face Recognition and Pose Estimation

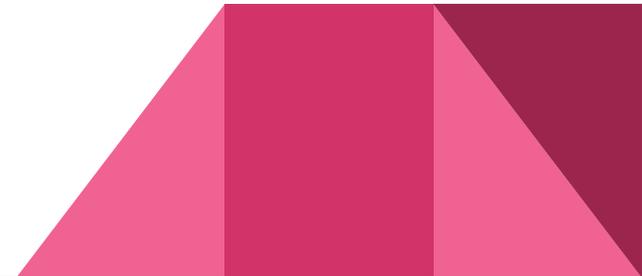*Dipan K. Pal*, Felix Juefei Xu and Marios Savvides*

CVPR 2016

The problem
Two complementary tasks

To perform two complementary tasks simultaneously using a single unsupervised feature extractor
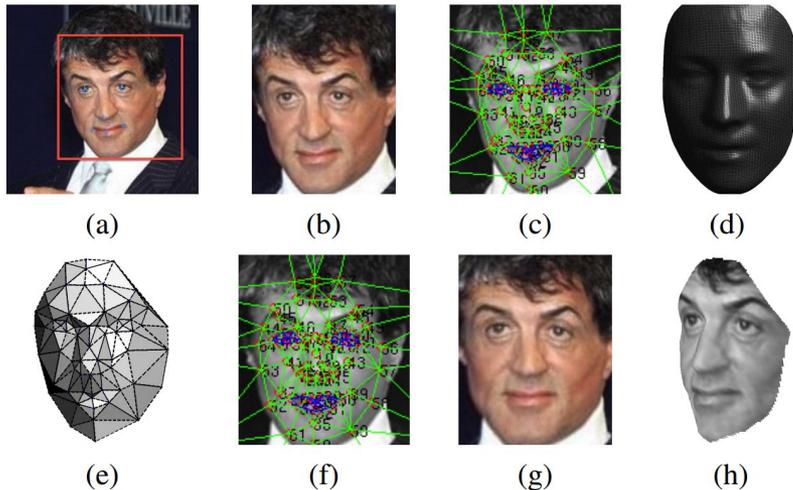
Who is this subject?

What is the subject's pose?

The problem
Landmark-free

The paper focuses on dense landmark-free (only two eye center locations) face recognition and pose estimation

Extends to a completely landmark-free approach which is also alignment free

This work:

(a)　(b)　(c)　(d)

(e)　(f)　(g)　(h)

Taigman, Yaniv, et al. "Deepface: Closing the gap to human-level performance in face verification." *CVPR* 2014.

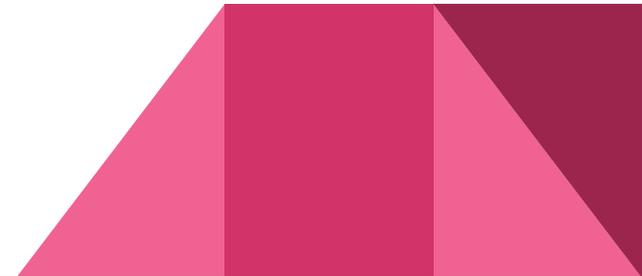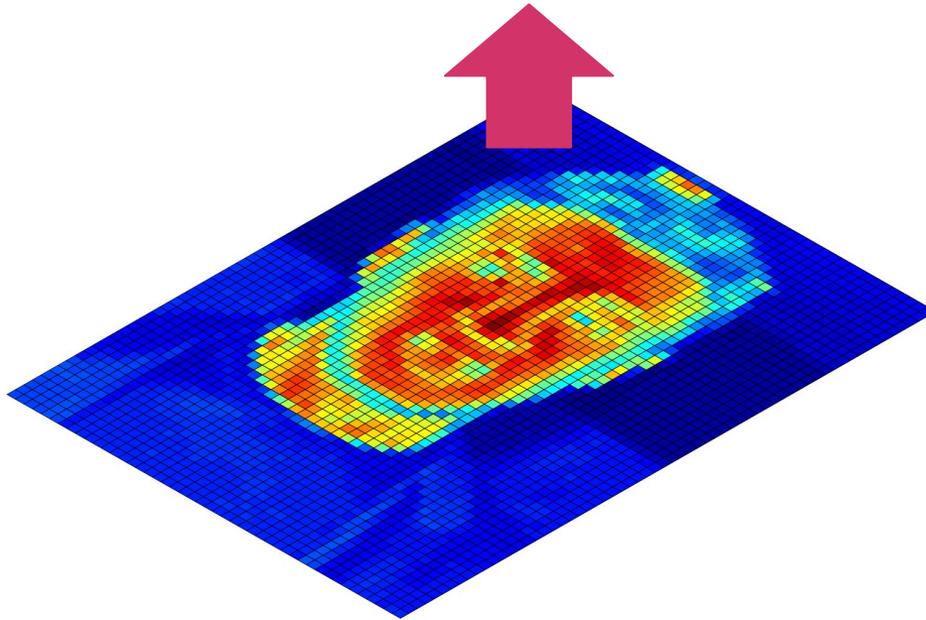# The problem
Discriminative Invariant Feature

We extract a single highly discriminative provably group invariant non-linear feature for both tasks from raw pixels

Invariant feature extraction from raw pixels.

The approach
Invariance to Transformations

Nuisance transformations groups such as the translation, rotation group, increase complexity of the learning problem

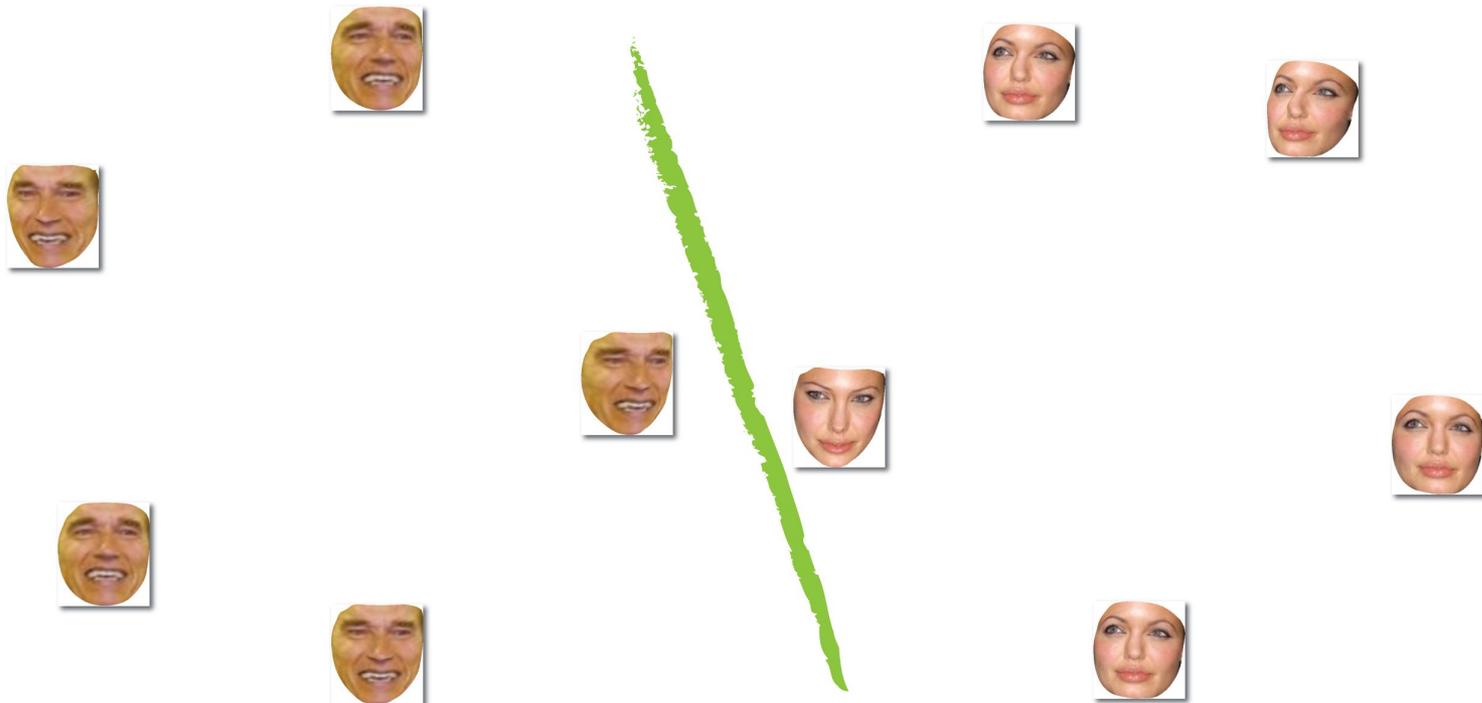Invariance to such transformations can drastically reduce complexity

The approach
Invariance to Transformations

Nuisance transformations groups such as the translation, rotation group, increase complexity of the learning problem

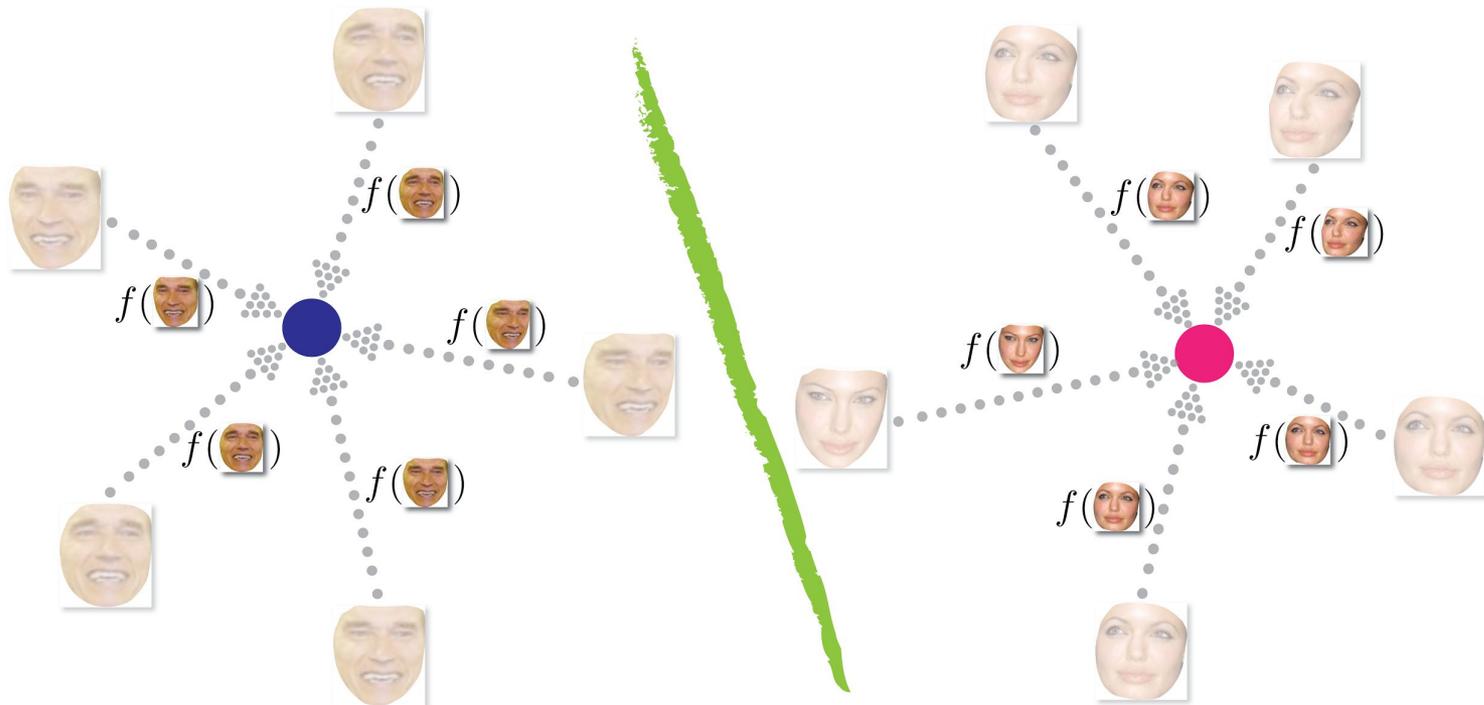Invariance to such transformations can drastically reduce complexity

The approach
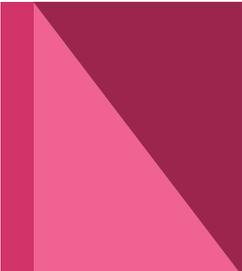## Invariance to Transformations

Nuisance transformations groups such as the translation, rotation group, increase complexity of the learning problem

Invariance to such transformations can drastically reduce complexity

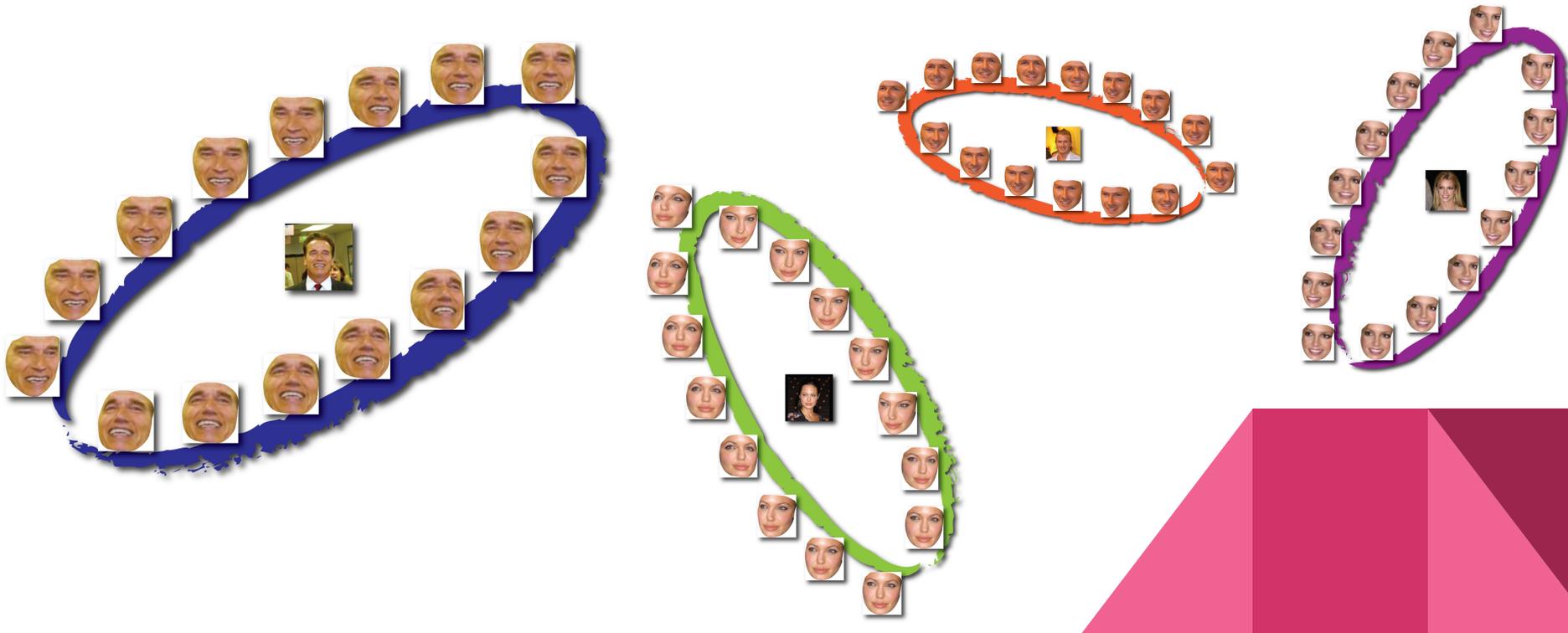$$f(\ ) = \ldots = f(\ )$$

$$f(\ ) = \ldots = f(\ )$$

Previous work
Linear Invariant Features

Previous work builds linear invariant that are implicitly (but not explicitly) discriminative

When a group of transformations act on an object, they create an orbit

Previous work
Linear Invariant Features

Previous work builds linear invariant that are implicitly (but not explicitly) discriminative

The orbit is unique to the object, and is an invariant to the transformation group

is invariant

Previous work
Linear Invariant Features

Previous work builds linear invariant that are implicitly (but not explicitly) discriminative

Hence any measure of the orbit is an invariant implicitly discriminative feature
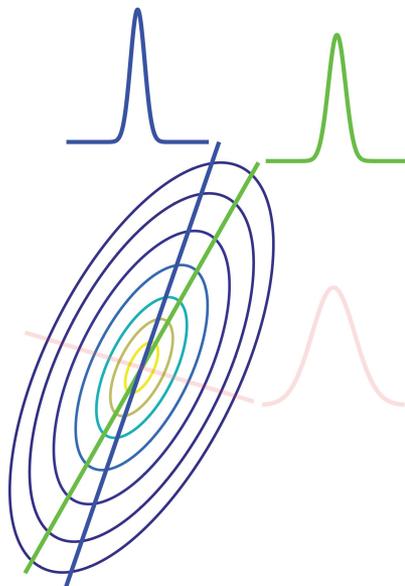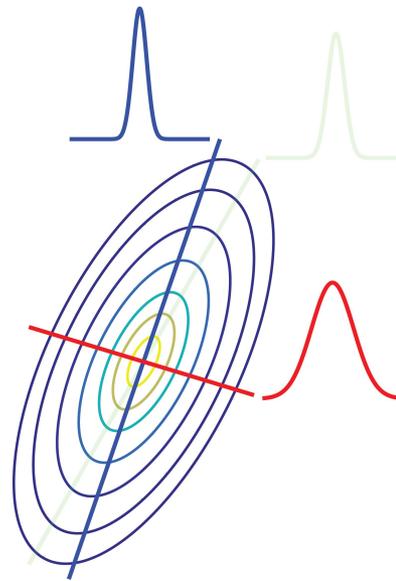

$f\left(\right)$ is invariant

Our approach
Linear Discriminative Invariance

To characterize the orbit, previously simply sampled templates were used

Explicit discrimination provides better matching. More over the learnt templates still form a group of transformed templates, hence invariance theory holds.
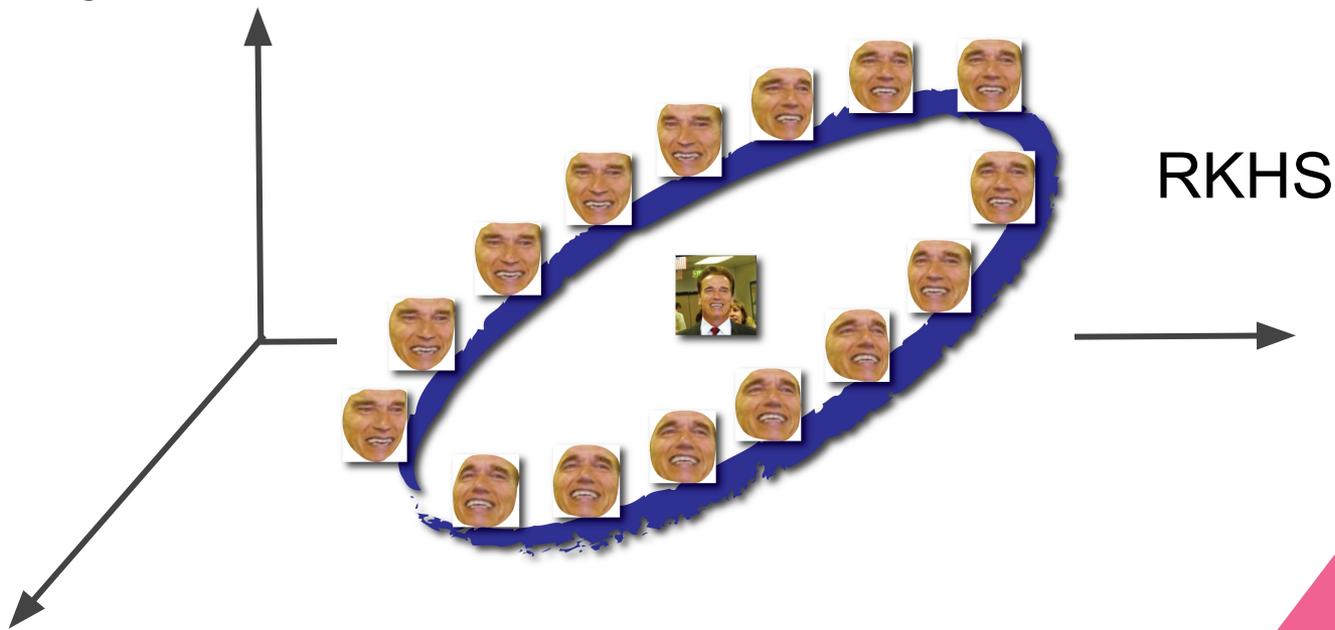

Sampled templates   Discriminatively learned templates

Our approach
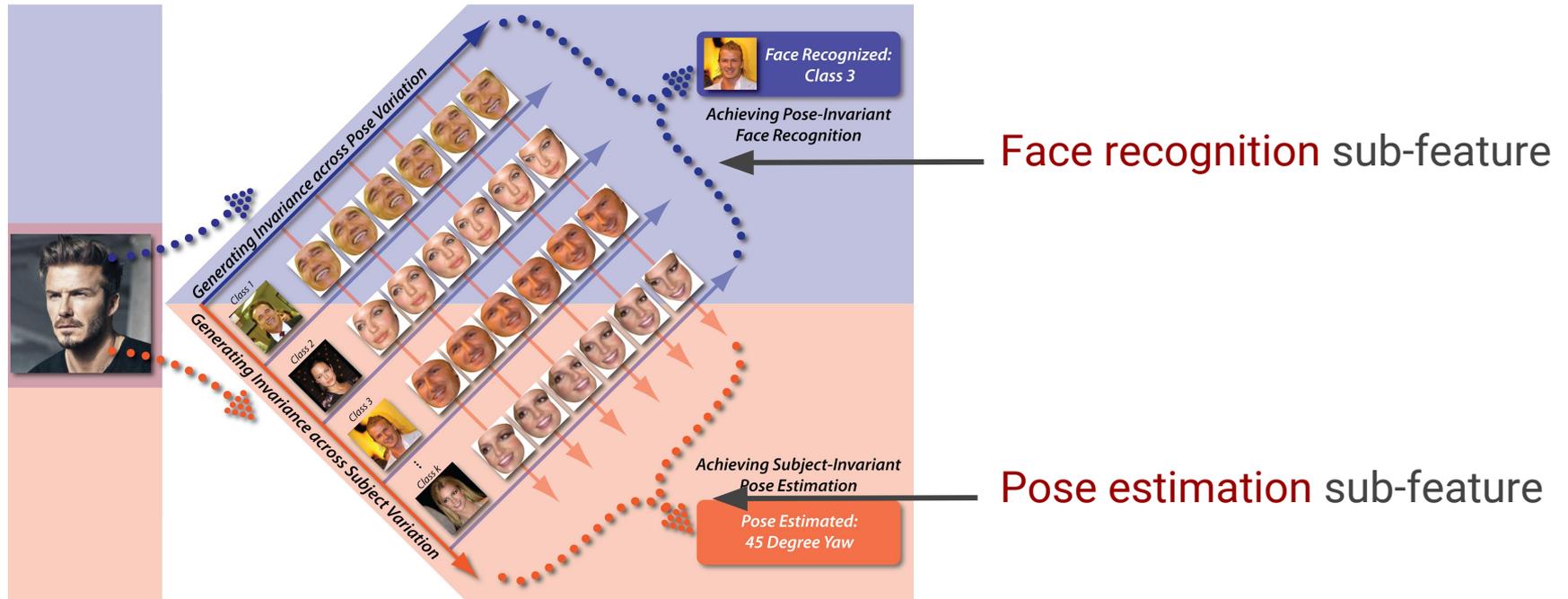## Non-linear Discriminative Invariance

To improve discrimination, we can compute invariant features in the RKHS

We show the discriminative **non-linear** templates form a group in the RKHS, leading to Discriminative Invariant Kernel Features
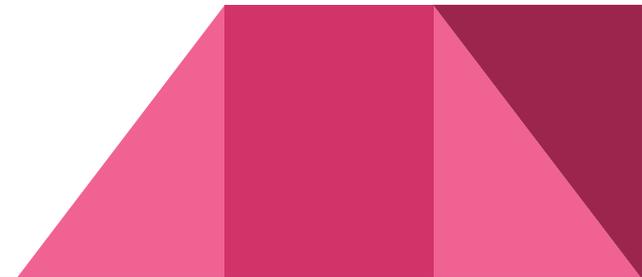
RKHS

Our System
Final system is versatile

Face recognition sub-feature
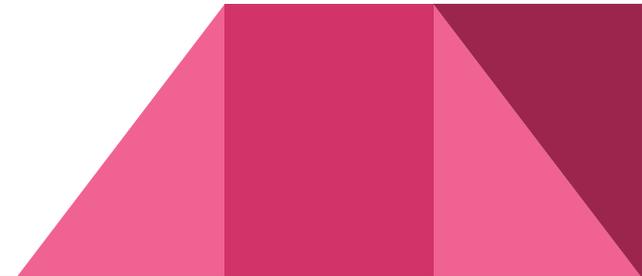
Pose estimation sub-feature

A snapshot of results
Semi Synthetic Face Data

A snapshot of results
Semi Synthetic Face Data

- ~153,000 semi-synthetic image dataset of 1000 subjects with 153 poses each.

A snapshot of results
Semi Synthetic Face Data

- ~153,000 semi-synthetic image dataset of 1000 subjects with 153 poses each.
- Images rendered from a 3D model with real texture.

A snapshot of results
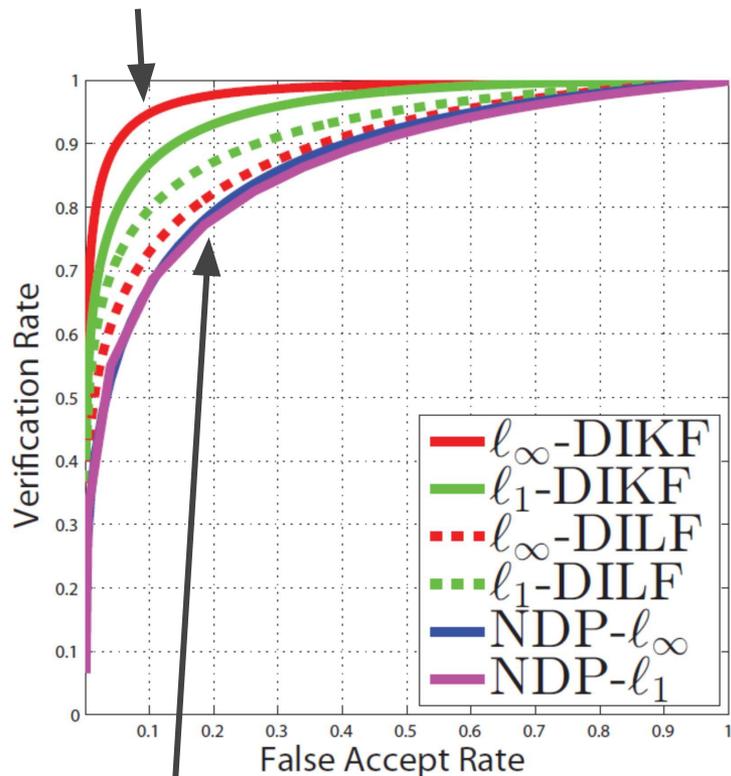## Semi Synthetic Face Data

- ~153,000 semi-synthetic image dataset of 1000 subjects with 153 poses each.
- Images rendered from a 3D model with real texture.
- We compare DIKF against sampled templates (NDP) and discriminative linear templates (DILF).

A snapshot of results
Semi Synthetic Face Data

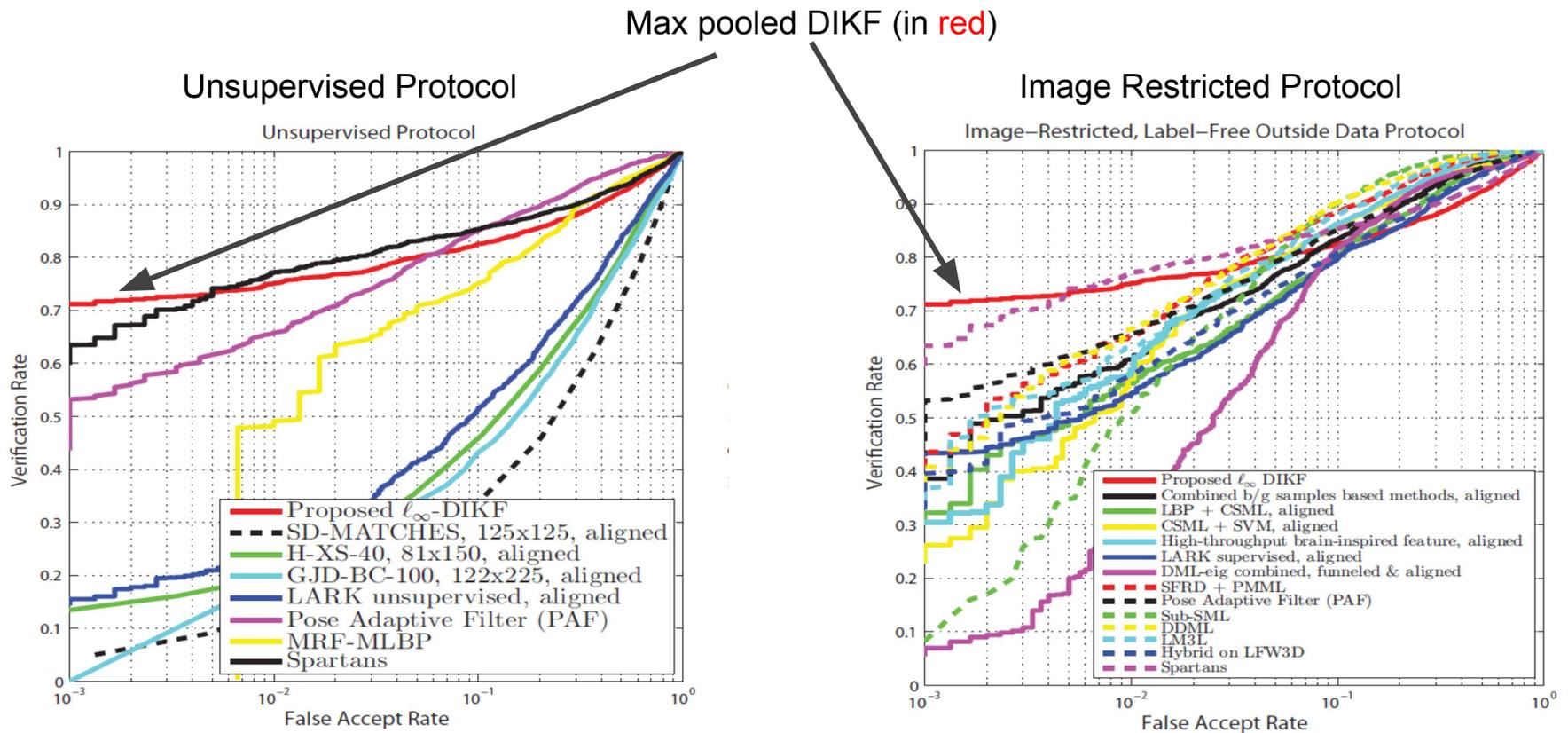Max Pooled Discriminative Kernel Features

Sampled templates max/mean pooled

A snapshot of results
Labeled Faces in the Wild (LFW)

Max-pooled DIKF matches state-of-the-art results on two LFW protocols, despite being simpler than competing methods and working on raw pixels

Max pooled DIKF (in red)

Unsupervised Protocol

Image Restricted Protocol

Find us at Poster # 32

Dipan K. Pal

ECE PhD, CMU

Visual representation, invariant features, sparse signal processing, machine learning

Felix Juefei Xu

ECE PhD, CMU

Computer vision, machine learning, unconstrained face recognition and biometrics

Marios Savvides

Research Professor, CMU

Director of CyLab Biometrics Center, CMU