# Robust Principal Component Analysis?

## John Wright

Microsoft Research

#### **ROBUST PRINCIPAL COMPONENT ANALYSIS?**

#### Joint work with Emmanuel Candès, Xiaodong Li and Yi Ma

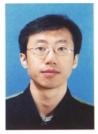






Contributions from Zhouchen Lin, Yang Xu, Arvind Ganesh, Zihan Zhou, many MSR interns...









## **CONTEXT** – data increasingly massive, high-dimensional...



**Images** 

> 1M dimensions

**Videos** 

> 1B dimensions

U.S. COMMERCE'S ORTNER SAYS YEN UNDERVALUED

Commerce Dept. undersecretary of economic affairs Robert Ortner said that he believed the dollar at current levels was fairly priced against most European currencies.

In a wide ranging address sponsored by the Export-Import Bank, Ortner, the bank's senior economist also said he believed that the yen was undervalued and could go up by 10 or 15 pct.

"I do not regard the dollar as undervalued at this point against the yen, as said.

On the other hand, Orther said that he thought that "the yen is still little bit undervalued," and "could go up another 10 or 15 pct."

In addition, Orther, who said he was speaking personally, said

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Turning to Brazil and Mexico, Ortner made it clear that i almost impossible for those countries to earn enough foreign exch the service on their debts. He said the best way to deal with this the policies outlined in Treasury Secretary James Baker's debt in











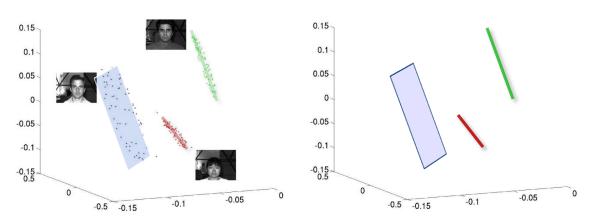
#### Web data



> 10B+ dimensions?

#### ... but intrinsic structures are low-dimensional.





How can we exploit **low-dimensional structure** in **high-dimensional data?** 

## CONTEXT – Good solutions impact many applications



**Images** 

Recognition Inpainting

Denoising

**Videos** 



Compression Transmission Stabilization Repair U.S. COMMERCE'S ORTNER SAYS YEN UNDERVALUED

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Indexing
Ranking
Search
Collaborative filtering...

#### But ... its NOT EASY



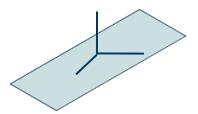
Real application data often contain **missing observations**, **corruption** or even **malicious errors** and **noise**.

Classical algorithms (e.g., least squares, PCA) break down ...

## **THIS TALK – Robust Principal Component Analysis?**



How do we develop provably correct and efficient algorithms for recovering low-dimensional linear structure from corrupted high-dimensional observations?



#### THIS TALK - Outline

- □ Robust PCA via Convex Programming
- Main Result: Exact Recovery from Gross Errors
- ☐ Implications on Matrix Completion
- Algorithms, Simulations, and Experiments
- □ Open Problems and Future Directions

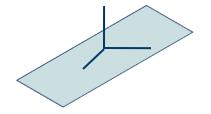
## CLASSICAL PCA — Fitting data with a subspace

If degenerate observations are stacked as columns of a matrix

$$X = [\mathbf{x}_1 \mid \dots \mid \mathbf{x}_n] \in \mathbb{R}^{m \times n}$$

then

$$r \doteq \operatorname{rank}(X) \ll m$$
.



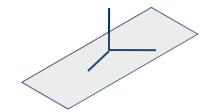
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Principal Component Analysis (PCA) via singular value decomposition (SVD):

- Stable, efficient computation
- ullet Optimal estimate of X under iid Gaussian noise Y=X+Z
- Fundamental statistical tool, huge impact in image processing, vision, search, bioinformatics...

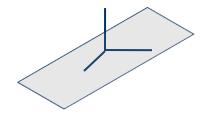
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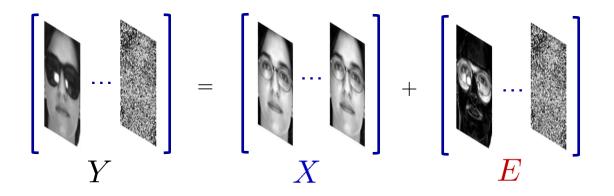


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But... PCA breaks down under even a single corrupted observation.

#### PROBLEM FORMULATION - Robust PCA?



Given Y = X + E, with X low-rank, E sparse, recover X.

#### Numerous approaches to Robust PCA in the literature:

- Multivariate trimming [Gnanadeskian + Kettering '72]
- Random sampling [Fischler + Bolles '81]
- Alternating minimization [Ke + Kanade '03]
- Influence functions [de la Torre + Black '03]

No polynomial-time algorithm with strong performance guarantees...

#### Some related solutions...

Classical PCA/SVD – low rank + noise [Hotelling '35, Karhunen+Loeve '72,...]

From Y = X + Z, recover X.

Stable, efficient algorithm, theoretically optimal → huge impact

#### Matrix Completion – low rank, missing data

[Candes + Recht '08, Candes + Tao '09, Keshevan, Oh, Montanari '09]

From  $Y = \mathcal{P}_{\Omega}[X]$ , recover X.

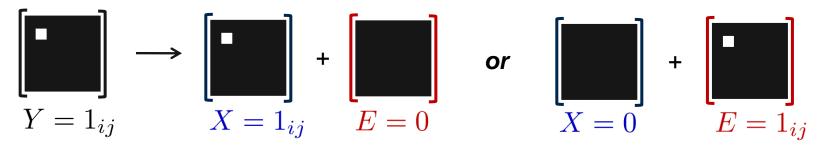
Increasingly well-understood; solvable if X is low rank and  $\Omega$  large enough:

E.g., 
$$|\Omega| \ge C\mu^2 nr(\log^2 n)$$
 suffices.

Our problem, with Y = X + E, looks more difficult...

## Why is the problem with Y = X + E difficult?

#### Some very sparse matrices are also low-rank:



Can we recover X that are **incoherent** with the standard basis?

#### Certain sparse error patterns E make recovering X impossible:

Can we correct *E* whose support is not **adversarial**?

## When is there hope?

## Can we recover X that are **incoherent** with the standard basis from **almost all** errors E?

Incoherence condition on singular vectors, singular values arbitrary:

Singular vectors of 
$$X$$
 not too sparse: 
$$\begin{cases} \max_i \|U_i\|^2 \leq \mu r/m. \\ \max_i \|V_i\|^2 \leq \mu r/n. \end{cases}$$

not too cross-correlated:  $||UV^*||_{\infty} \leq \sqrt{\mu r/mn}$ 

Uniform model on error support, signs and magnitudes arbitrary:

$$\operatorname{supp}(\mathbf{E}) \sim \operatorname{uni}({}^{[m]\times[n]}_{\rho mn}) \qquad \Omega \sim \operatorname{uni}({}^{[m]\times[n]}_{\rho' mn})$$

#### Naïve optimization approach

Look for a low-rank X that agrees with the data up to some sparse error *E*:

$$\min \ \mathrm{rank}(X) + \gamma \|E\|_0 \ \ \mathrm{subj} \ \ X + E = Y.$$
 
$$\mathrm{rank}(X) = \#\{\sigma_i(X) \neq 0\}. \quad \|E\|_0 = \#\{E_{ij} \neq 0\}.$$

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## INTRACTABLE

#### Naïve optimization approach

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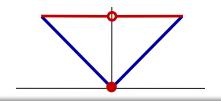
$$\min \operatorname{rank}(X) + \gamma \|E\|_0 \quad \operatorname{subj} \quad X + E = Y.$$

#### Convex relaxation

$$\operatorname{rank}(X) = \#\{\sigma_i(X) \neq 0\}. \qquad \|E\|_0 = \#\{E_{ij} \neq 0\}.$$

$$\downarrow \downarrow \qquad \qquad \downarrow \downarrow$$

$$\|X\|_* = \sum_i \sigma_i(X). \qquad \|E\|_1 = \sum_{ij} |E_{ij}|.$$



#### Naïve optimization approach

Look for a low-rank X that agrees with the data up to some sparse error *E*:

$$\min \operatorname{rank}(X) + \gamma \| \underline{E} \|_0 \quad \operatorname{subj} \quad X + \underline{E} = Y.$$

#### Convex relaxation

$$\min \|X\|_* + \lambda \|E\|_1 \quad \text{subj} \quad X + E = Y.$$

Semidefinite program, solvable in polynomial time – "efficient" algorithm.

Practical thanks to steady advances in large-scale convex programming

## Does this actually work?

#### Key question

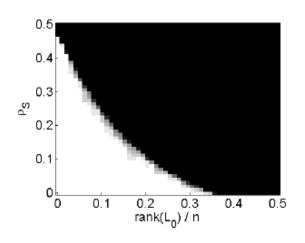
Does this practical surrogate actually solve the problem?

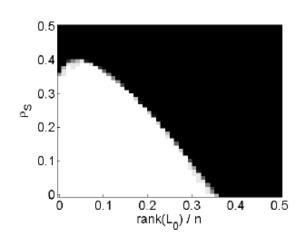
$$\min \ \mathrm{rank}(X) + \gamma \|E\|_0 \ \ \mathrm{subj} \ \ X + E = Y.$$
 
$$\bigoplus \ \ \mathrm{equivalent?} \ \ \bigoplus \ \ \\ \min \ \|X\|_* + \lambda \|E\|_1 \ \ \mathrm{subj} \ \ X + E = Y.$$

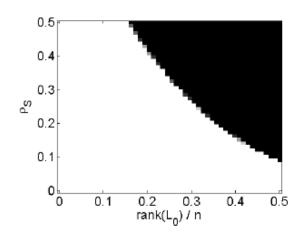
**Not always** – original problem is NP-hard.

But maybe it succeeds for the cases we care about?

## Does this actually work?







(a) Robust PCA, Random Signs

(b) Robust PCA, Coherent Signs

$$Y = \mathcal{P}_{\Omega}[X]$$

(c) Matrix Completion

$$Y = X + E$$

**Apparently yes...** white regions are problems with perfect recovery.

Correct recovery when X is indeed **low-rank** and E is indeed **sparse**?

## MAIN RESULTS – Exact Solution by Convex Optimization

Theorem 1 (Principal Component Pursuit). If  $X_0 \in \mathbb{R}^{m \times n}$ ,  $m \geq n$  has rank

$$r \leq \rho_r \frac{n}{\mu \log^2(m)}$$

and  $E_0$  has Bernoulli support with error probability  $\rho \leq \rho_s^{\star}$ , then with very high probability

$$(X_0, E_0) = \arg\min \|X\|_* + \frac{1}{\sqrt{m}} \|E\|_1 \quad \text{subj} \quad X + E = X_0 + E_0,$$

and the minimizer is unique.

"Convex optimization recovers matrices of rank  $O\left(\frac{n}{\log^2 m}\right)$  from errors corrupting  $O\left(mn\right)$  entries"

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Theorem 1 (Principal Component Pursuit). If  $X_0 \in \mathbb{R}^{m \times n}$ ,  $m \geq n$  has rank

 $r < o_r - \frac{n}{2}$ and  $E_0$  has Bernoulli support probability

Non-adaptive weight factor

 $(X_0, E_0) = \arg\min \|X\|_* + \underbrace{\frac{1}{\sqrt{m}}}_{E}\|_1 \quad \text{subj} \quad X + E = X_0 + E_0,$ 

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"Convex optimization recovers matrices of rank  $O\left(\frac{n}{\log^2 m}\right)$  from errors corrupting  $O\left(mn\right)$  entries"

with very high

## ROBUST PCA — Comparison to existing results

Chandrasekaran et. al. 2009 give an incoherence condition for correct recovery. Set:

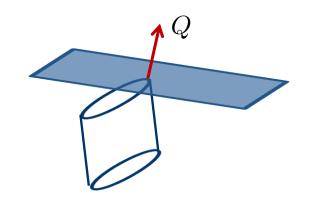
$$T = \{UW^* + QV^*\}, X_0 = USV^*,$$
  
$$\xi \doteq \sup_{M \in T, ||M|| \le 1} ||M||_{\infty},$$
  
$$\mu \doteq \sup_{M \in \Omega, ||M||_{\infty} < 1} ||M||,$$

Correct recovery occurs if  $\xi \times \mu < \frac{1}{6}$ .

- Strong point: deterministic condition
- For random problems, success when  $||E||_0 \le Cm^{1.5}/r^{.5}\log m$ .

#### MAIN IDEAS OF THE PROOF

As in the vector case, construct a dual certificate:



Clever iterative construction due to **D. Gross** – the "golfing scheme":

$$R_{k+1} = R_k + q^{-1} \mathcal{P}_{\Omega_{k+1}} \mathcal{P}_T (UV^* - R_k), \quad Q_L = \mathcal{P}_{T^{\perp}} R_{k^*}.$$

Showing this construction succeeds requires a detailed analysis of a certain random operator:  $\mathcal{P}_T \mathcal{P}_O \mathcal{P}_T \approx \rho \mathcal{P}_T$ 

Builds on results by E. Candes + B. Recht.

## MAIN RESULTS – Corrupted, Incomplete Matrix

$$Y = \mathcal{P}_{\Omega}[X_0 + E_0], \quad \Omega \sim \operatorname{uni}\binom{[m] \times [n]}{mn}$$

Theorem 2 (Matrix Completion and Recovery). If  $X_0, E_0 \in \mathbb{R}^{m \times n}, m \ge n$ , with

$$\operatorname{rank}(X_0) \leq C \frac{n}{\mu \log^2(m)}, \quad and \quad ||E_0||_0 \leq \rho^* m n,$$

and we observe only a random subset of size  $|\Omega| = mn/10$  entries, then with very high probability, solving the convex program

$$\min \|X\|_* + \frac{1}{\sqrt{m}} \|E\|_1 \quad \text{subj} \quad P_{\Omega}[X + E] = Y,$$

uniquely recovers  $(X_0, E_0)$ .

"Convex optimization succeeds with large fractions of errors and missing entries."

#### MAIN RESULTS – Dense Random Errors

**Theorem 3** (Dense Error Correction). If  $X_0$  has rank  $r \leq \rho_r \frac{m}{\mu \log^2(n)}$  and  $E_0$  has random signs and Bernoulli support with error probability  $\rho < 1$ , then with very high probability

$$(X_0, E_0) = \arg\min \|X\|_* + \lambda \|E\|_1 \quad \text{subj} \quad X + E = X_0 + E_0,$$

and the minimizer is unique.

"If the error sign pattern is random, large fractions of errors can be corrected"

## MAIN RESULTS – Stable recovery with noise

**Theorem 4** (Robust PCA with Noise). Given  $Y = X_0 + E_0 + Z$  for any  $||Z||_F \leq \eta$ , if  $X_0$  has rank  $r \leq \rho_r \frac{m}{\mu \log^2(n)}$  and  $E_0$  has Bernoulli support with error probability  $\rho \leq \rho_s^*$ , then with very high probability

$$(\hat{X}, \hat{E}) = \arg\min \|X\|_* + \frac{1}{\sqrt{m}} \|E\|_1 \quad \text{subj} \quad \|Y - X - E\|_F \le \eta,$$

sastisfies  $\|(\hat{X}, \hat{E}) - (X_0, E_0)\| \le C\eta$  for some C > 0 independent of  $\eta$ .

"When exact recovery occurs, the recovery is also stable under noise"

#### Rapid development in fast algorithms...

For a 1000x1000 matrix of rank 50, with 10% (100,000) entries randomly corrupted:  $\min \|X\|_* + \lambda \|E\|_1 \quad \text{subj} \quad X + E = Y$ .

Algorithms	Accuracy	Rank	E  _0	# iterations	time (sec)
IT	5.99e-006	50	101,268	8,550	119,370.3
DUAL	8.65e-006	50	100,024	822	1,855.4
APG	5.85e-006	50	100,347	134	1,468.9
APG <sub>P</sub>	5.91e-006	50	100,347	134	82.7
EALM <sub>P</sub>	2.07e-007	50	100,014	34	37.5
IALM <sub>P</sub>	3.83e-007	50	99,996	23	11.8

10,000 times speedup!

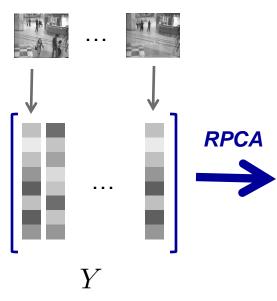
Provably Robust PCA with only ~20 times more computation than SVD.

## APPLICATIONS — Background modeling from video

Static camera surveillance video

200 frames, 144 x 172 pixels,

Significant foreground motion



Video Y = Low-rank appx. X + Sparse error E

















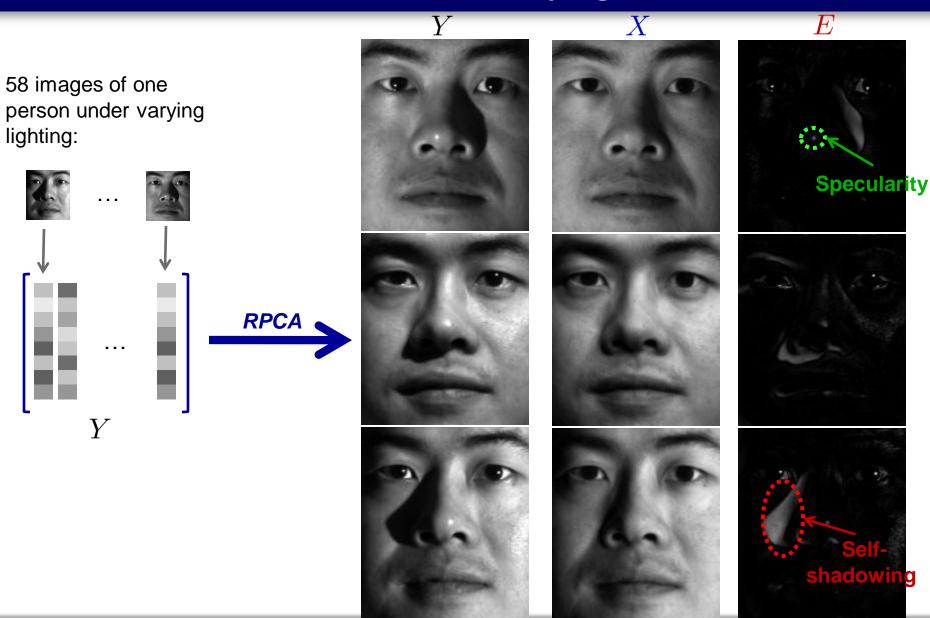


## APPLICATIONS — Background modeling from video

Surveillance video: 250 frames, 128 x 160 pixels, with significant illumination variation

By RPCA Video Results of Black and de la Torre

## APPLICATIONS - Faces under varying illumination



Candes, Li, Ma, and Wright, submitted to JACM, 2009.

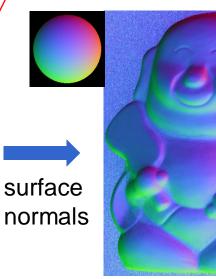
## **High-quality photometric stereo**

$$D = N_{m imes 3} L_{3 imes n} + E$$
 specularities, shadows...

















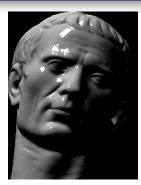
motion blurs...

## **High-quality photometric stereo**

Input images









min 
$$||A||_* + \lambda ||E||_1$$
 subj  $D = \mathcal{P}_{\Omega}(A + E)$ .  $\Omega^c \sim \operatorname{shadow}(20.7\%)$   
 $E \sim \operatorname{specularities}(13.6\%)$ 

Ground truth



Mean error Max error

Robust PCA



0.014° 0.20°

Robust LS

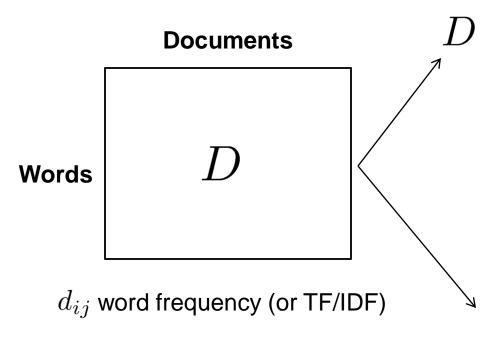


0.96°

8.0°

## **APPLICATIONS: Web document corpus analysis**

## Classical solution (LSI)



$$D = A + N$$

$$= U_1 \Sigma_1 V_1^T + U_2 \Sigma_2 V_2^T$$

Dense, difficult to interpret

#### A better model/solution

$$D = A + E$$

Low-rank "background" topic model

Informative, discriminative "keywords"

## **APPLICATIONS: Document retrieved by title words**

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#### **APPLICATIONS: Web document corpus analysis**

Reuters-21578 dataset: 1,000 longest documents; 3,000 most frequent words

#### CHRYSLER SETS STOCK SPLIT, HIGHER DIVIDEND

Chrysler Corp said its board declared a three-for-two stock split in the form of a 50 pct stock dividend and raised the quarterly dividend by seven pct.

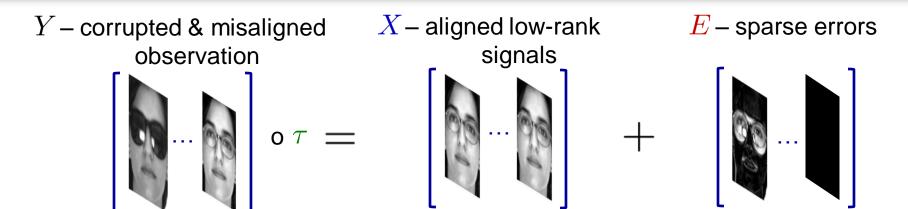
The company said the dividend was raised to 37.5 cts a share from 35 cts on a pre-split basis, equal to a 25 ct dividend on a post-split basis.

Chrysler said the stock dividend is payable April 13 to holders of record March 23 while the cash dividend is payable April 15 to holders of record March 23. It said cash will be paid in lieu of fractional shares.

With the split, Chrysler said 13.2 mln shares remain to be purchased in its stock repurchase program that began in late 1984. That program now has a target of 56.3 mln shares with the latest stock split.

Chrysler said in a statement the actions "reflect not only our outstanding performance over the past few years but also our optimism about the company's future."

## Robust Alignment via Sparse and Low-rank Decomposition



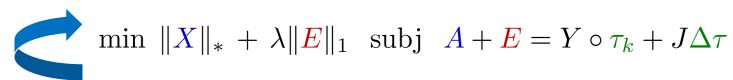
**Problem**: Given  $Y \circ \tau = X_0 + E_0$ , recover  $\tau$ ,  $X_0$  and  $E_0$ .

Parametric deformations (rigid, affine, projective...)

Low-rank component Sparse component

**Solution**: Robust Alignment via Low-rank and Sparse (RASL) Decomposition

#### *Iterate*



## APPLICATIONS - Aligning Bill Gates faces from the Internet



#### **APPLICAITONS** – Bill Gates faces detected

**Input**: faces detected by a face detector (D)



Average



#### APPLICATIONS - Bill Gates faces aligned

**Output**: aligned faces (  $D \circ \tau$  )



Average



#### APPLICAITONS - Bill Gates faces cleaned

Output: clean low-rank faces (A)

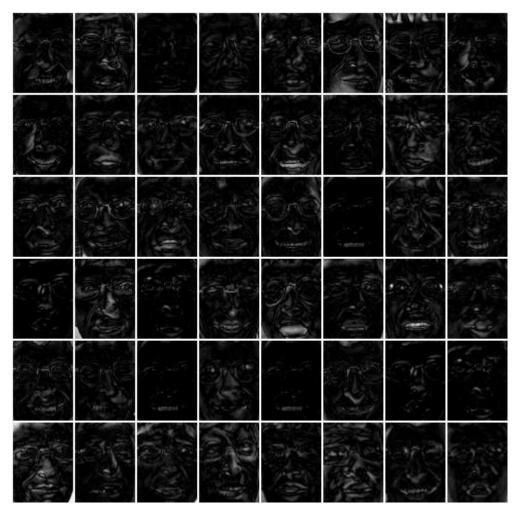


Average



## APPLICATIONS – Sparse errors of Bill Gates face images

**Output**: sparse error images (E)



#### APPLICATIONS - Celebrity images from the Internet

#### Average face before alignment



Gloria Macapagal Arroyo Jennifer Capriati Laura Bush Serena Williams Barack Obama **Ariel Sharon** Arnold Schwarzenegger Colin Powell Donald Rumsfeld George W Bush Gerhard Schroeder Hugo Chavez Jacques Chirac Jean Chretien John Ashcroft Junichiro Koizumi Lleyton Hewitt Luiz Inacio Lula da Silva Tony Blair Vladimir Putin

## APPLICATIONS – Face recognition with less controlled data?

#### Average face after alignment



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#### REFERENCES + ACKNOWLEDGEMENT

#### References:

http://perception.csl.uiuc.edu/matrix-rank/home.html

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- RASL: Robust Alignment by Sparse and Low-rank Decomposition for Linearly Correlated Images, Peng, Ganesh, Wright, and Ma, to appear in CVPR'10, 2010.
- Decomposing Background Topics from Keywords by Principal Component Pursuit, Min, Zhang, Wright, and Ma, submitted to SIGIR'10, 2010.

#### **Collaborators:**

Prof. Yi Ma (UIUC)

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Xiaodong Li (Stanford)

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Yigang Peng (Tsinghua)

Kerui Min (Fudan)

Wenxuan Liang (MSRA)

Zhengdong Zhang (MSRA)

#### **THANK YOU!**

Questions, please?