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Face Recognition

21 / 02 / 2017 Philipp Omenitsch

FACE RECOGNITION

Verification (1:1)

Identification (1:N)

Try to compete with our face recognition engine

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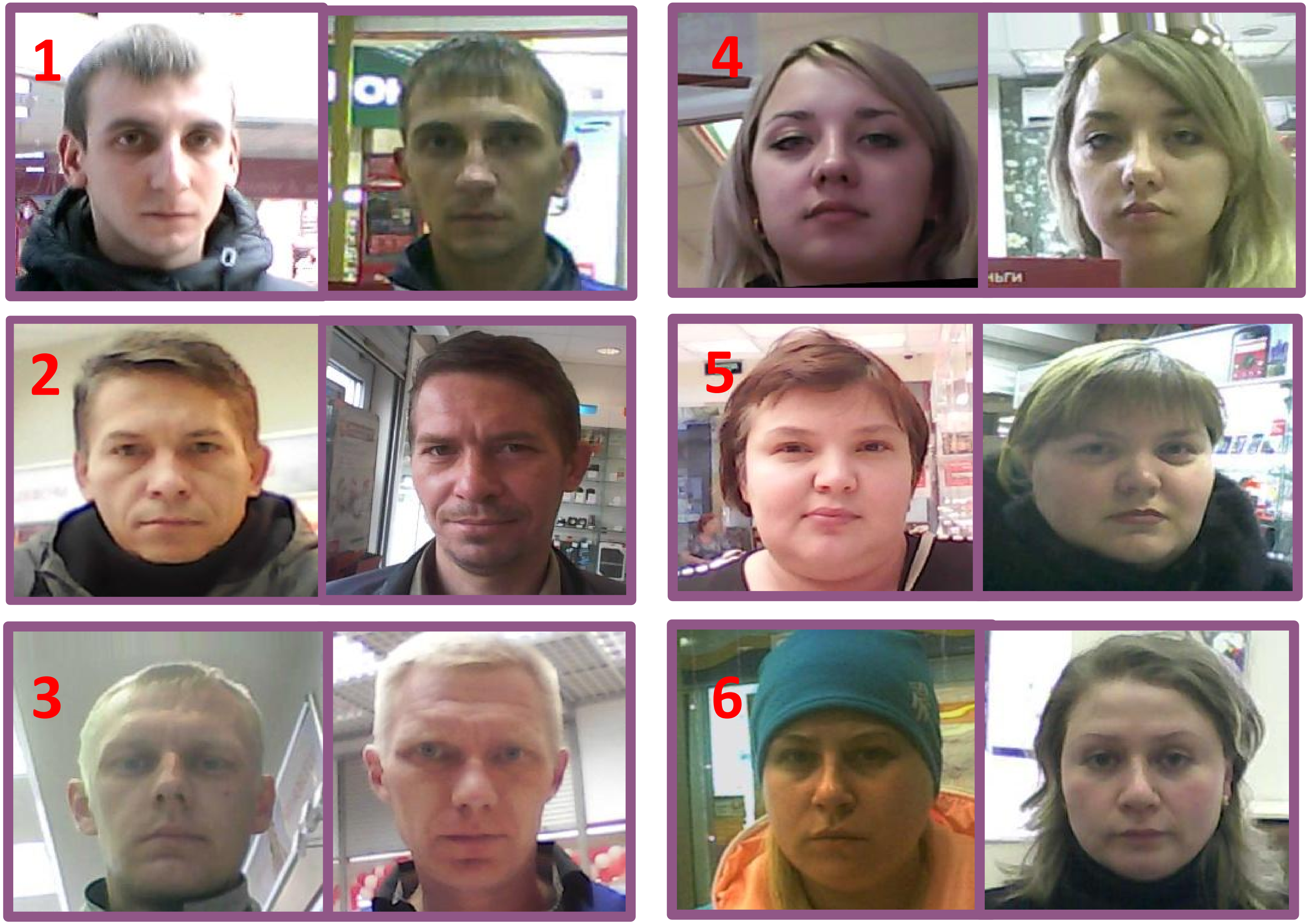

Compare the pairs, same or different?

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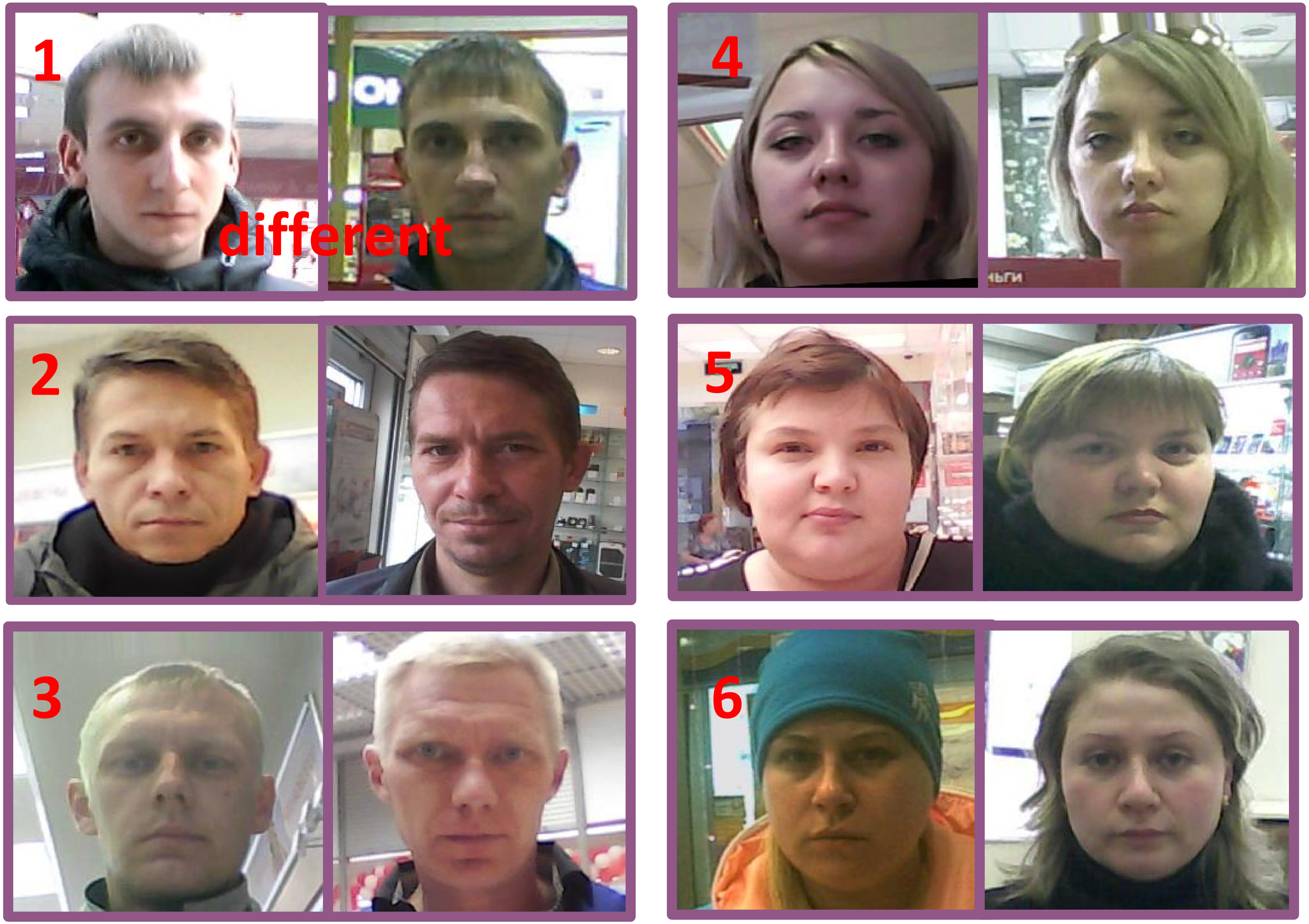

Our algorithm gets 6/6 right

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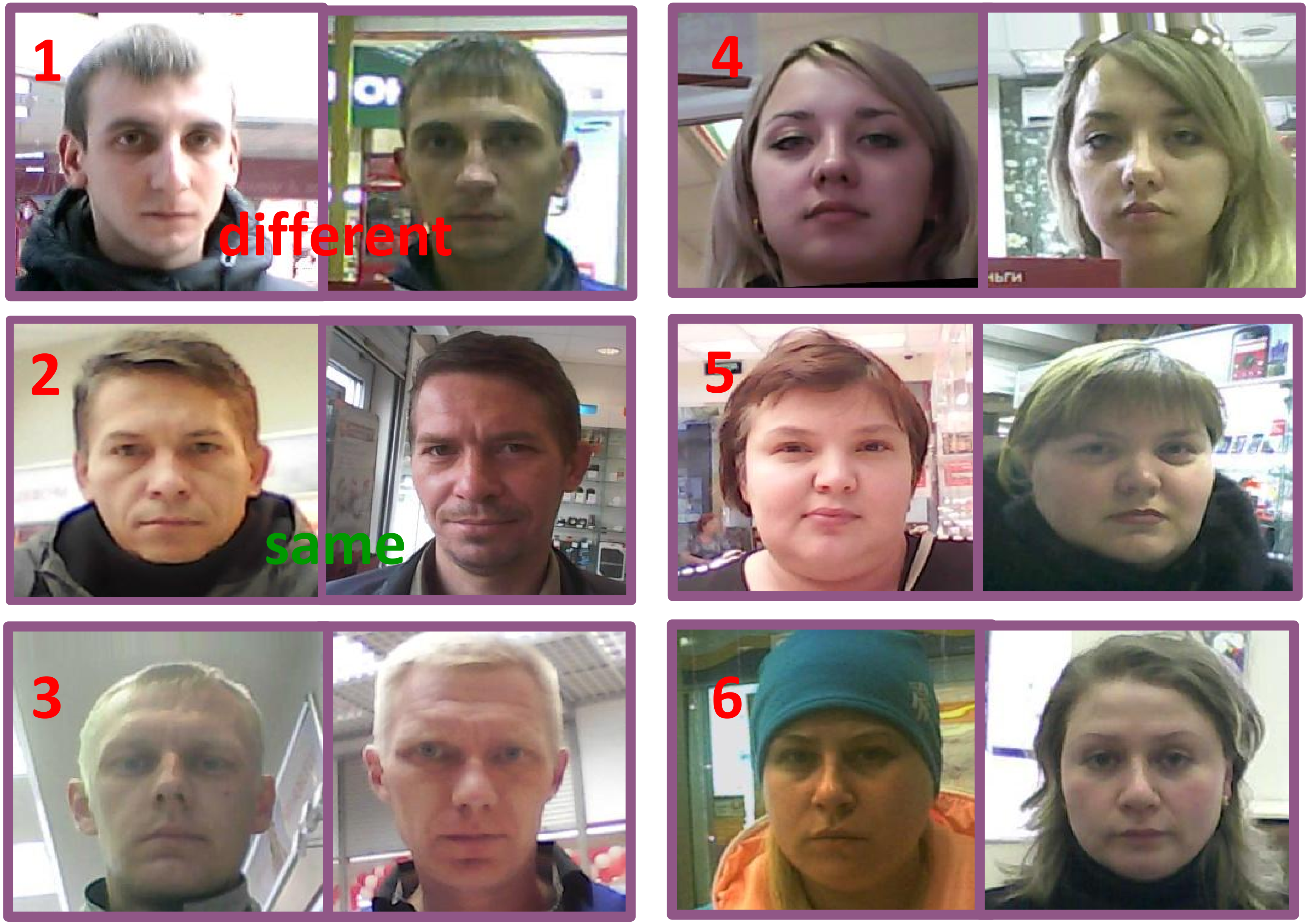

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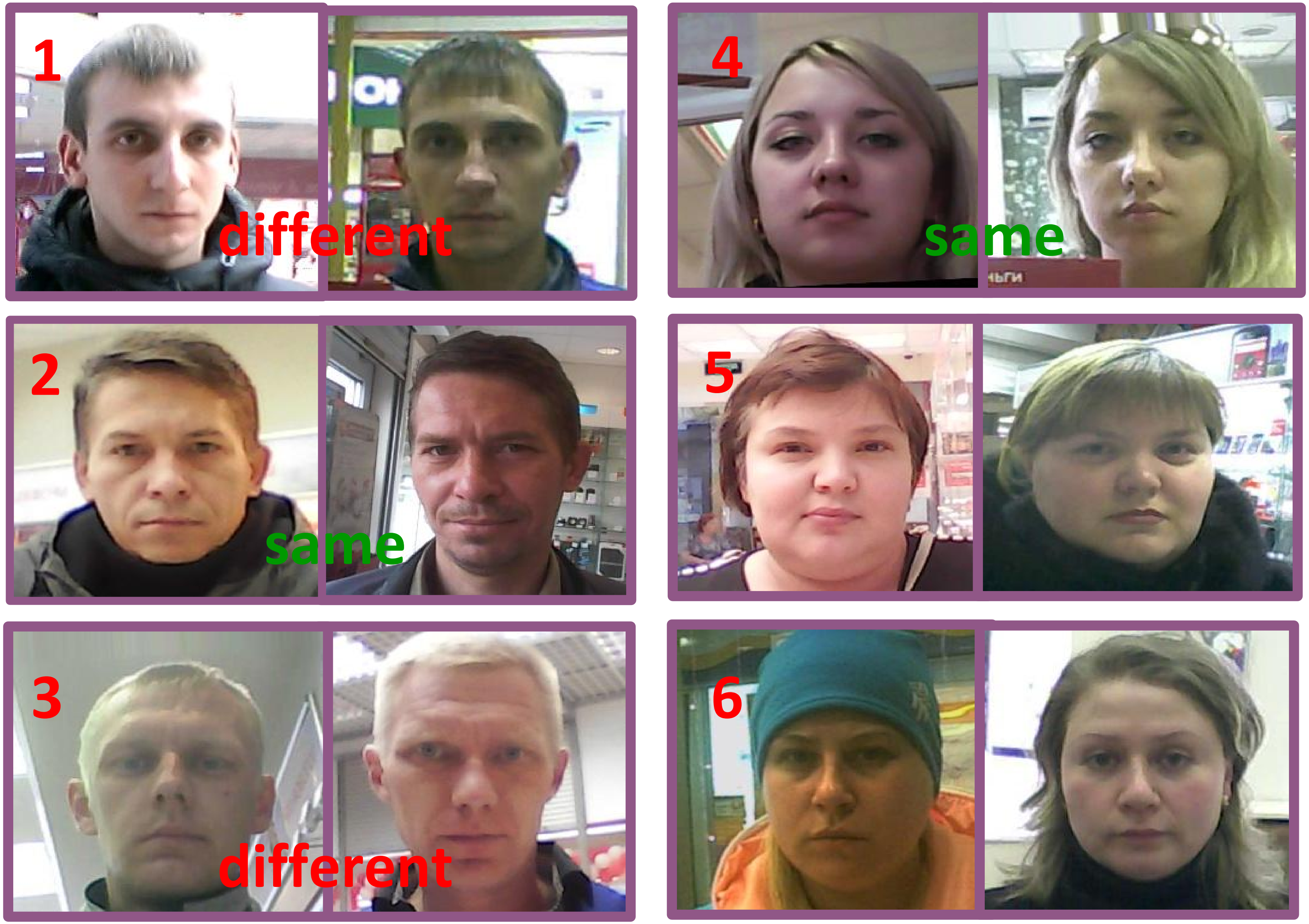

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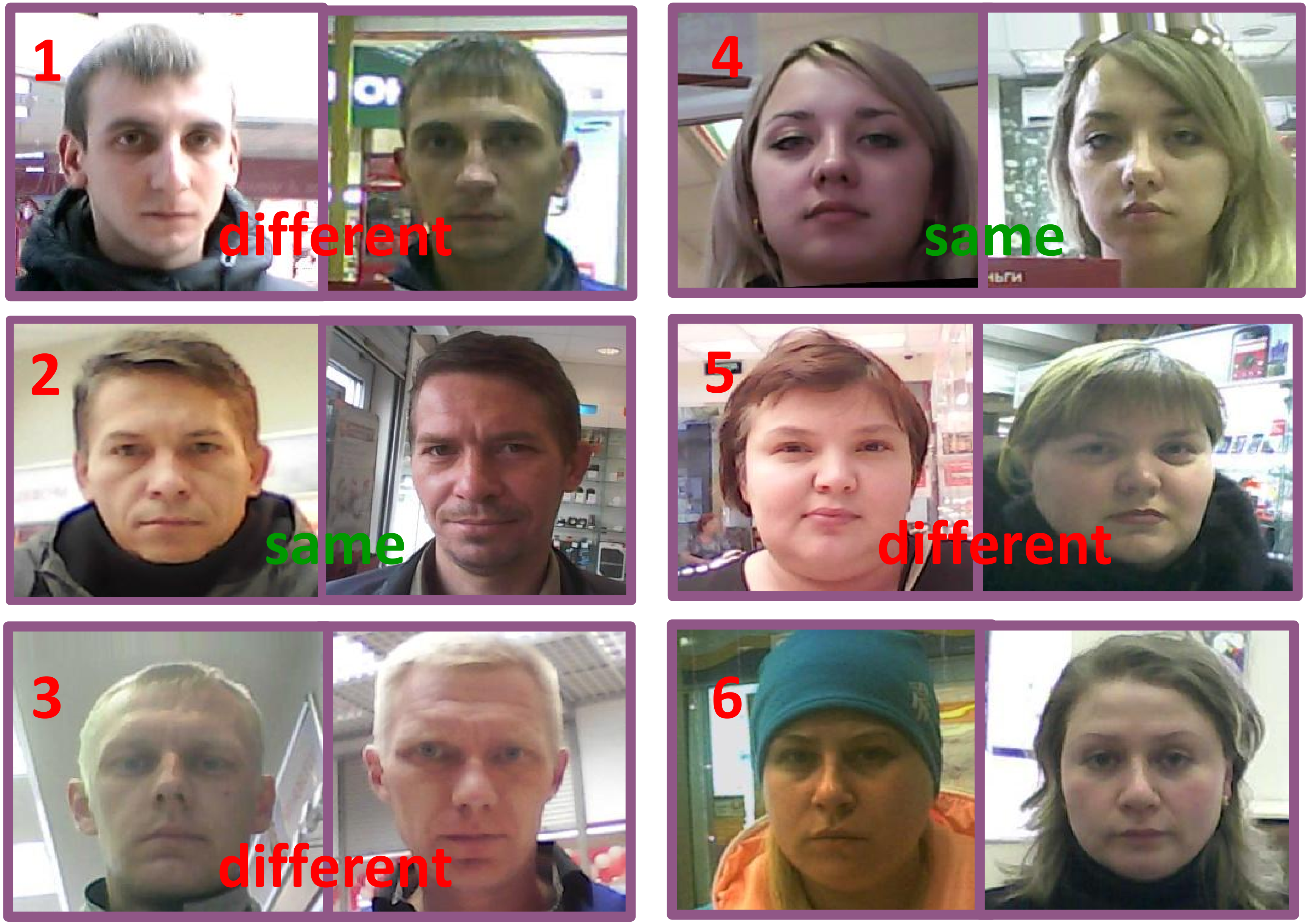

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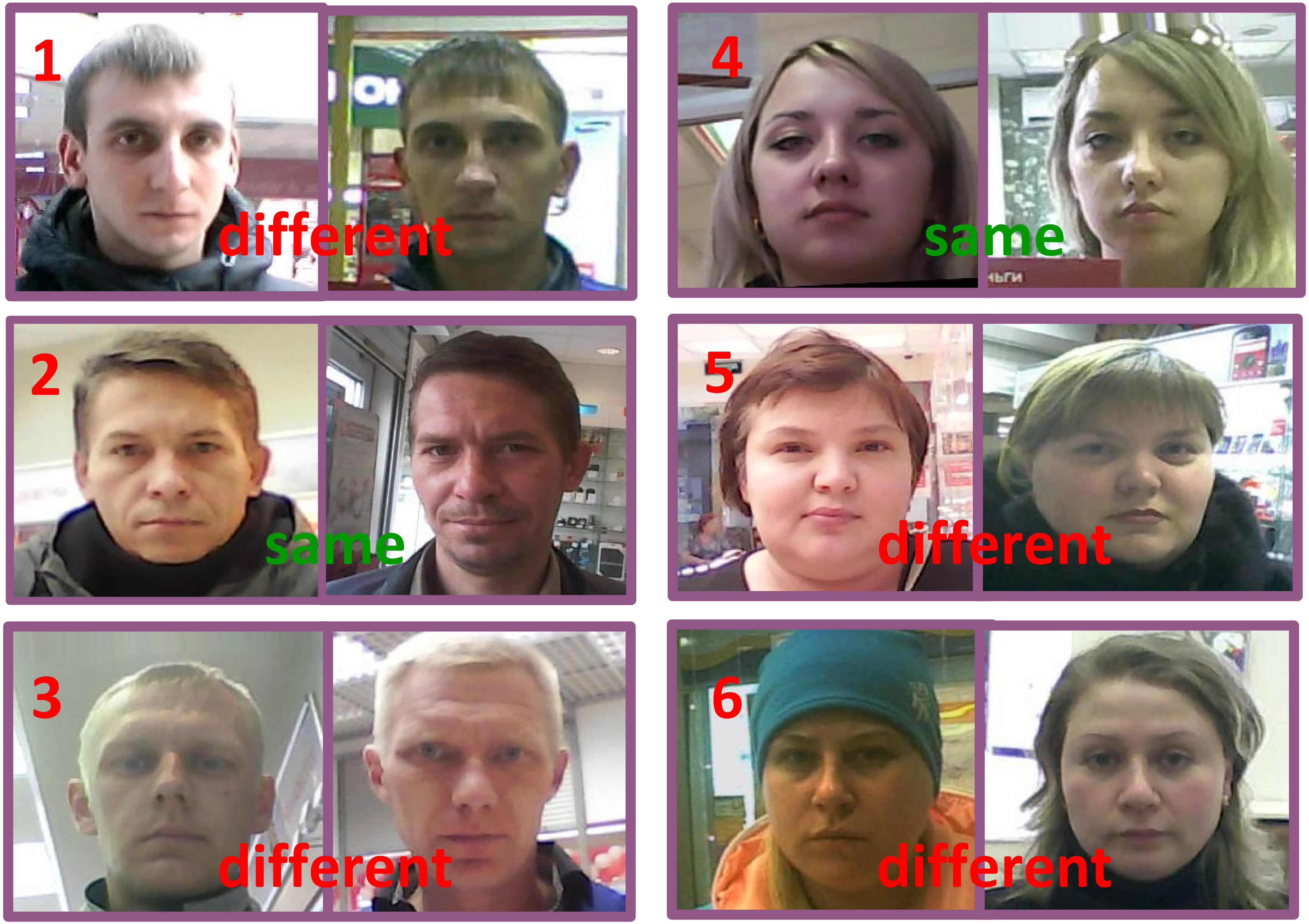

Our algorithm gets 6/6 right

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WHY IS IT SO HARD FOR HUMANS?

- Subtle intrapersonal and interpersonal variations
- Intrinsic factors – makeup, hair styles, emotions
- Extrinsic factors – scaling, noise, occlusion, etc.

WHY THE FACE?

- Doesn’t need interaction for capture
- Doesn’t require any special / expensive hardware

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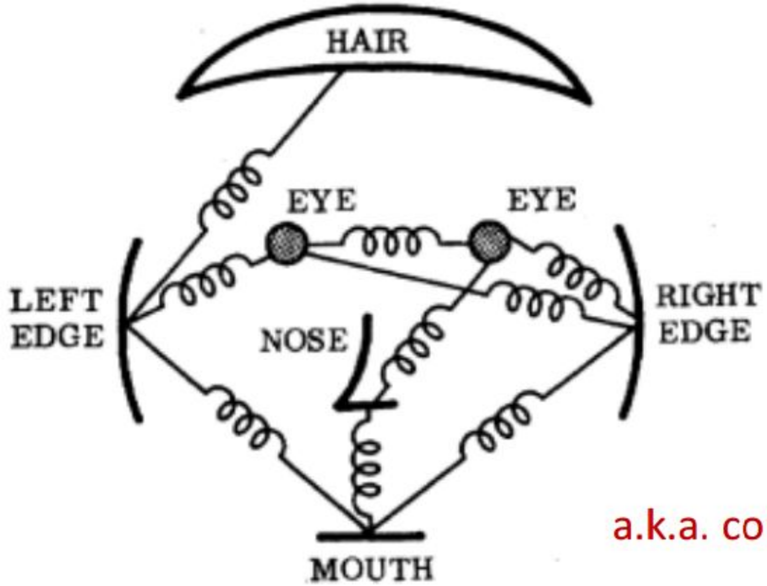
TECHNOLOGY

PREREQUISITES

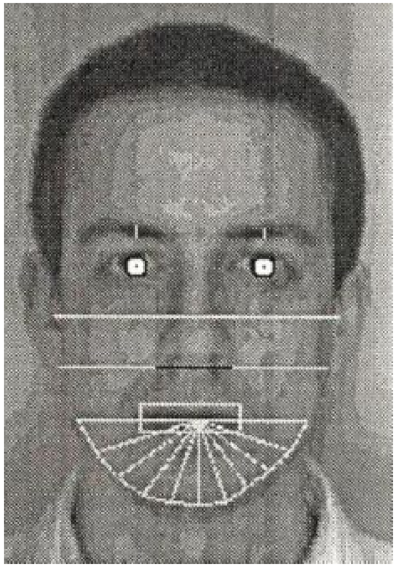
- **Lots of data**
  - access to millions of annotated faces
- **Hardware (GPUs)**
  - currently 12 NVIDIA TITAN X
- **State-of-the-art Neural networks**
  - we are doing our own research and our employees publish papers

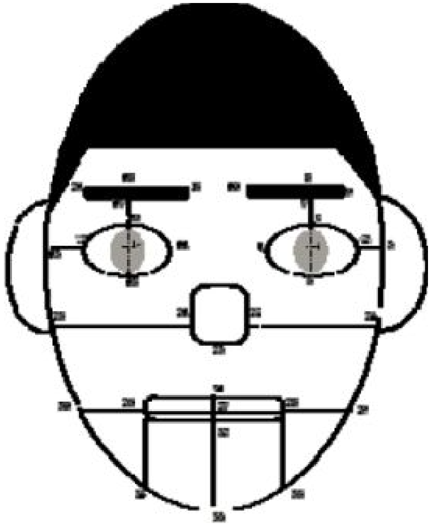
FROM THE VERY BEGINNING…

1973



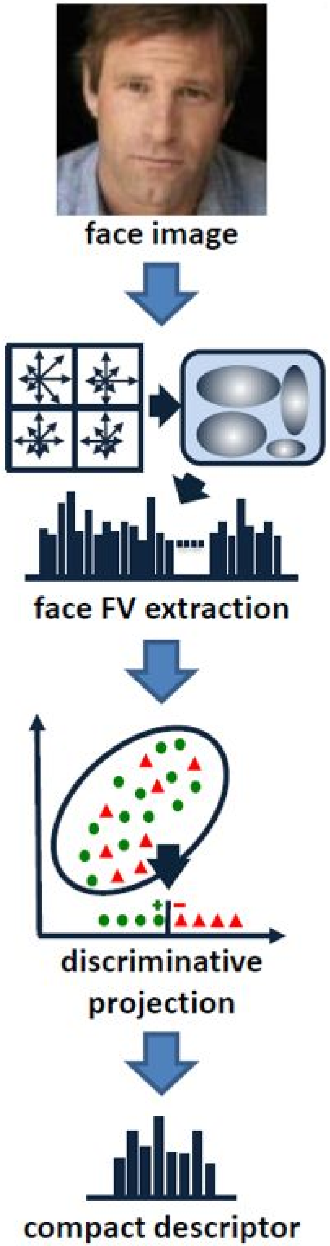
a.k.a. constellation model



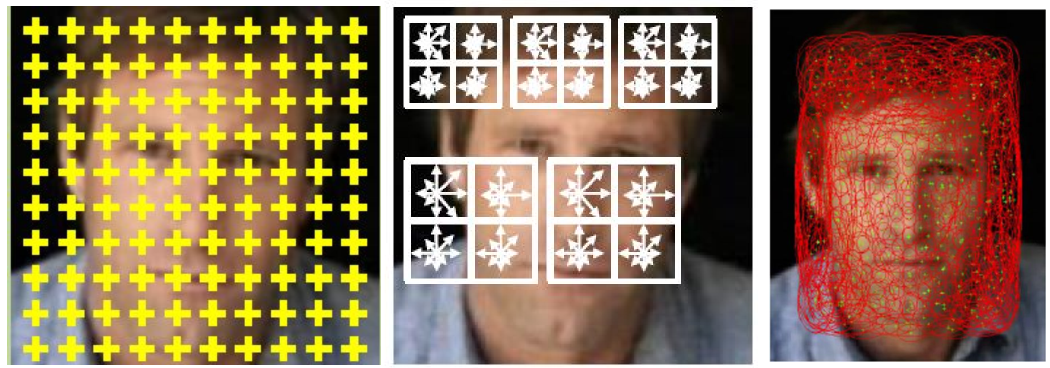


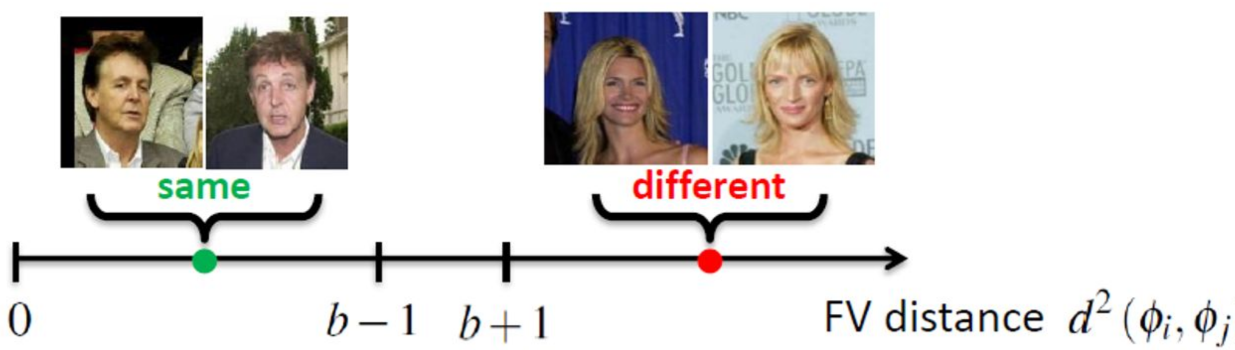
The representation and matching of pictorial structures, Fischler and Elschlager, 1973

OVER HAND CRAFTED FEATURES…

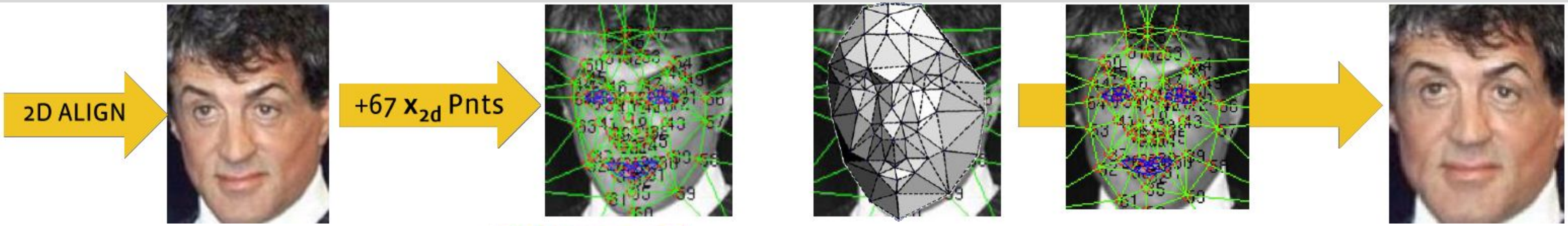


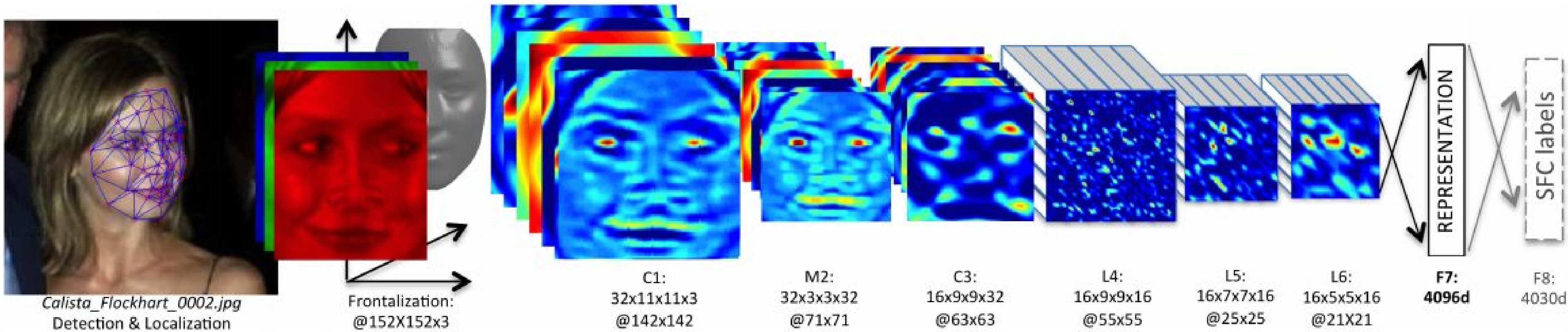
Perronnin 2010, Simonyan 2013 Fisherfaces

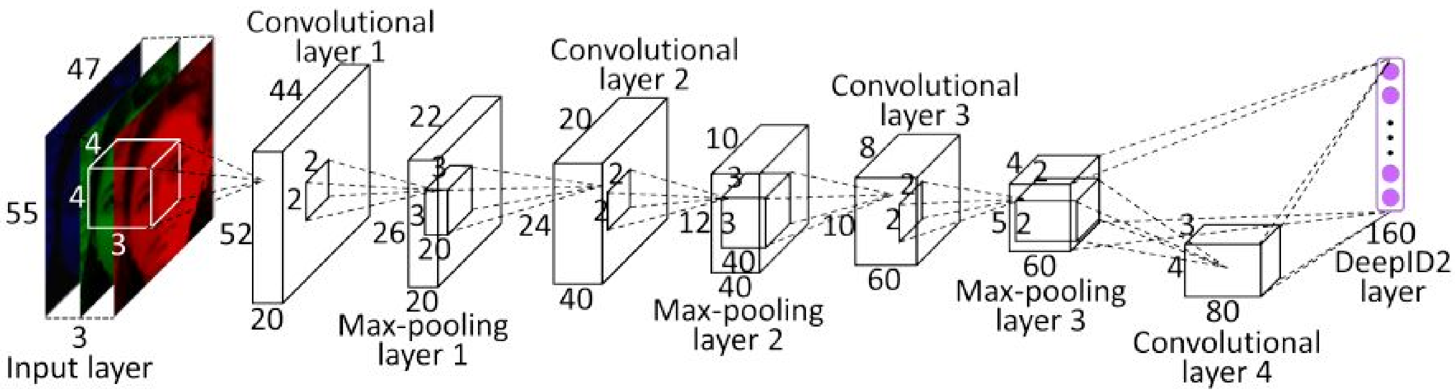




TO NOWADAYS







[1-2] Deepface 2015, Facebook
[3] DeepID Sun et al. 2014

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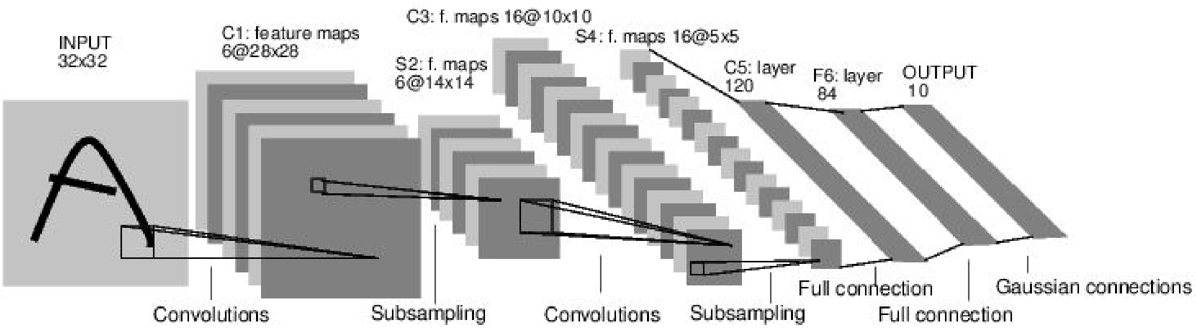
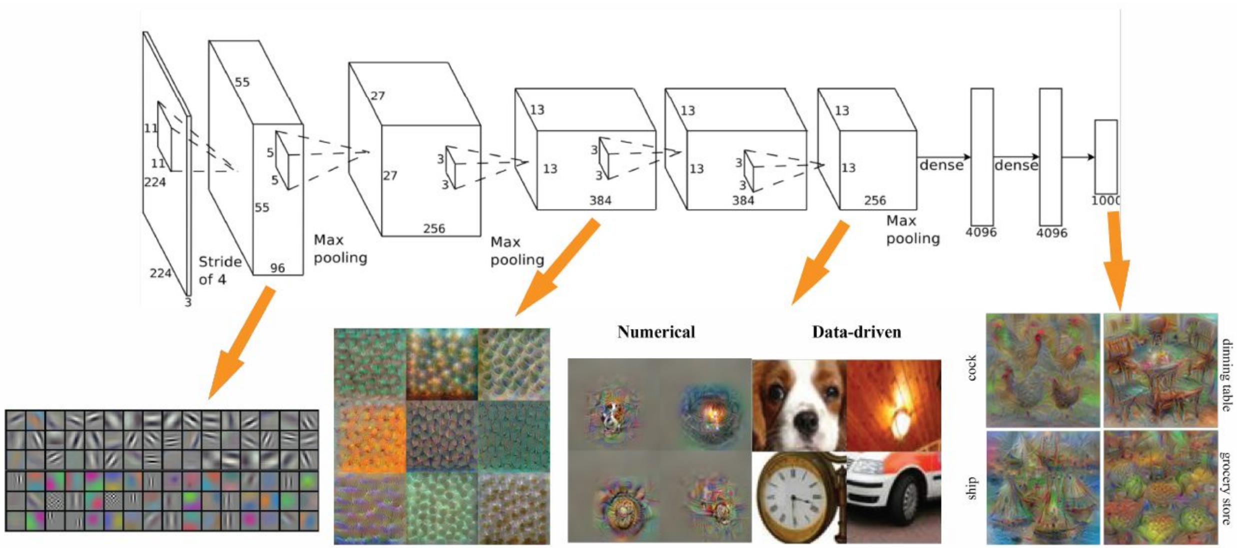
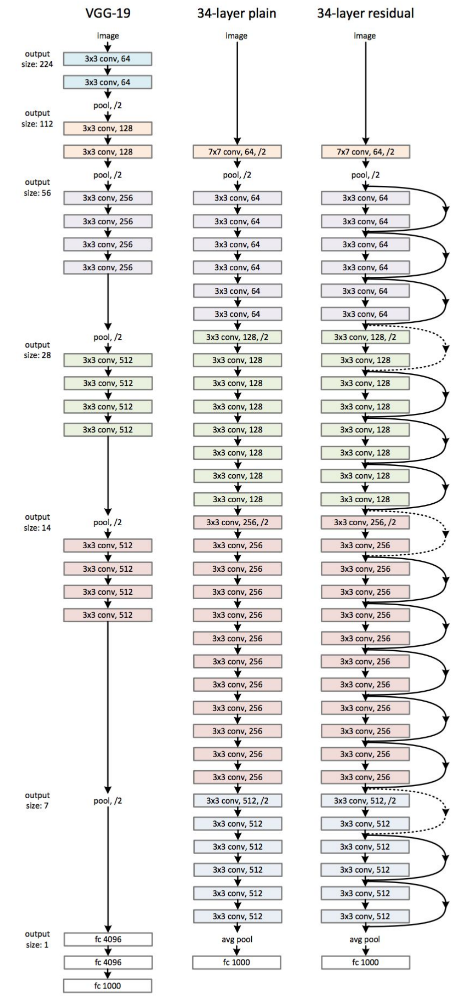
NETWORK ARCHITECTURES





Conv 1: Edge+Blob Conv 3: Texture Conv 5: Object Parts Fc8: Object Classes



[1] Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner. Gradient-based learning applied to document recognition Proceedings of the IEEE, 86(11):2278–2324, 1998.
[2] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In Advances in neural information processing systems, pages 1097–1105, 2012.
[3] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. arXiv preprint arXiv:1512.03385, 2015.

2015 ResNet (ILSVRC'15) 3.57

Year	Codename	Error (percent)	99.9% Conf Int
2014	**GoogLeNet**	**6.66**	**6.40 - 6.92**
2014	VGG	7.32	7.05 - 7.60
2014	MSRA	8.06	7.78 - 8.34
2014	AHoward	8.11	7.83 - 8.39
2014	DeeperVision	9.51	9.21 - 9.82
2013	Clarifai†	11.20	10.87 - 11.53
2014	CASIAWS†	11.36	11.03 - 11.69
2014	Trimps†	11.46	11.13 - 11.80
2014	Adobe†	11.58	11.25 - 11.91
2013	**Clarifai**	**11.74**	**11.41 - 12.08**
2013	NUS	12.95	12.60 - 13.30
2013	ZF	13.51	13.14 - 13.87
2013	AHoward	13.55	13.20 - 13.91
2013	OverFeat	14.18	13.83 - 14.54
2014	Orange†	14.80	14.43 - 15.17
2012	SuperVision†	15.32	14.94 - 15.69
2012	**SuperVision**	**16.42**	**16.04 - 16.80**
2012	ISI	26.17	25.71 - 26.65
2012	VGG	26.98	26.53 - 27.43
2012	XRCE	27.06	26.60 - 27.52
2012	UvA	29.58	29.09 - 30.04

Microsoft ResNet, a 152 layers network

GoogLeNet, 22 layers network

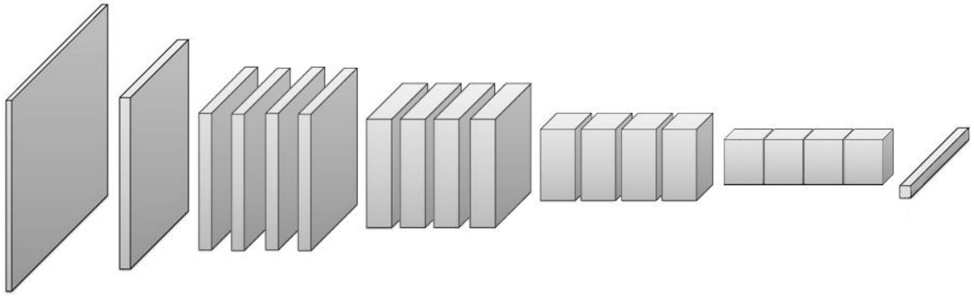
U. of Toronto, SuperVision, a 7 layers network

human error is around *5.1%* on a subset

FACE DESCRIPTOR

Deep CNN model

Millions of face images
with person IDs



+

- Pre-training networks for the face classification task
- Fine-tuning face descriptors with similarity loss
- Network architectures with multiple image resolutions
- Full training with 4 NVIDIA Titan X GPUs done in 2 days enables fast development, optimization and deployment of new models
- Training in this setup on CPU is infeasible for us

HOW TO MEASURE SUCCESS?

Same faces if $D_{i,j} < T$

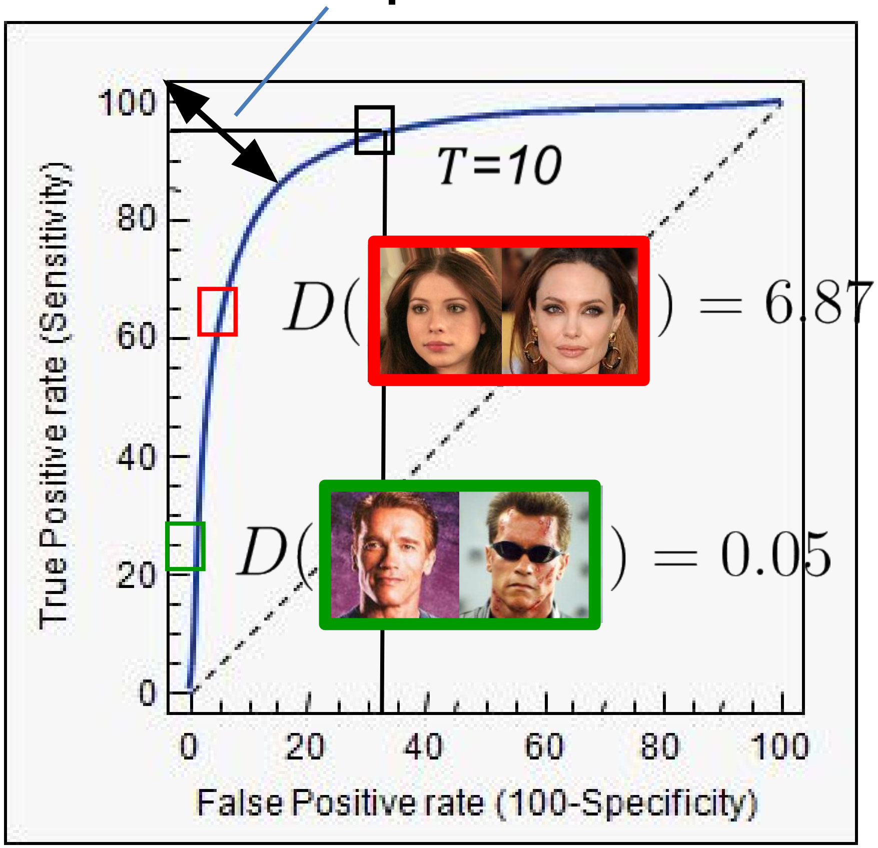
True Positive Rate

$$\frac{\# \; correct \; (T)}{\# \; all \; correct}$$

False Positive Rate

$$\frac{\# \; wrong \; (T)}{\# \; all \; wrong}$$

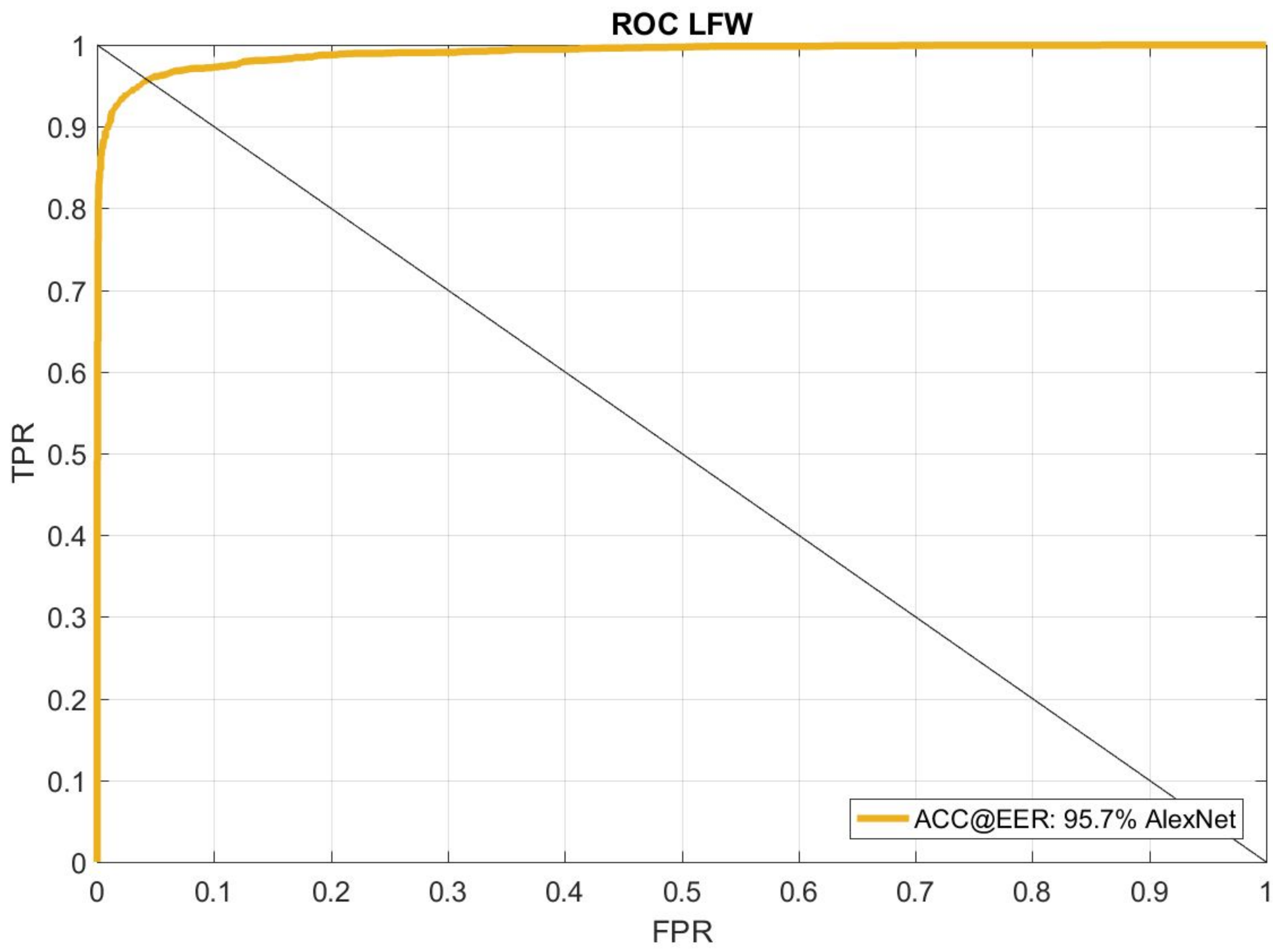
Equal error rate



ROC curve

http://en.wikipedia.org/wiki/Receiver_operating_characteristic

TEST ON LFW BENCHMARK



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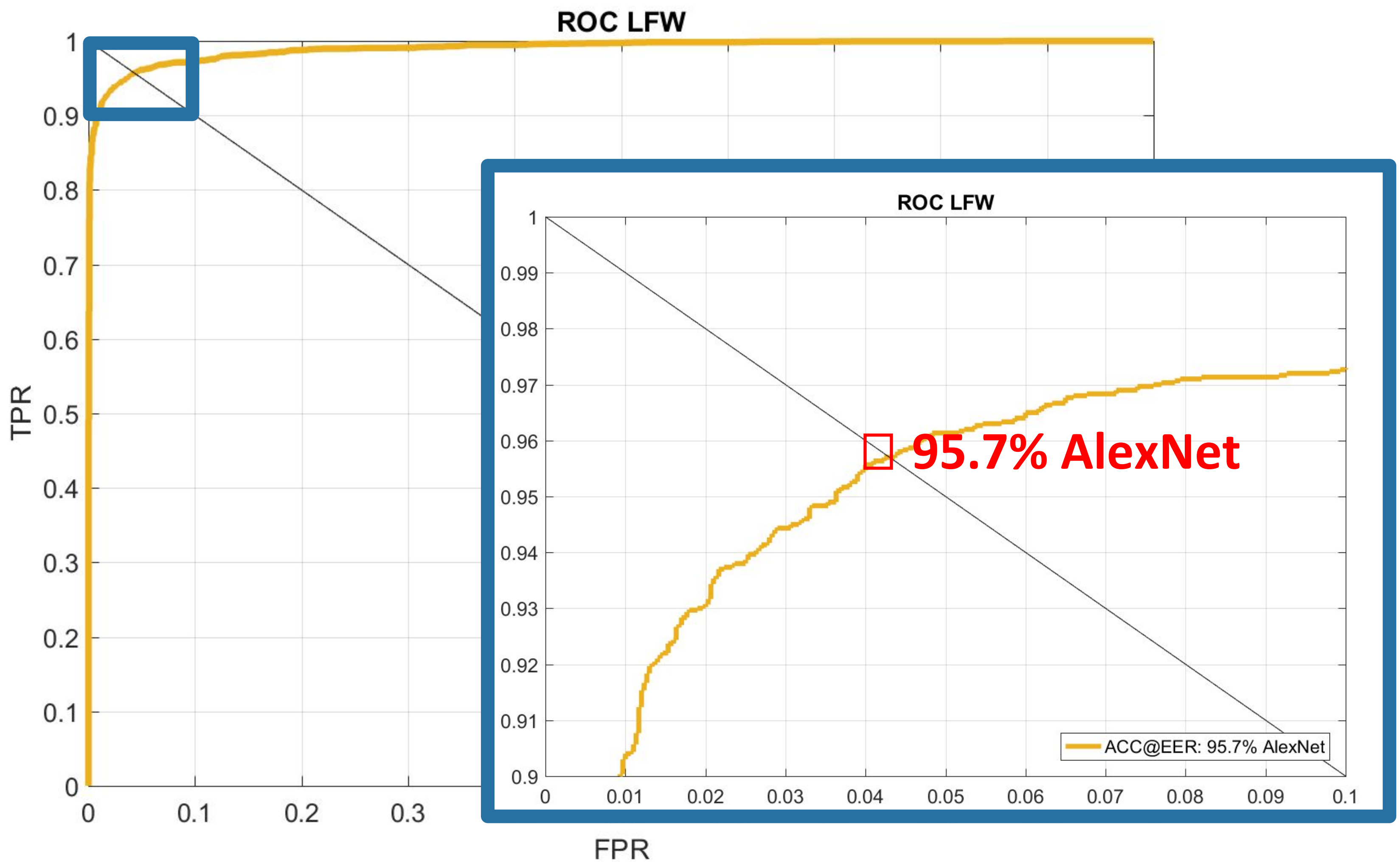

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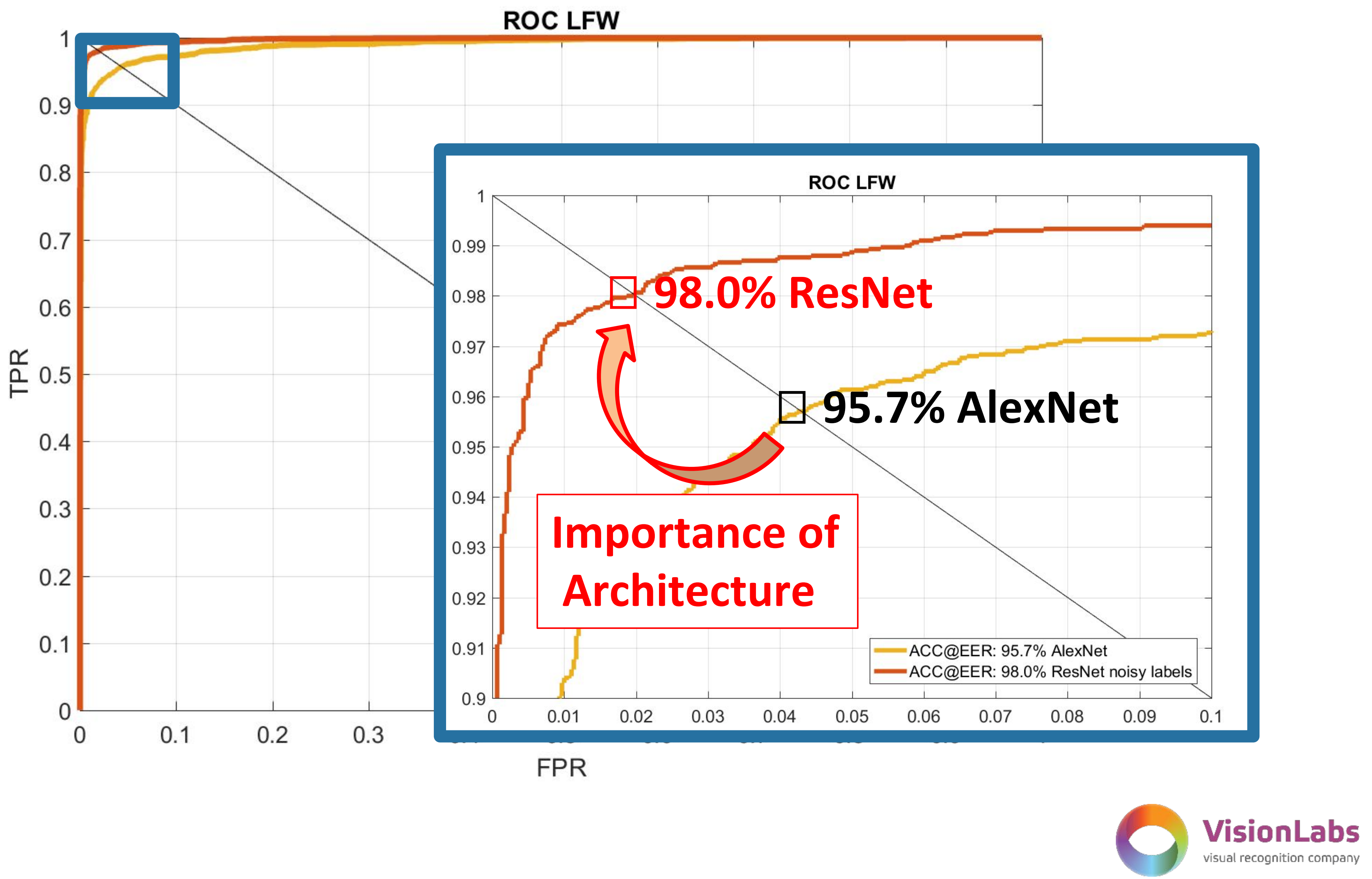
IMPROVEMENT ON LFW BENCHMARK

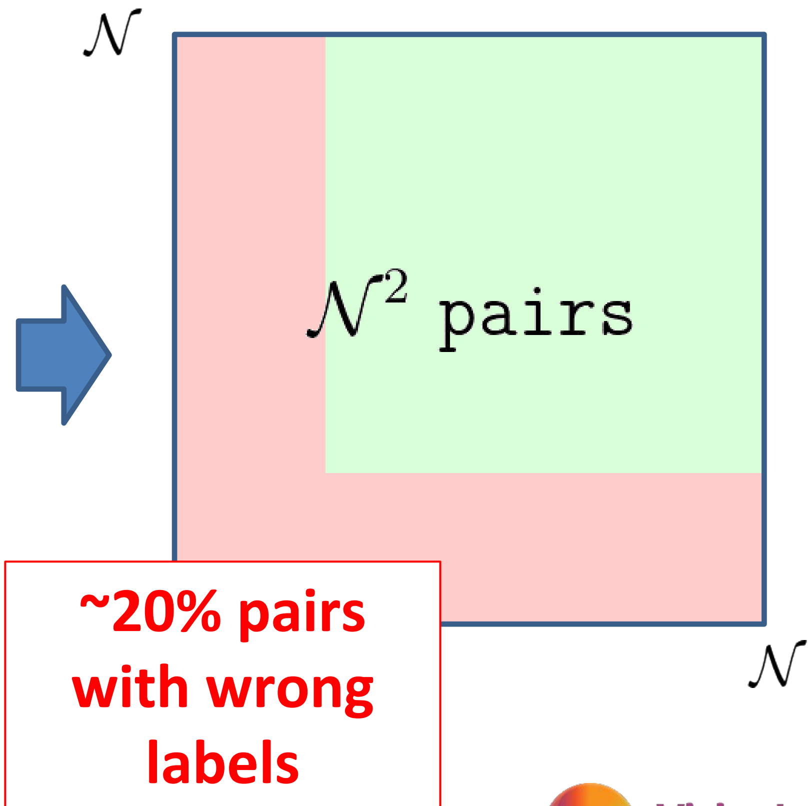


TRAINING DATA

Automatically collected
large-scale face datasets
from the Web

$$\mathcal{N} = 1\ 000\ 000$$

Training with pair-wise
similarity loss
suffers from wrong labels



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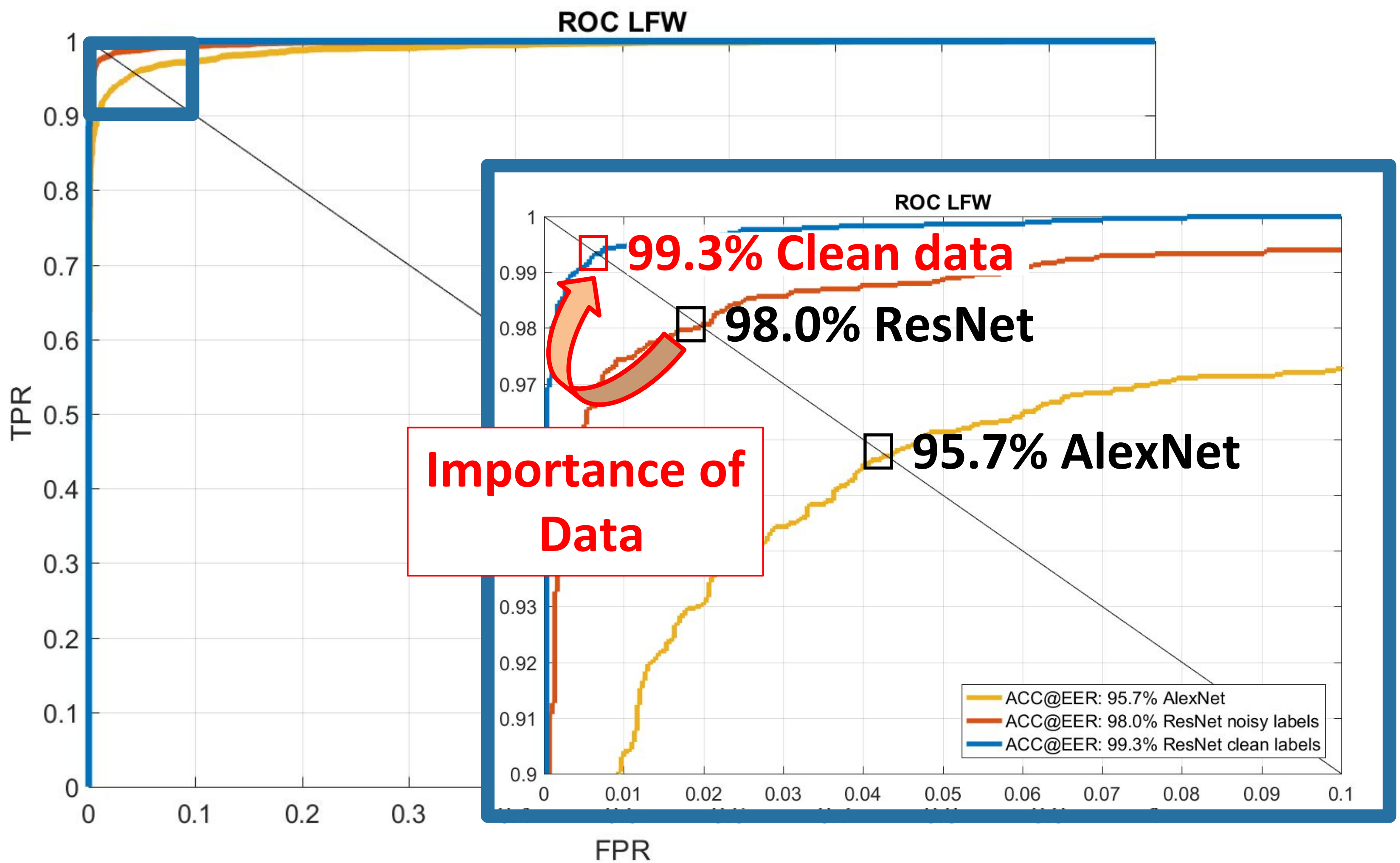

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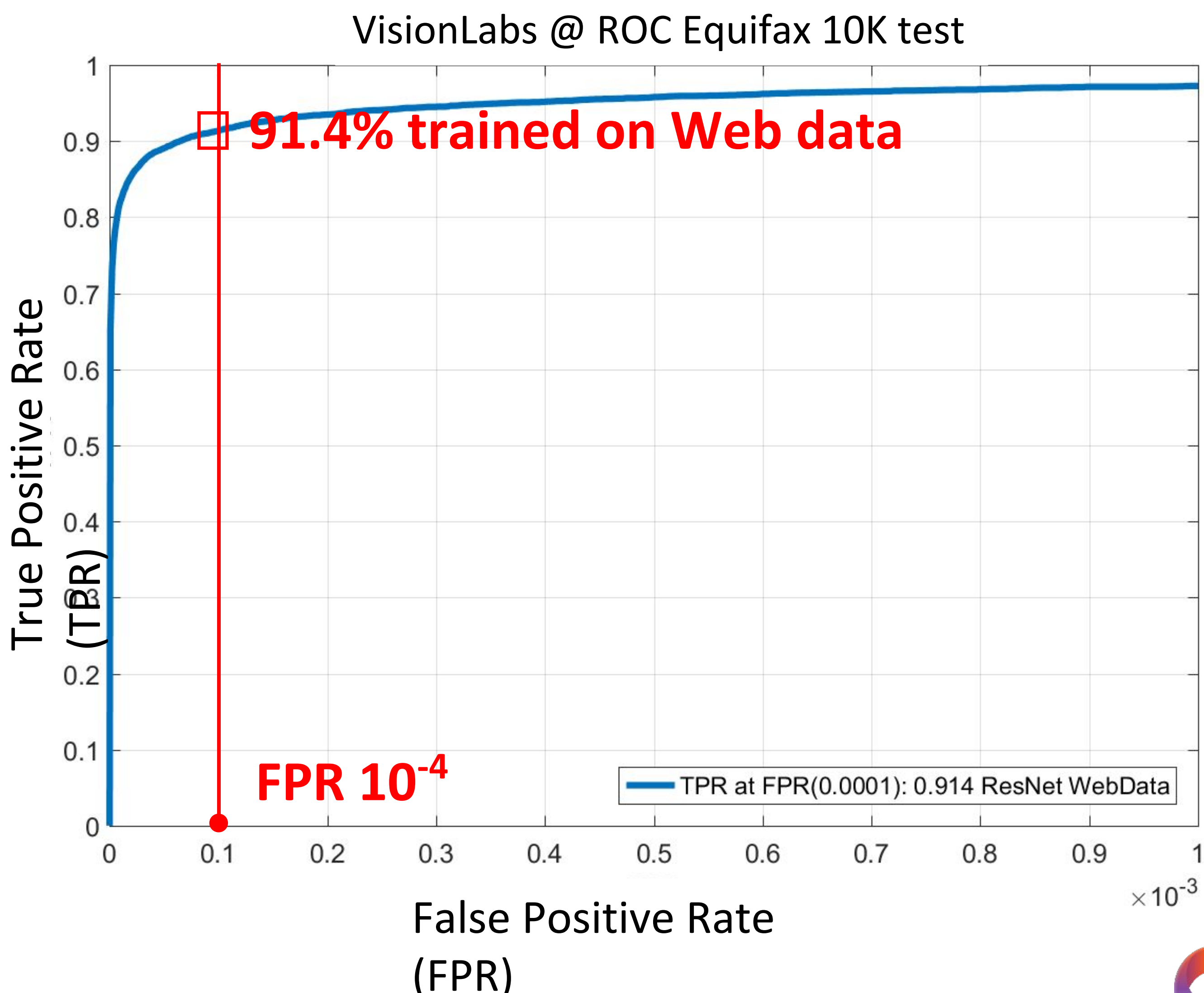
LARGE DATASETS: NEED HIGH TPR AT LOW FPR



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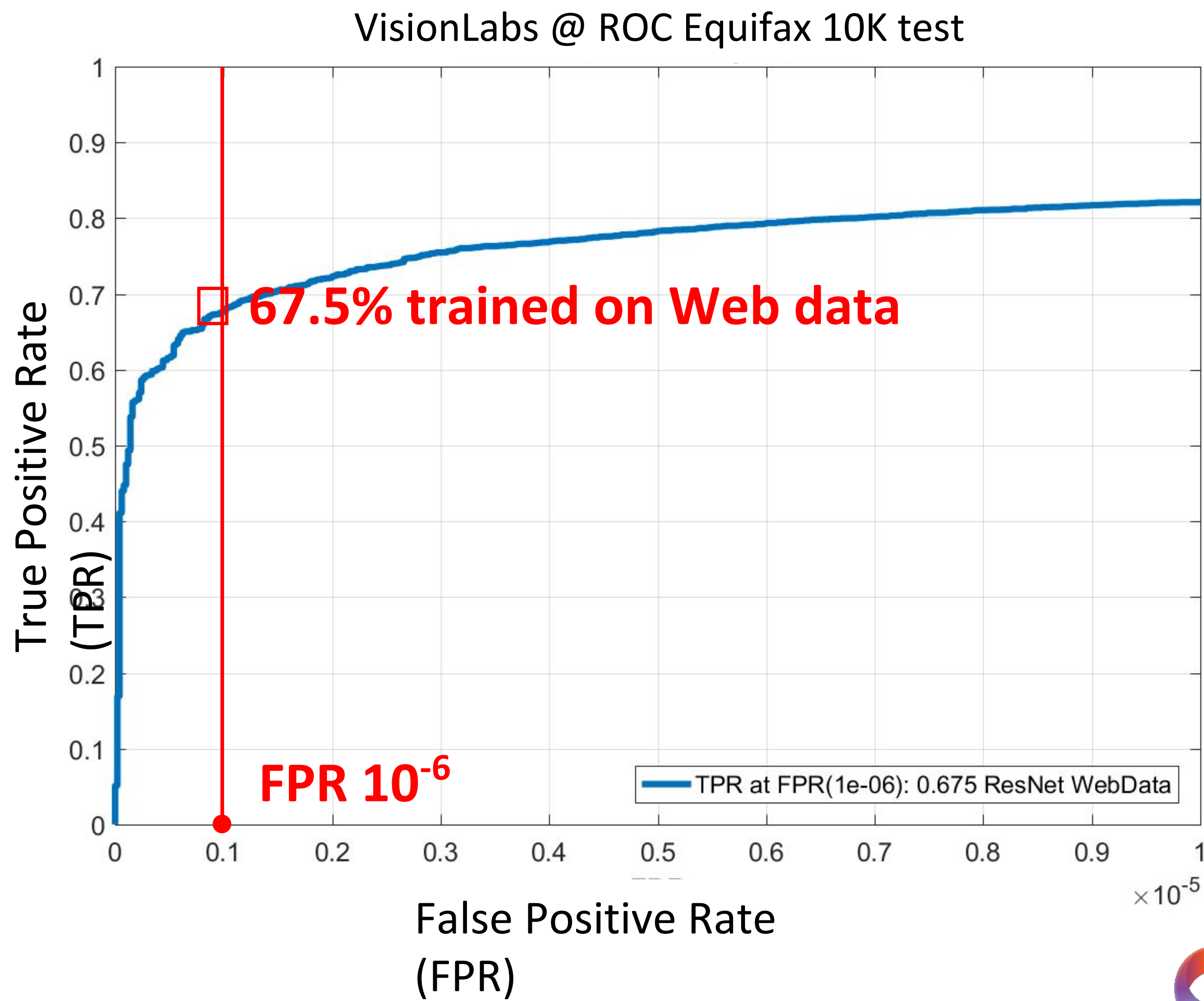
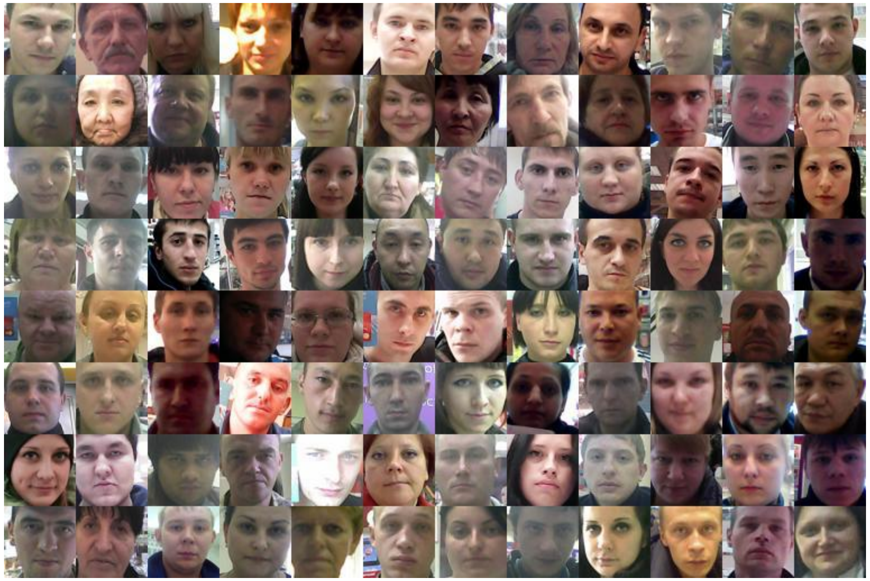
LARGE DATASETS:
NEED HIGH TPR AT EXTREMELY LOW FPR



UNIQUE TRAINING DATA

1. Real labeled face images from financial sector provided by our partner - Equifax



2. Celebrities images are collected and labeled by ourselves

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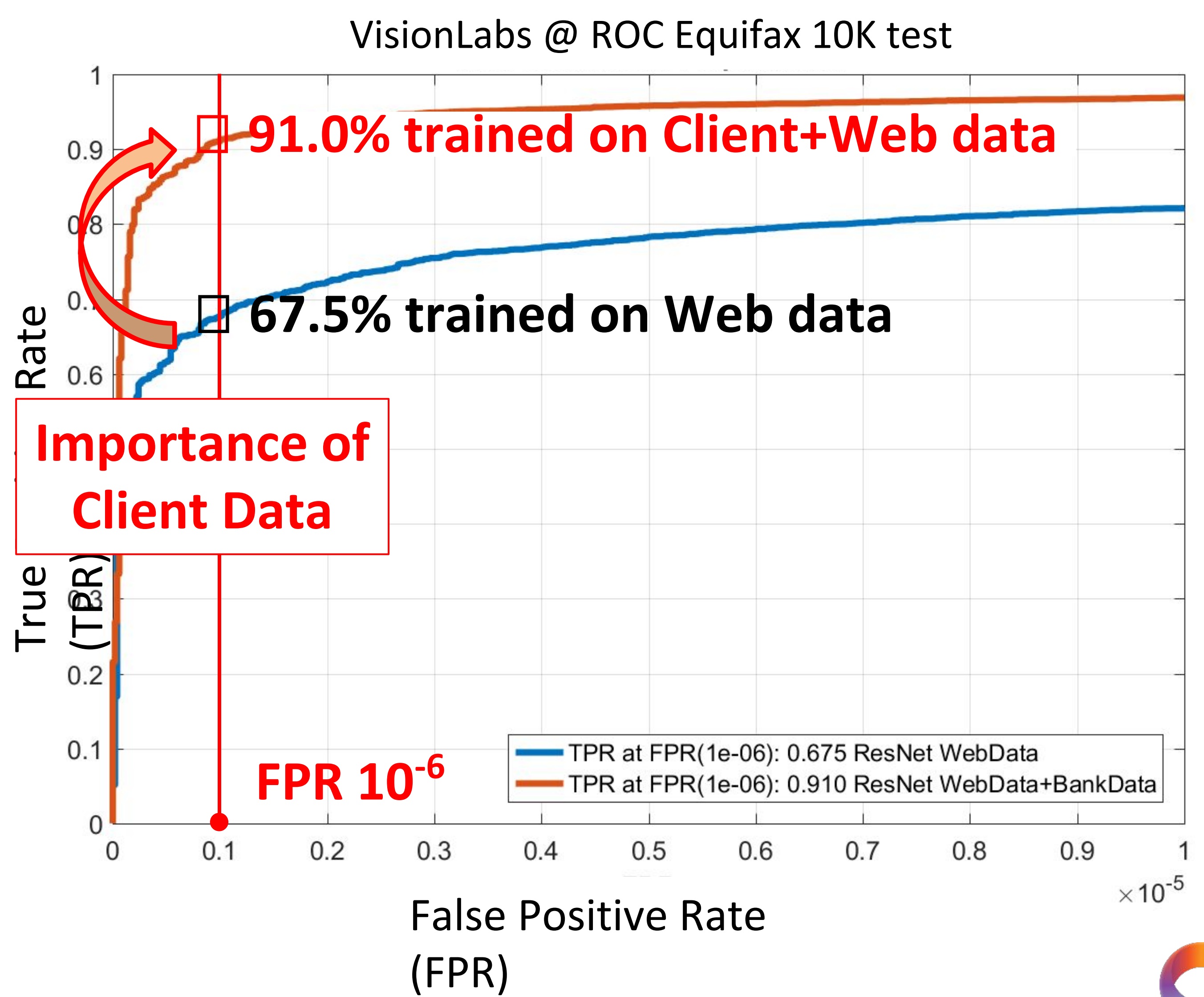
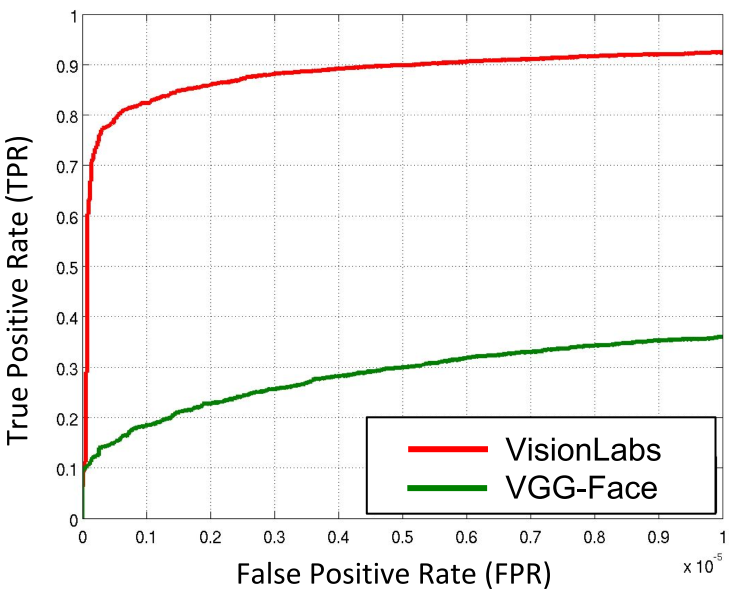
LARGE DATASETS:
NEED HIGH TPR AT EXTREMELY LOW FPR

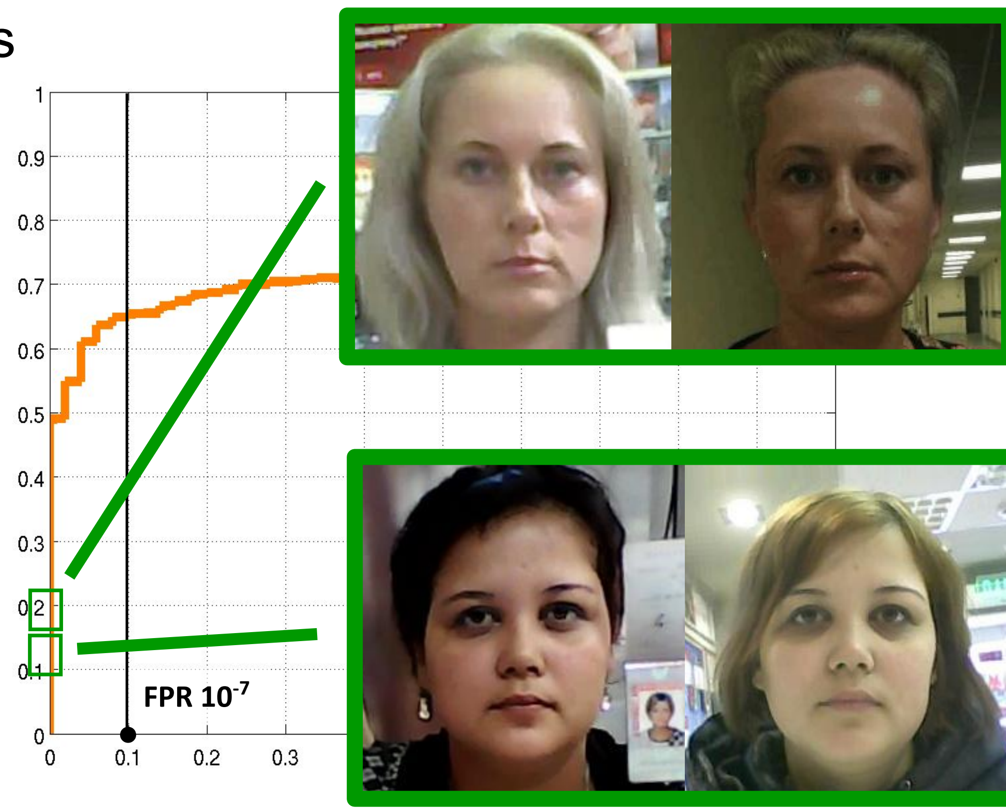


Face descriptors

- Compact: 160 bytes
  binary descriptors
- Fast matching: 40ms for 1M faces
  1 core Intel CPU E5-2650
- Accurate: ~82% TPR at 10^{-6} FPR
  on client image data



- Robust to hair style



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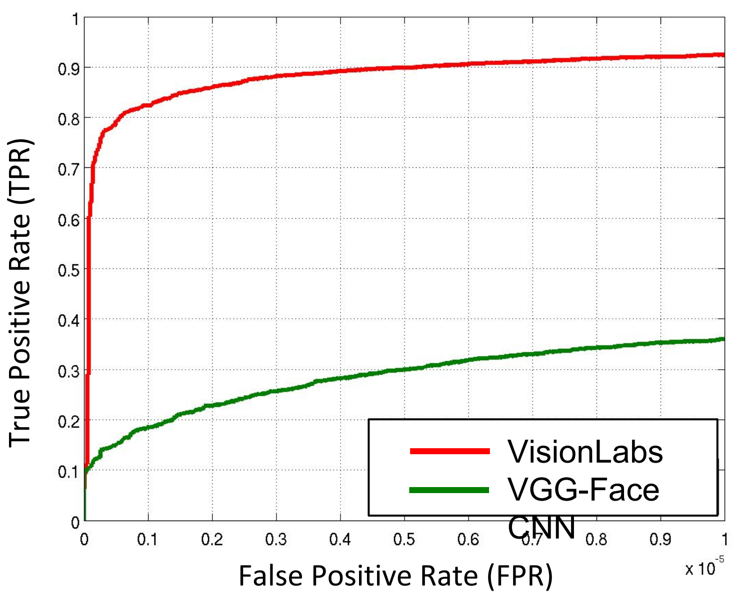
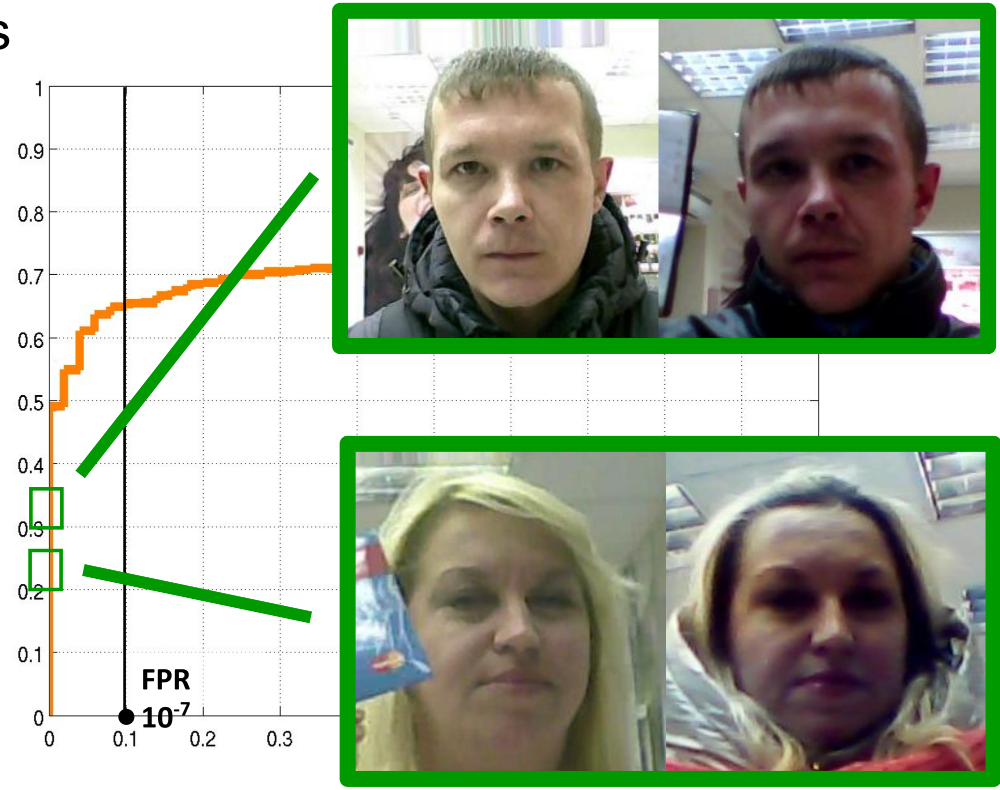


- Robust to poor lighting



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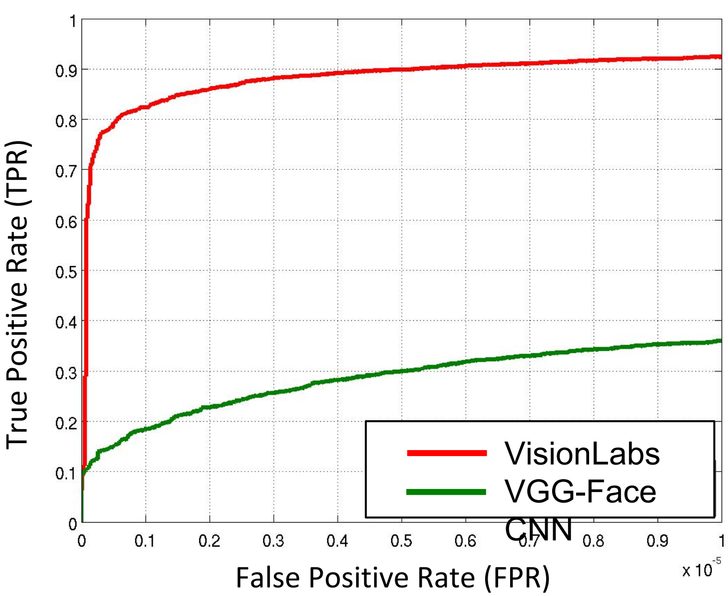
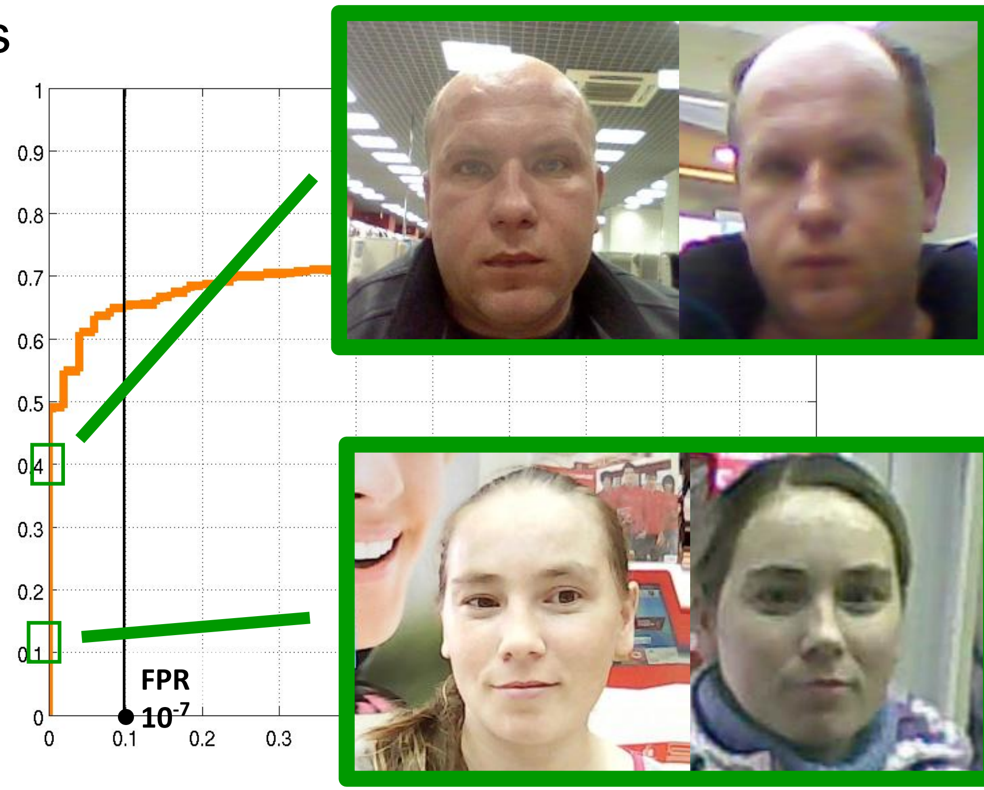


- Robust to low image quality



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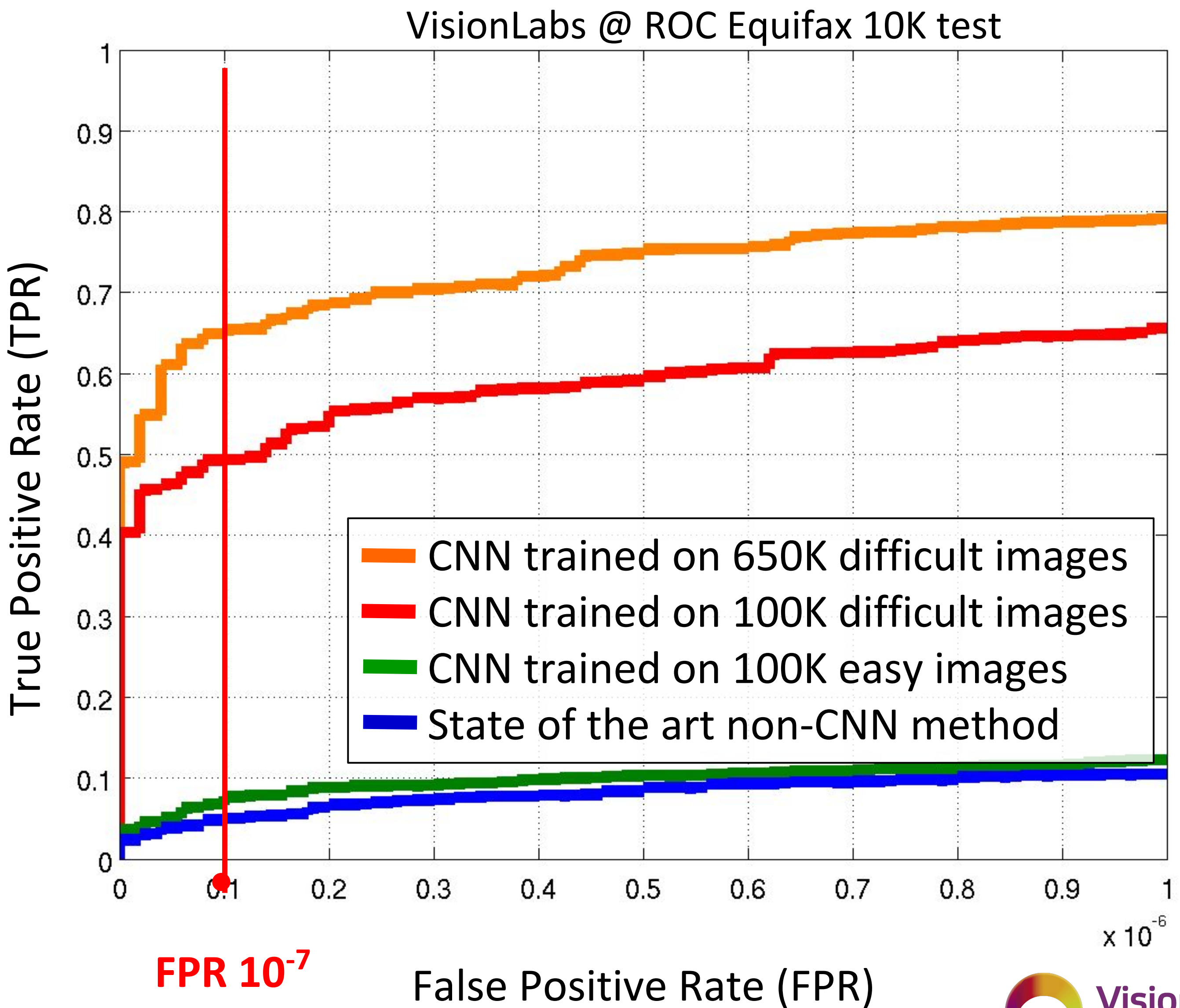
IMPORTANCE OF TRAINING DATA



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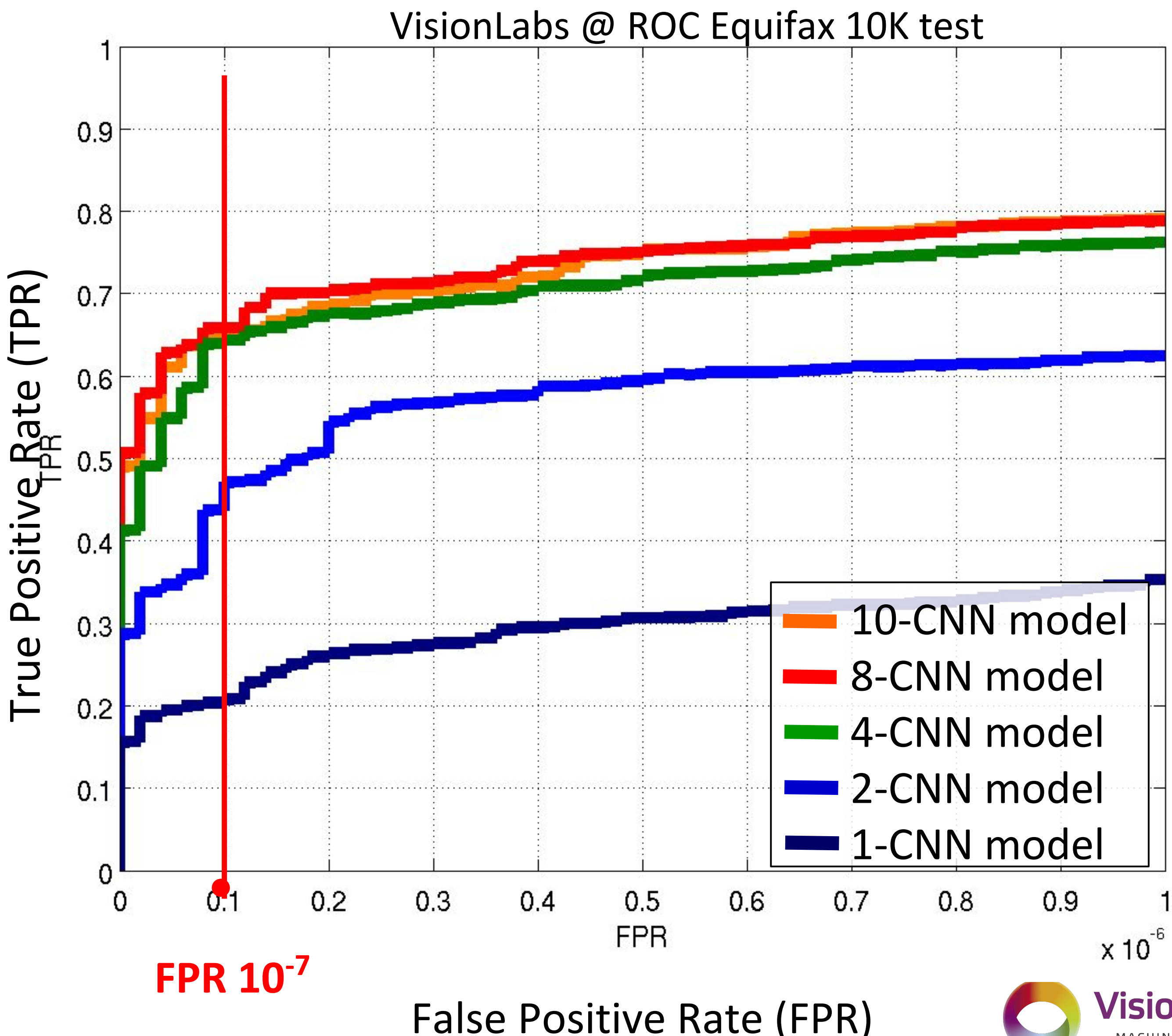
IMPORTANCE OF MODEL COMPLEXITY



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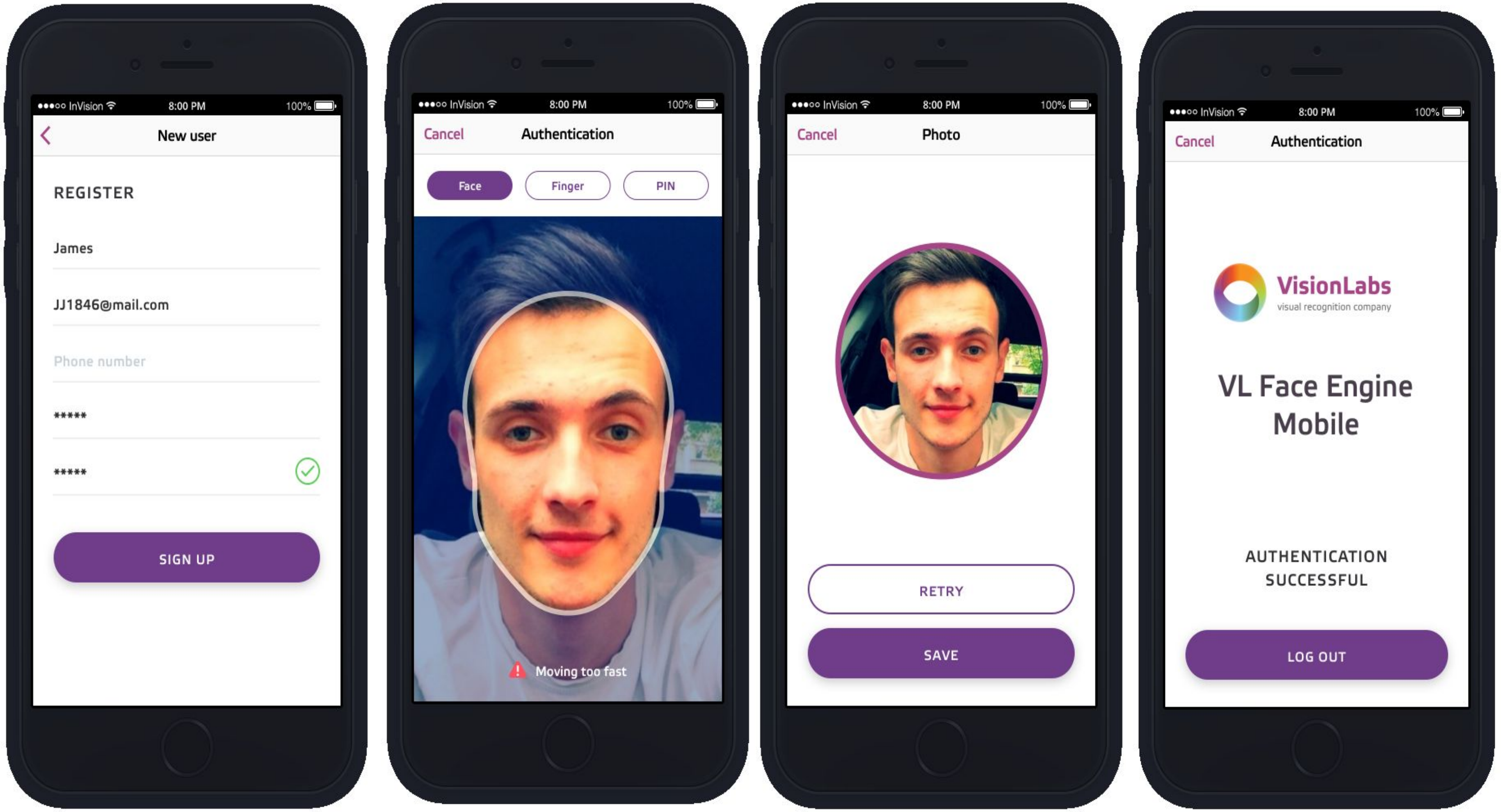
Challenges

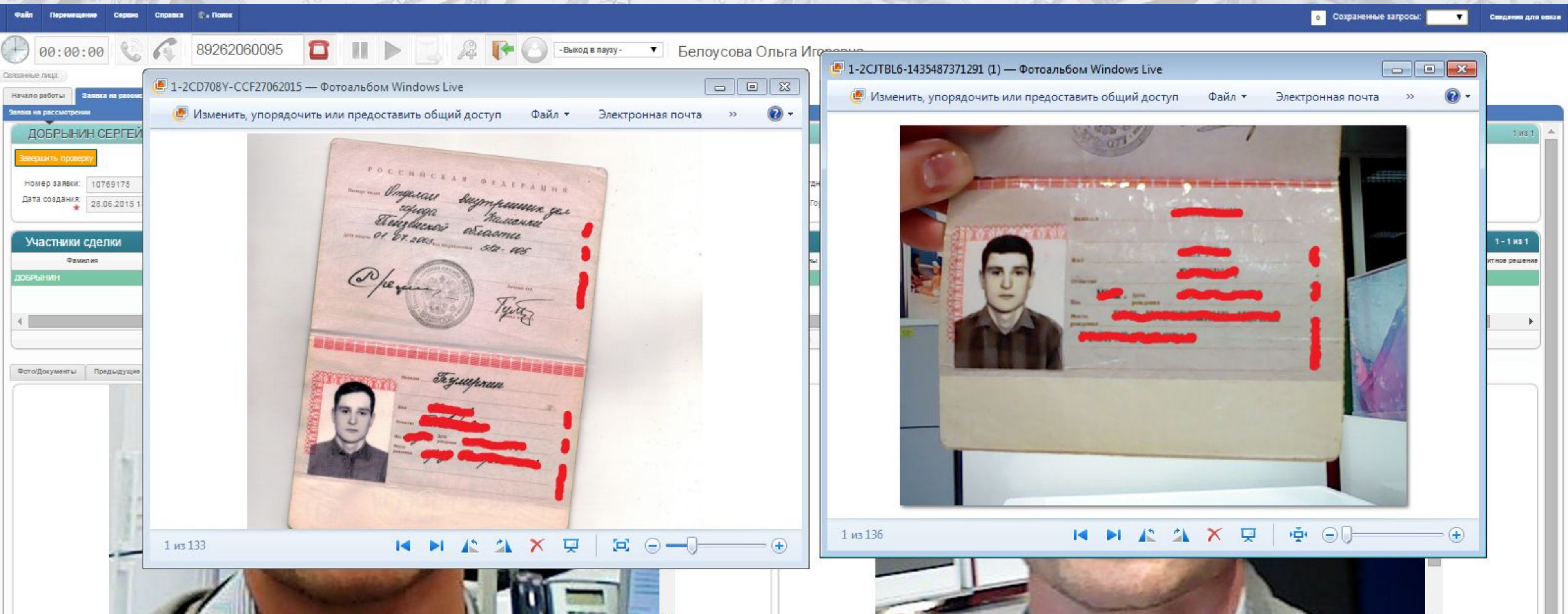
- **Speed**
  - Accuracy is nice, but expensive
- **Mobile devices**
  - Expect up to 100x slower execution and deal with it

MOBILE AUTHENTICATION



3D AVATAR FROM SINGLE IMAGE

FRAUD PREVENTION



- Cut fraud losses by up to 90%
- Improve the quality of the loan portfolio
- Stop fraudulent employees

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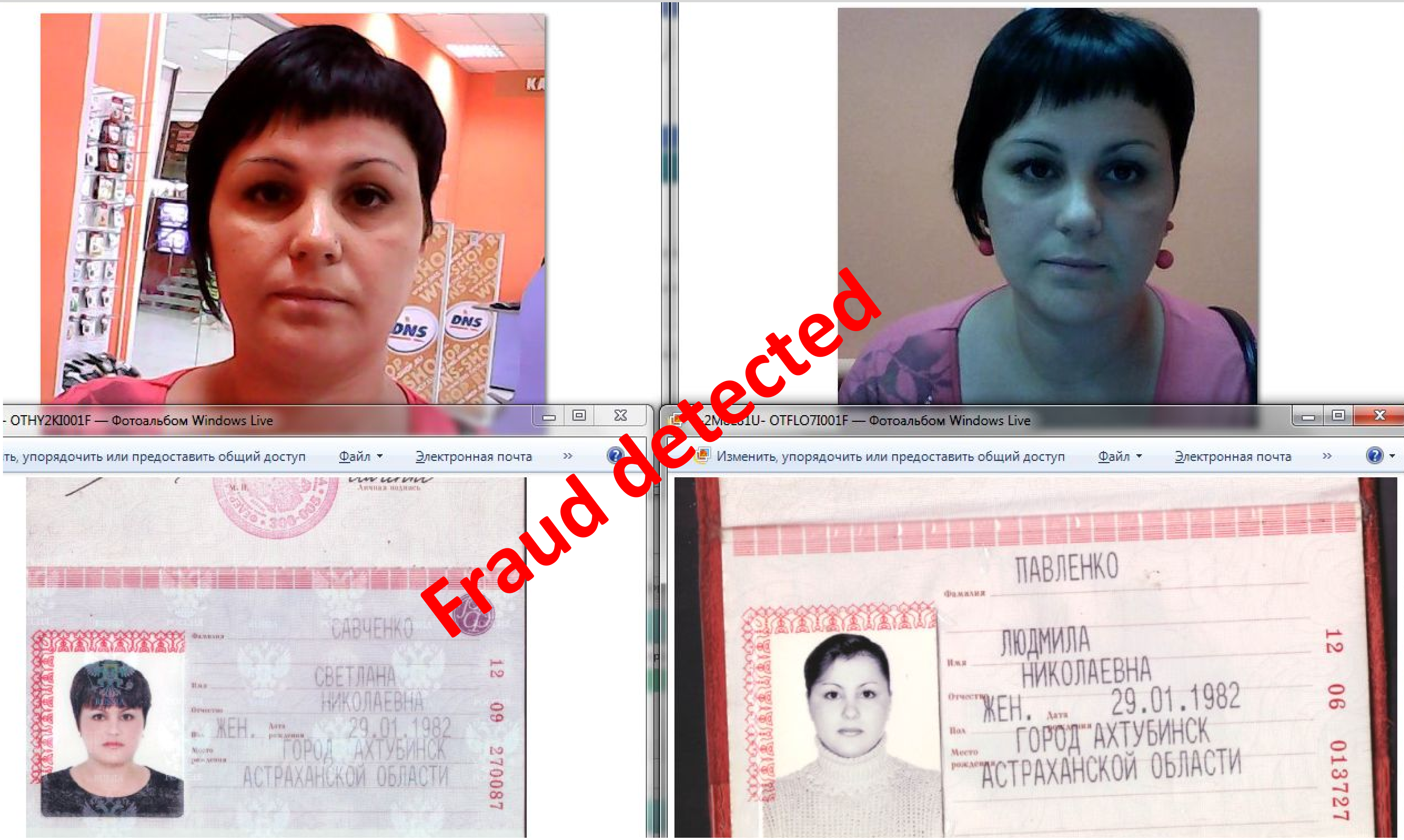
FRAUD DETECTED



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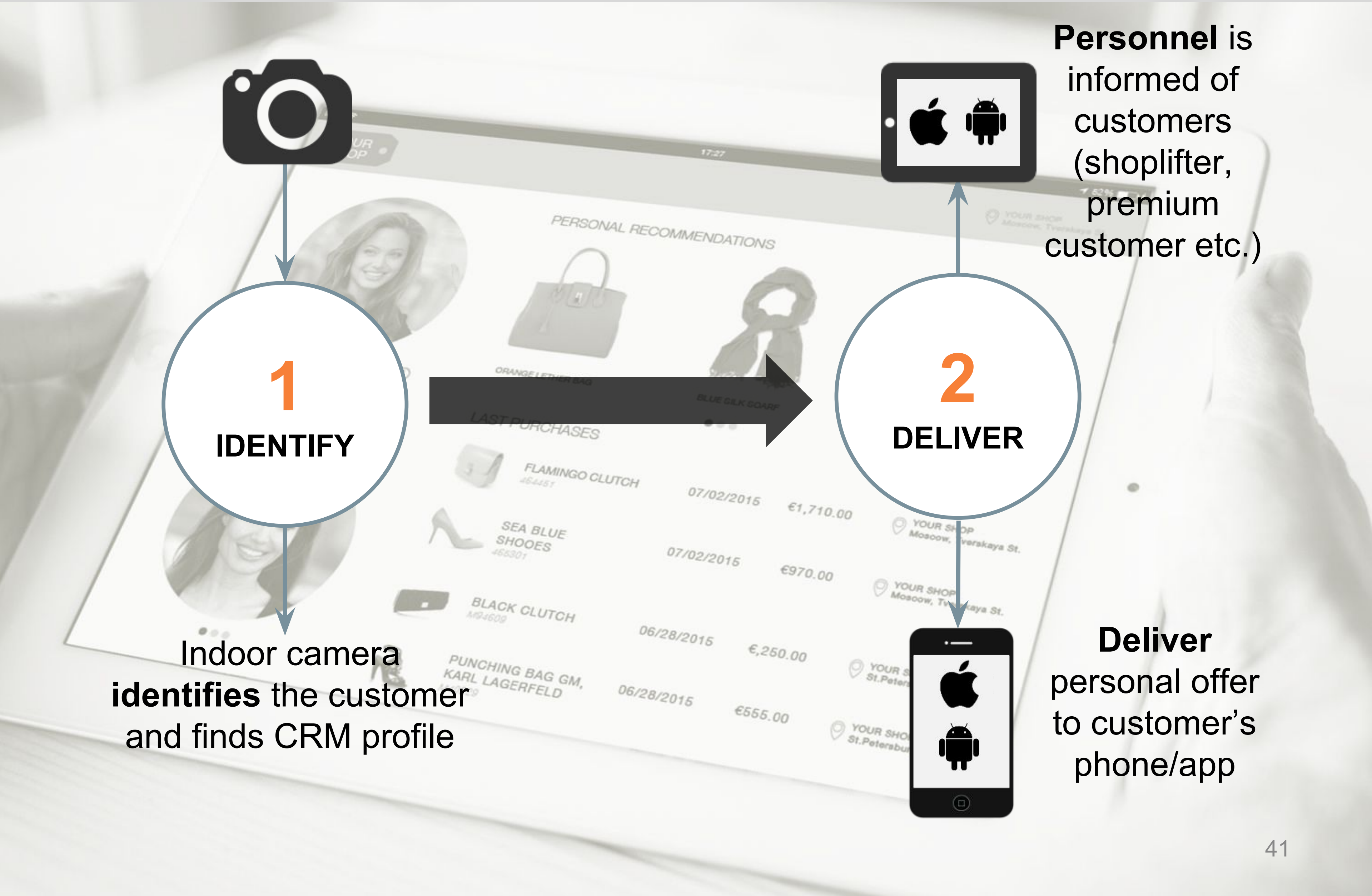
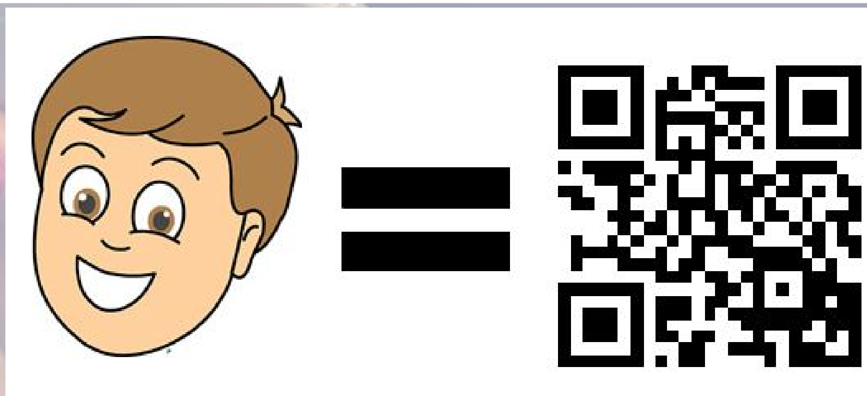
PERSONALIZED SERVICE



MULTIFACTOR AUTHENTICATION

1st FACTOR:
LOGIN + PASSWORD

2nd FACTOR:
LOGIN + FACE



Internal & External Secure Transactions

- "Something one knows" - a secret (PIN)
- "Something one has" - a passport (ID)
- "Something one is" - a biometric key

BLACK LISTING

- Match customers with database
- Inform if blacklisted people are recognized

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SEARCH PEOPLE

- Match criminals in historic data
- statistics of people behaviour

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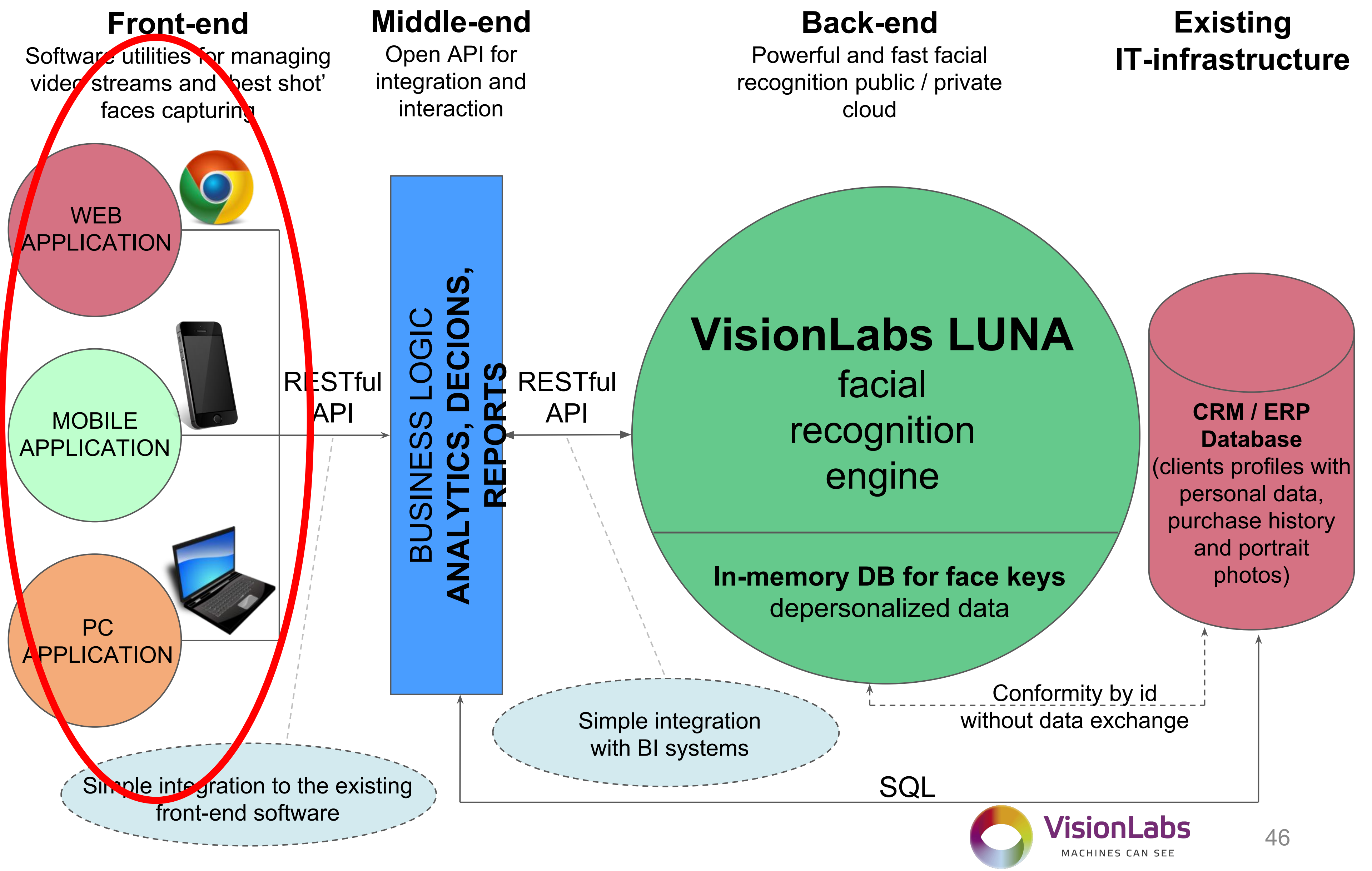
APPLICATIONS

FACIAL RECOGNITION PLATFORM

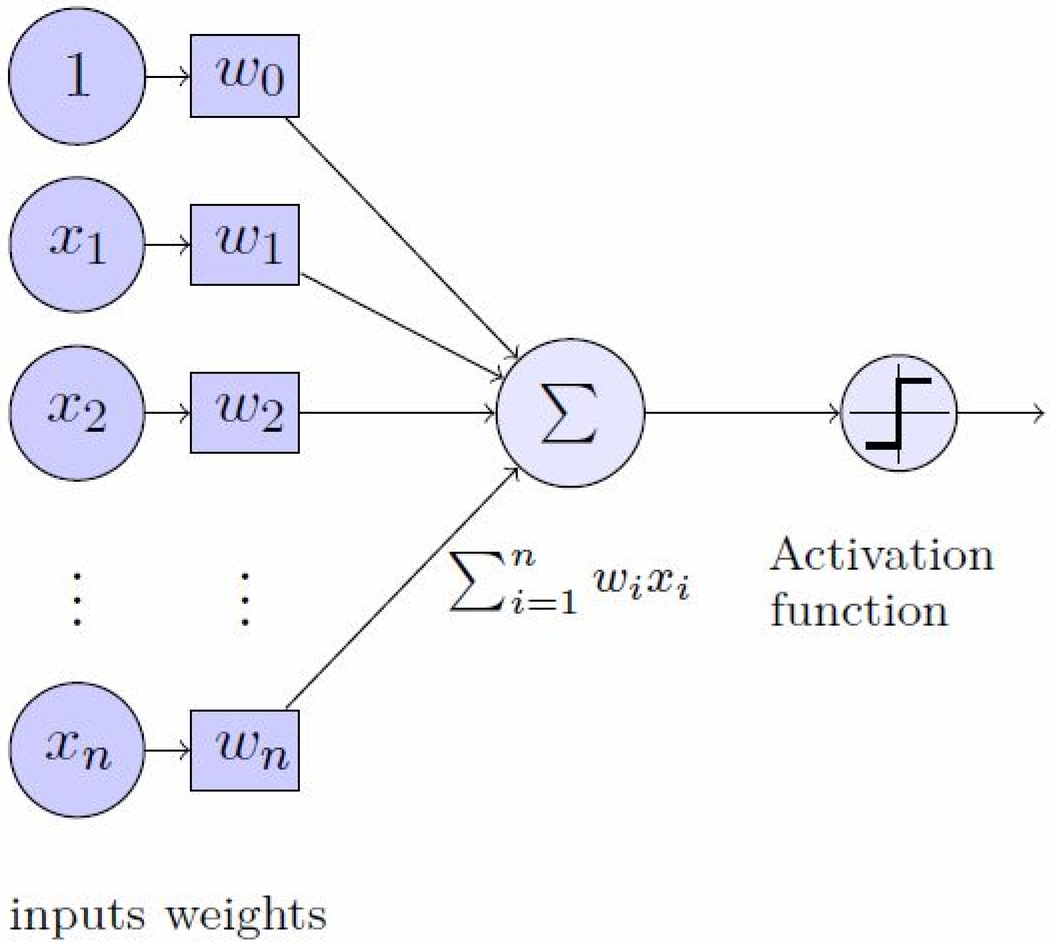


THANK YOU

E-MAIL: p.omenitsch@visionlabs.ru

WEB: www.visionlabs.ru

PERCEPTRON



1
w_0
x_1
w_1
x_2
w_2
x_n
w_n
Σ
$\sum_{i=1}^{n} w_i x_i$
Activation function
inputs weights

NEURAL NETWORK