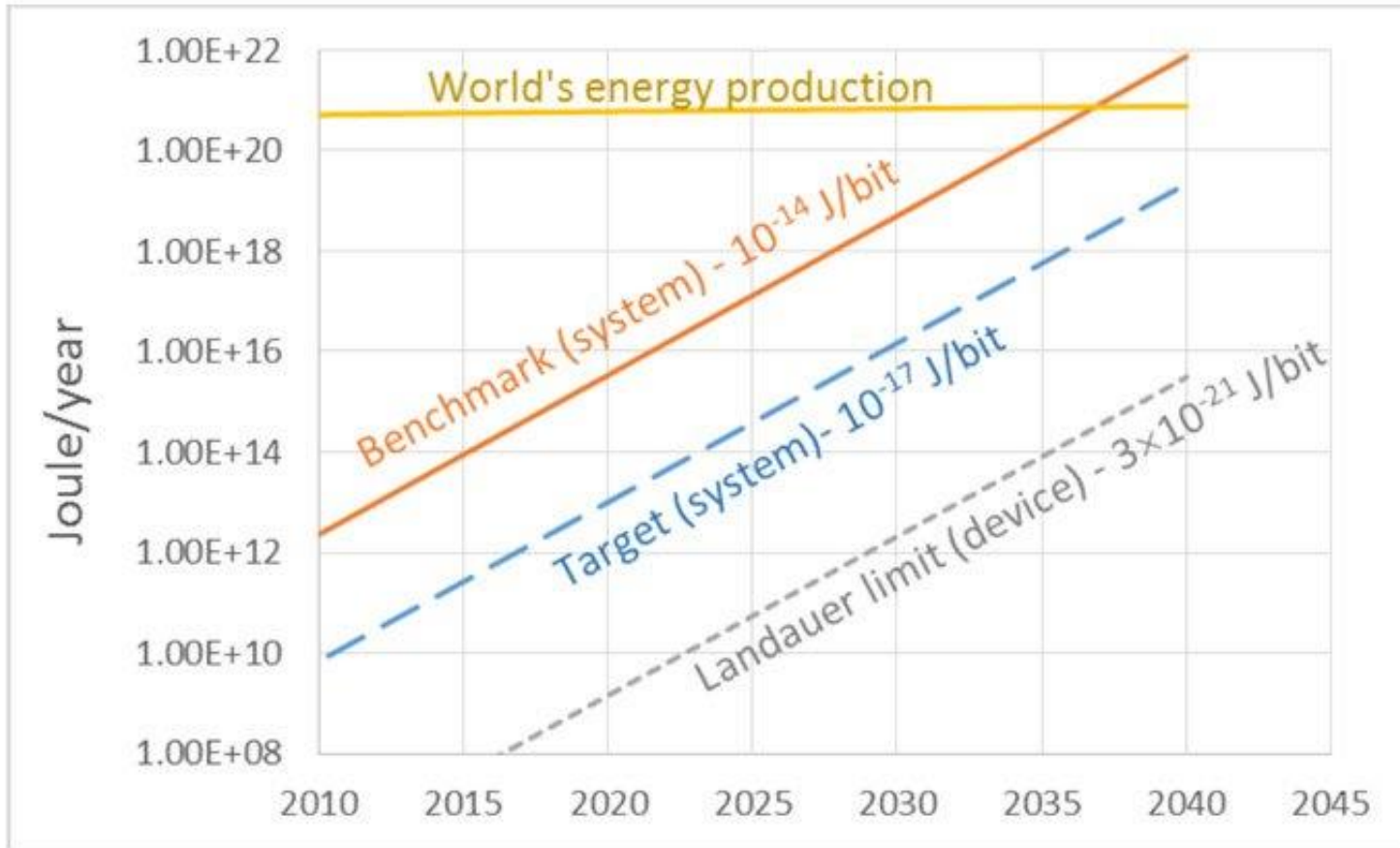


# Building Innovative Hardware in an Era of Artificial Intelligence

Igor Carron, CEO and Co-Founder

LightOn.ai

# Why Build Innovative Hardware?

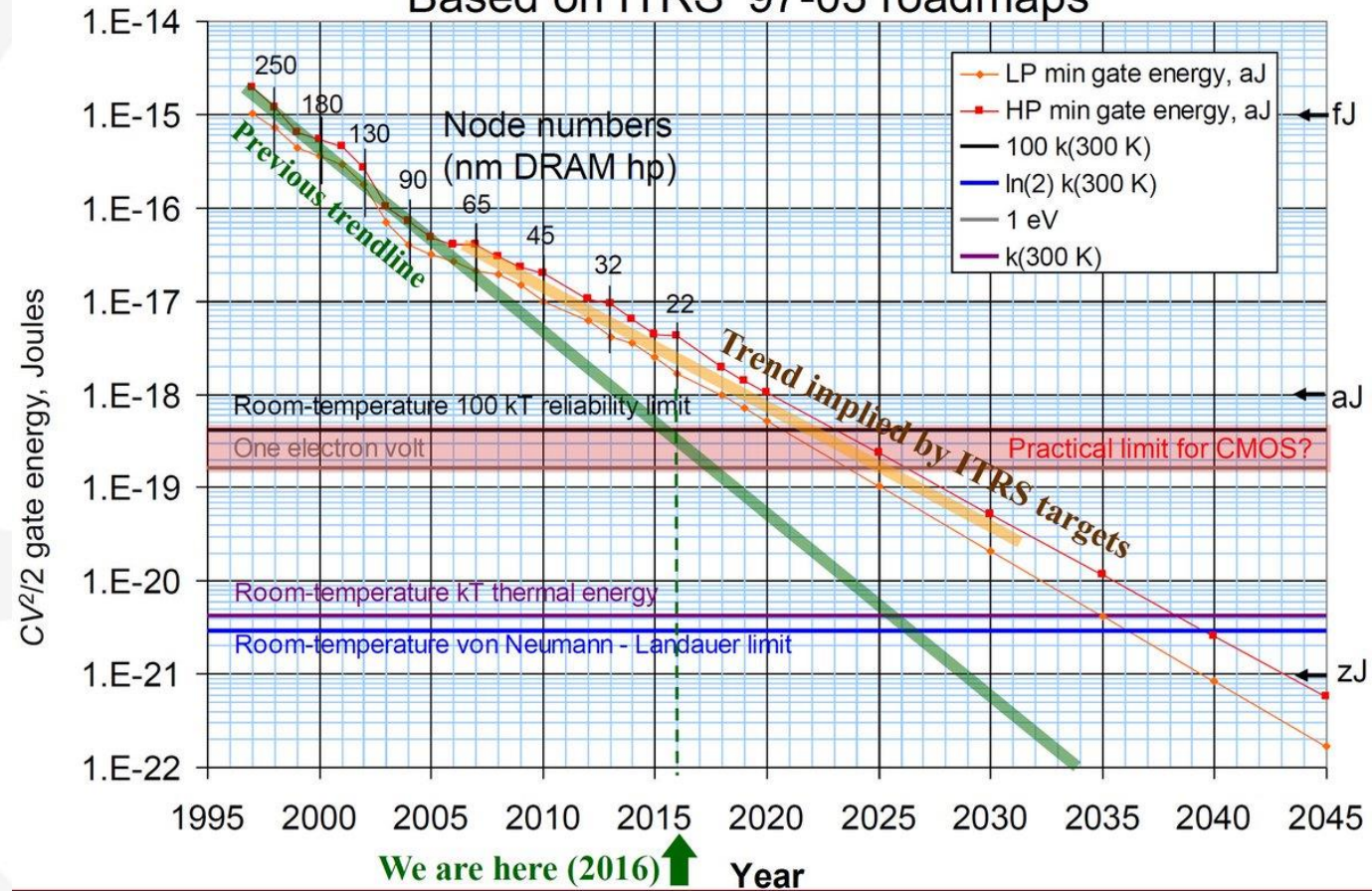


**Fig. A8. Total energy of computing.**



## Trend of Min. Transistor Switching Energy

Based on ITRS '97-03 roadmaps



Source: Mike P. Frank, SNL

# **It's worse!**



**blame it on the FWAlcohol**  
@nullhund

Suivre



crypto rush in one image

Traduire le Tweet



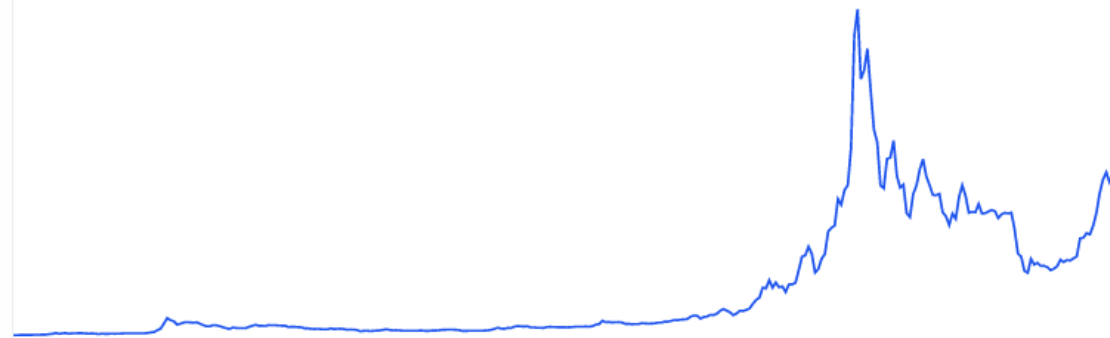
16:32 - 12 janv. 2018



**Bitcoin price** (BTC)

€7,295.28 +€7,291.02 (71.3K%)

1H 24H 1W 1M 1Y ALL



JAN 2013 JAN 2014 FEB 2015 MAR 2016 APR 2017 MAY 2018 JUN 2019

Market Cap ⓘ  
\$129.5B

Volume (24 hours) ⓘ  
\$16.6B

Circulating Supply ⓘ  
17.8M BTC

All-Time High ⓘ  
\$17,810.43



## Microsoft boss: World needs more computing power

By Joe Miller  
BBC News, Davos

🕒 23 January 2018

f 💬 🐦 ✉️ Share

Davos 2018



The world is rapidly "running out of computing capacity", the head of tech giant Microsoft has warned.

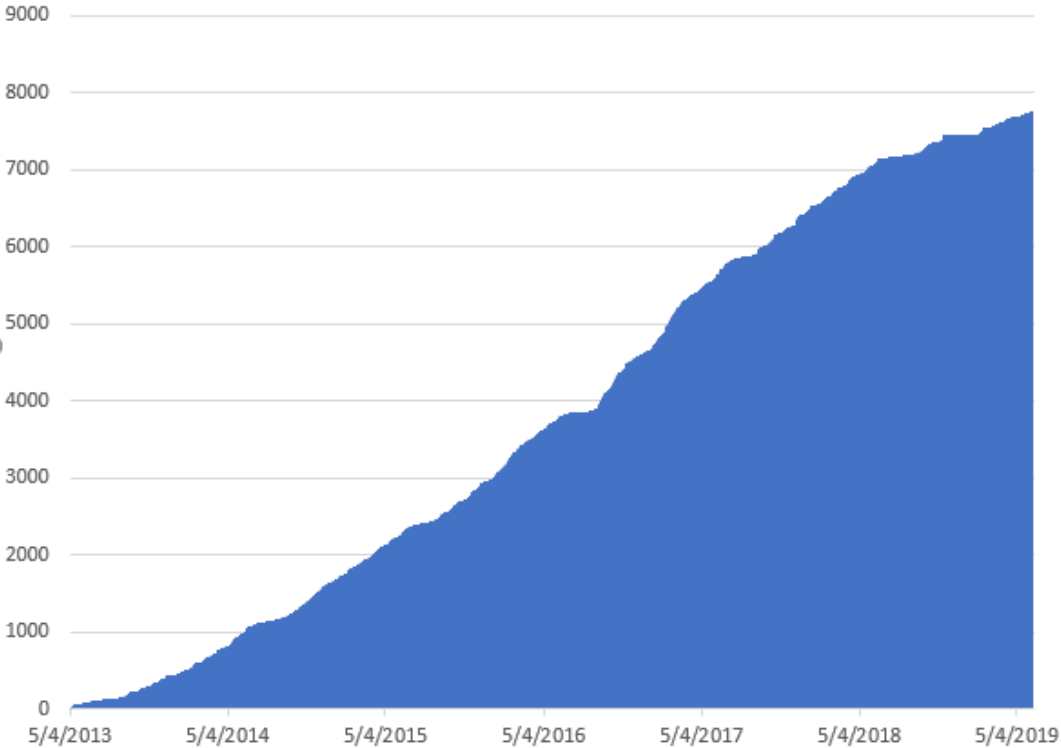
# It's much worse!



# The Footprint of Machine Learning



Paris Machine Learning Meetup Total Members





# Nuit Blanche

LightOn || Google Scholar



7

8

5

6

9

5

0



# reddit

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# MachineLearning

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Elizabeth Aubrey  
Mar 2, 2019 6:38 pm GMT



# Scaling up a new technology from the ground up....fast

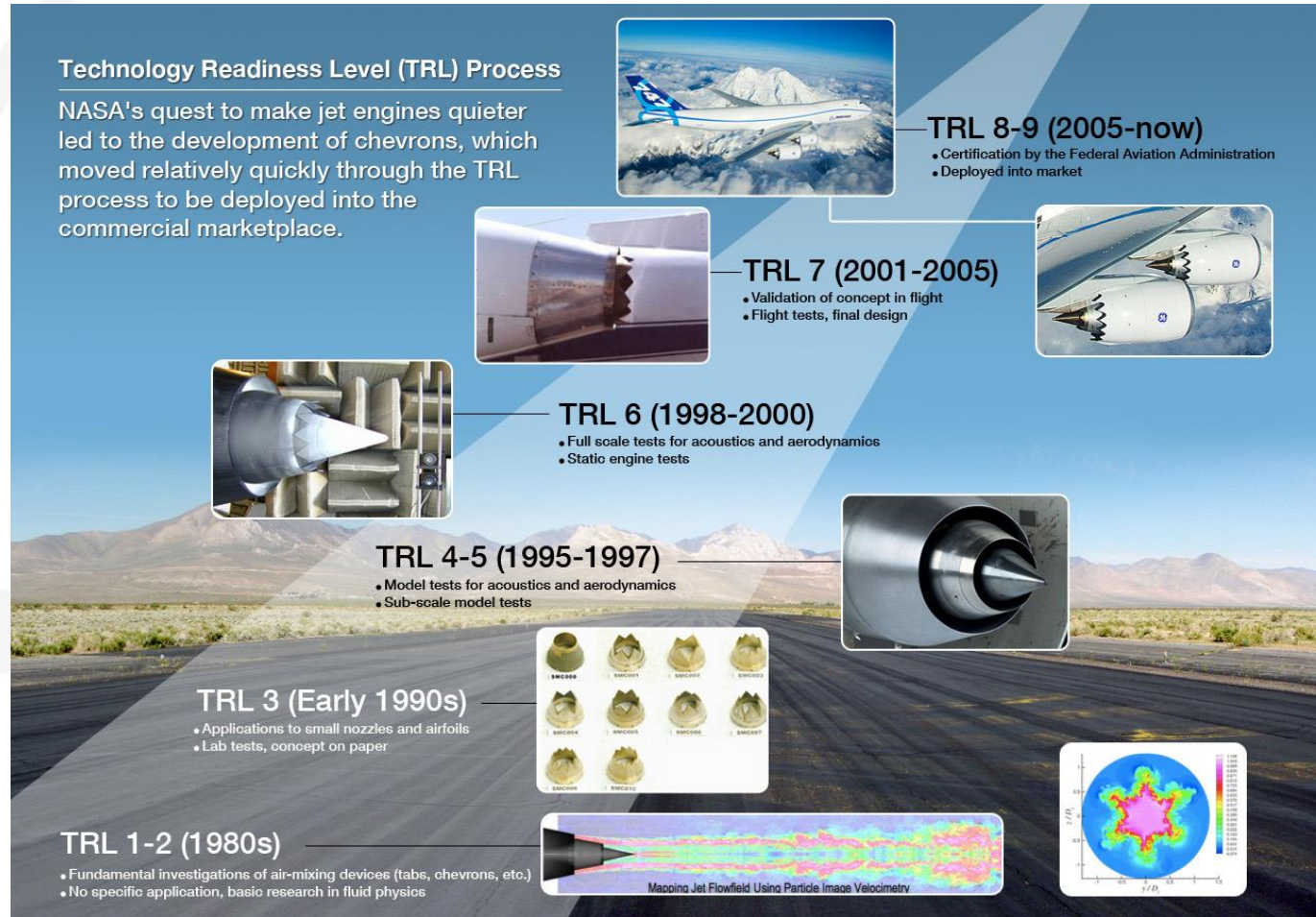


## Technology Readiness Levels

- TRL 0: Idea.** Unproven concept, no testing has been performed.
- TRL 1: Basic research.** Principles postulated and observed but no experimental proof available.
- TRL 2: Technology formulation.** Concept and application have been formulated.
- TRL 3: Applied research.** First laboratory tests completed; proof of concept.
- TRL 4: Small scale prototype** built in a laboratory environment ("ugly" prototype).
- TRL 5: Large scale prototype** tested in intended environment.
- TRL 6: Prototype system** tested in intended environment close to expected performance.
- TRL 7: Demonstration system** operating in operational environment at pre-commercial scale.
- TRL 8: First of a kind commercial system.** Manufacturing issues solved.
- TRL 9: Full commercial application,** technology available for consumers.



# Unlike NASA/FAA, we don't have 15+ years

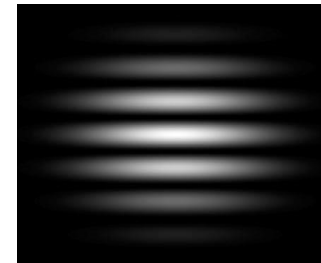
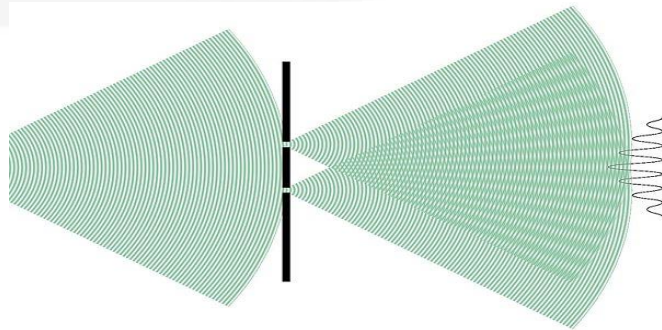


# Surfing on Moore's Law





# Surfing Moore's Law and Using Nature





# A Fast and Large Random Projection

Discrete  
input vector



$x$

$$\begin{pmatrix} h_{1,1} & h_{1,2} & \dots & h_{1,N} \\ h_{2,1} & h_{2,2} & \dots & h_{2,N} \\ \vdots & & \ddots & \vdots \\ h_{M,1} & h_{M,2} & \dots & h_{M,N} \end{pmatrix}$$

**Random** transmission matrix

$H$

Discrete  
output vector  
(speckle intensity)



$$y = |Hx|^2$$



EXTRA-LARGE  
 $H$  of size higher than  
 $10^6 \times 10^6$   
(TBs of memory)

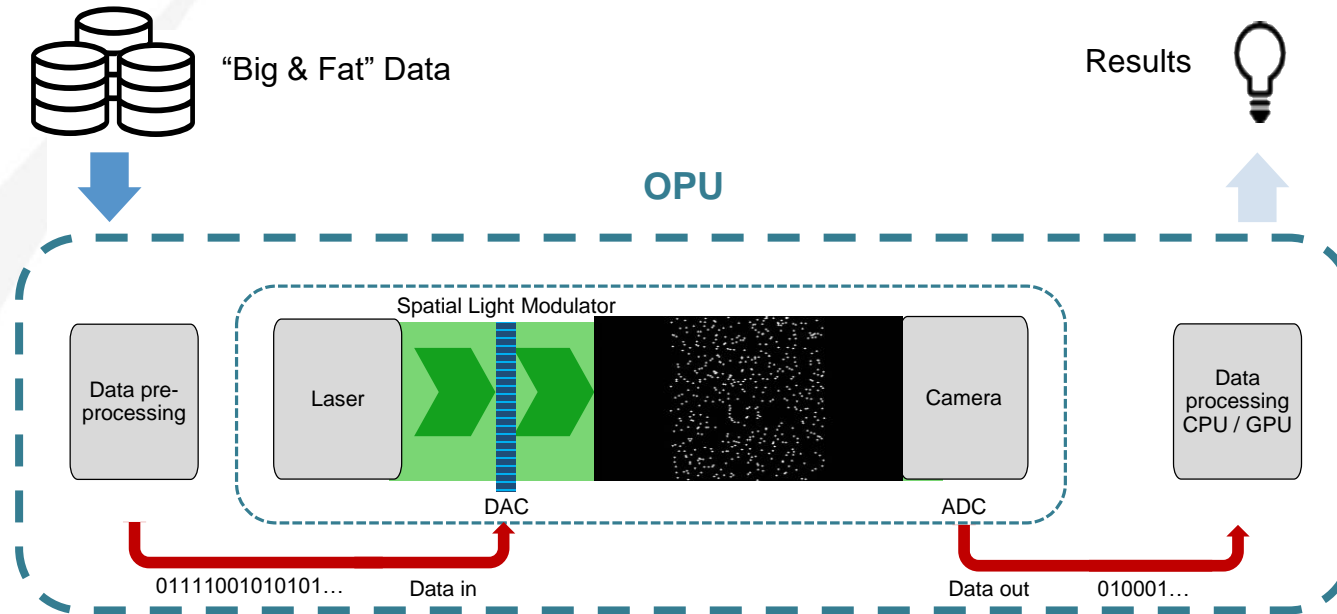
&

SUPER-FAST

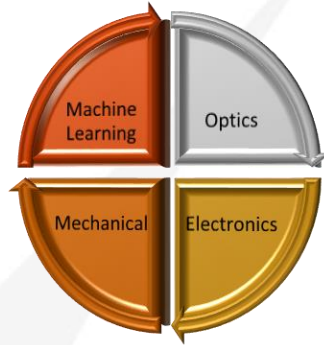
kHz operation  
 $\rightarrow 10^3$  such  
multiplies / s



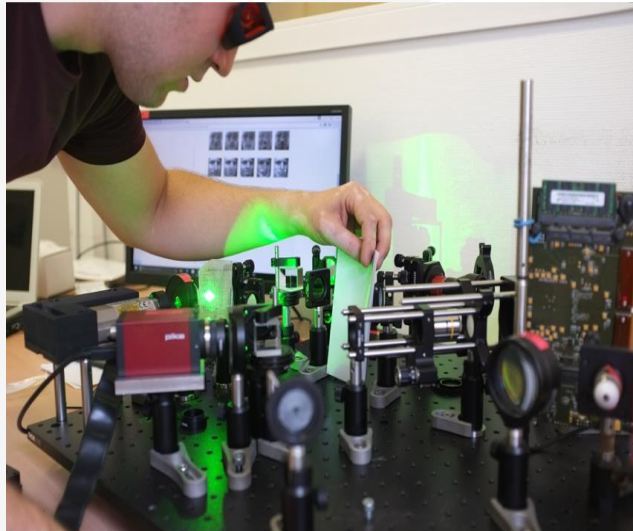
# How it works



# Climbing up the TRL scale fast



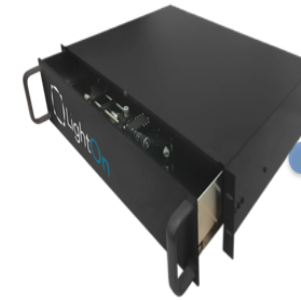
Fast prototyping among a diverse set of expertise



TRL 3-4 (2016)



TRL 5 (2017)



Rack-size prototype  
at the core of the  
LightOn Cloud



TRL 6-7 (2018-2019)





# Optical Processing Unit





# Why Random Projections?

## Johnson-Lindenstrauss Lemma

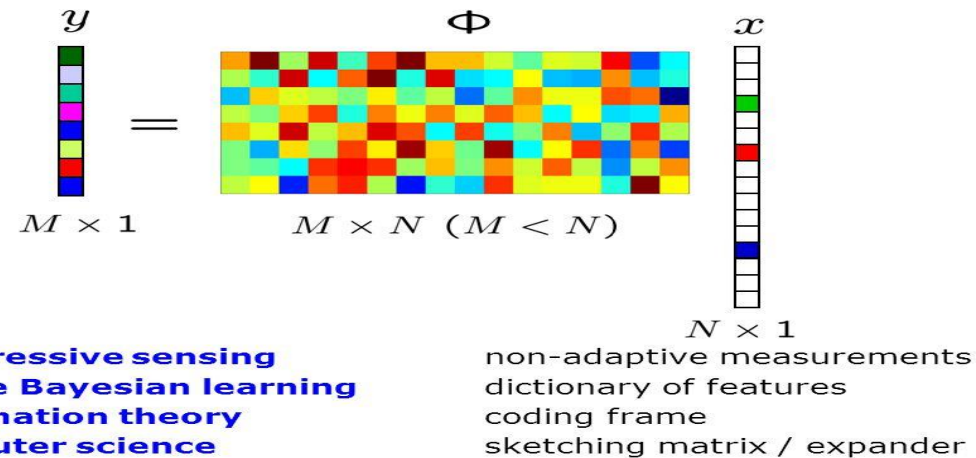
**Lemma** For any  $0 < \epsilon < 1$  and any integer  $n$  let  $k$  be a positive integer such that

$$k \geq \frac{24}{3\epsilon^2 - 2\epsilon^3} \log n$$

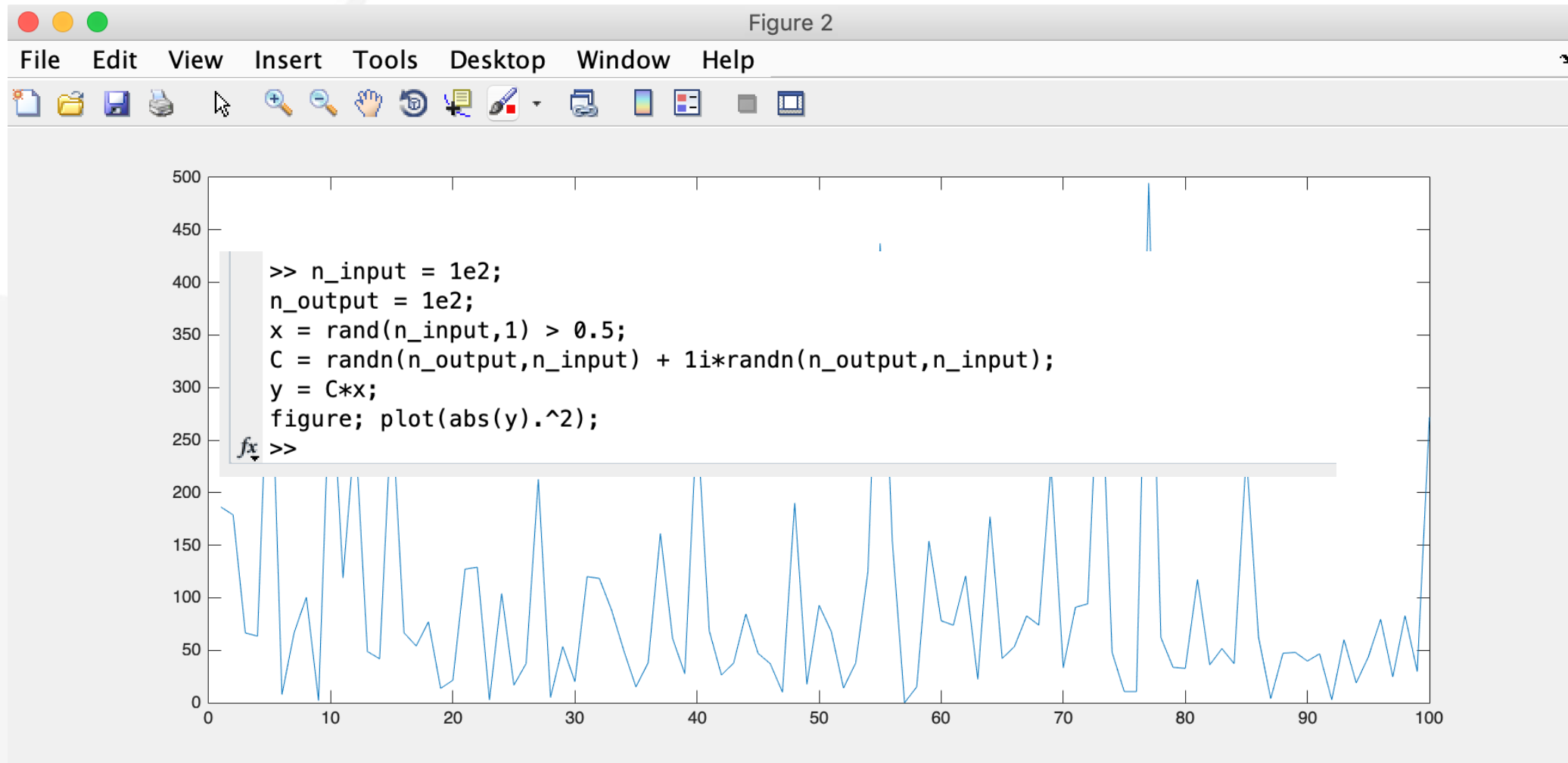
then for any set  $A$  of  $n$  points  $\in \mathbb{R}^d$  there exists a map  $f : \mathbb{R}^d \rightarrow \mathbb{R}^k$  such that for all  $x_i, x_j \in A$

$$(1 - \epsilon) \|x_i - x_j\|^2 \leq \|f(x_i) - f(x_j)\|^2 \leq (1 + \epsilon) \|x_i - x_j\|^2$$

## Dimensionality Reduction



# OPU: No need for large memory




# OPU: No need for large memory

```
n_input = 1e6;  
n_output = 1e6;  
x = rand(n_input,1) > 0.5;  
C = randn(n_output,n_input) + 1i*randn(n_output,n_input);  
y = C*x;  
figure; plot(abs(y).^2);
```

Error using **randn**

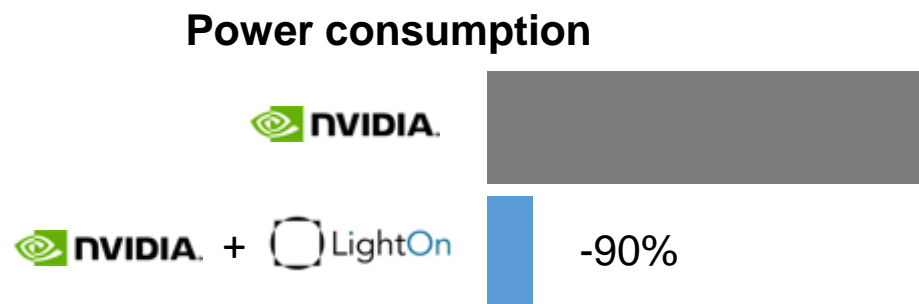
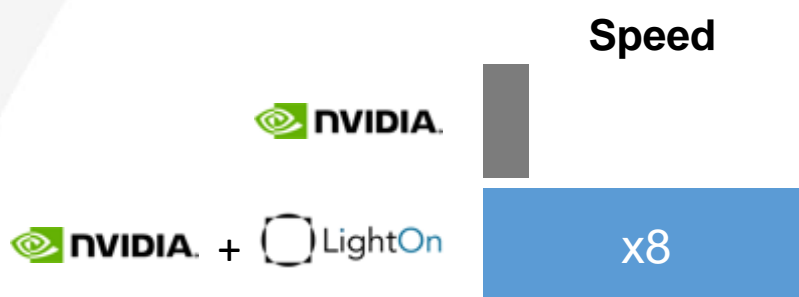
Requested 1000000x1000000 (7450.6GB) array exceeds maximum array size preference. Creation of arrays greater than this limit may take a long time and cause MATLAB to become unresponsive. See [array size limit](#) or preference panel for more information.

 >> |

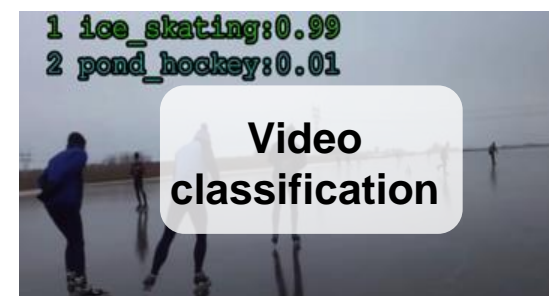
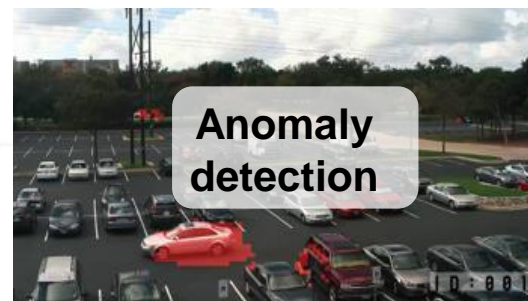
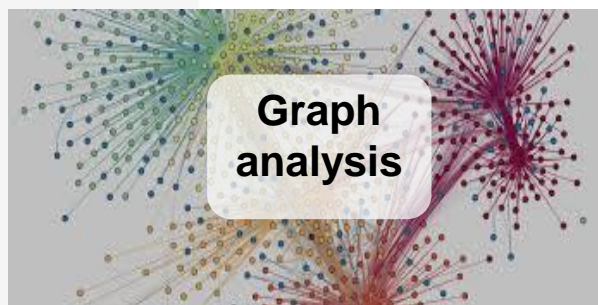
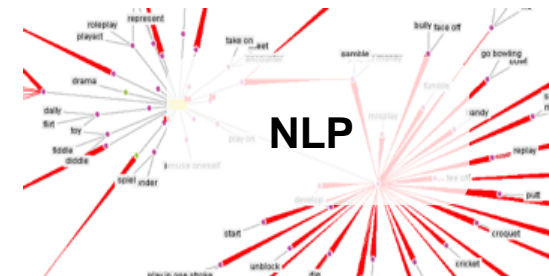
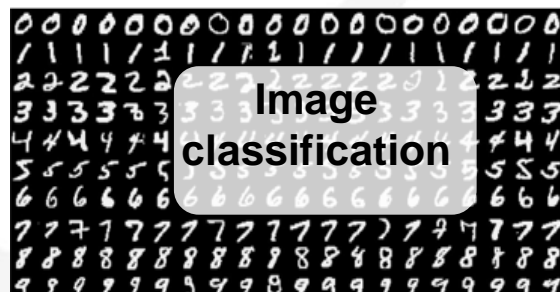


# A Machine Learning example

On a typical  
Machine Learning  
training task  
(transfer learning)



# Other Uses Already Investigated



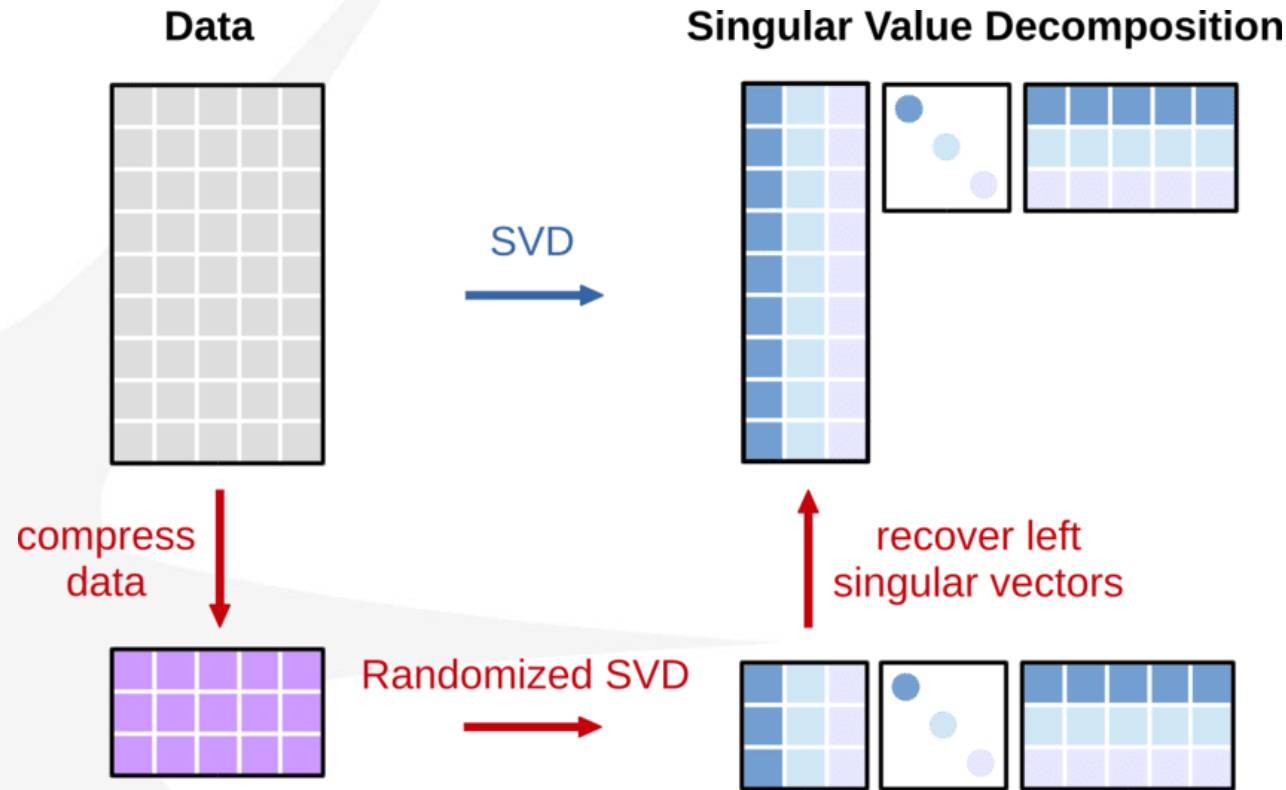
# Recommender Systems

Recommender Systems shape our lives at scale!





# Randomized Linear Algebra



Cornell University Library

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Mathematics > Numerical Analysis

**Finding structure with randomness: Probabilistic algorithms for constructing approximate matrix decompositions**

Nathan Halko, Per-Gunnar Martinsson, Joel A. Tropp

(Submitted on 22 Sep 2009 (v1), last revised 14 Dec 2010 (this version, v2))

Low-rank matrix approximations, such as the truncated singular value decomposition and the rank-revealing QR decomposition, play a central role in data analysis and scientific computing. This work surveys and extends recent research which demonstrates that randomization offers a powerful tool for performing low-rank matrix approximation. These techniques exploit modern computational architectures more fully than classical methods and open the possibility of dealing with truly massive data sets. This paper presents a modular framework for constructing randomized algorithms that compute partial matrix decompositions. These methods use random sampling to identify a subspace that captures most of the action of a matrix. The input matrix is then compressed—either explicitly or implicitly—to this subspace, and the reduced matrix is manipulated deterministically to obtain the desired low-rank factorization. In many cases, this approach beats its classical competitors in terms of accuracy, speed, and robustness. These claims are supported by extensive numerical experiments and a detailed error analysis.

Subjects: Numerical Analysis (math.NA); Probability (math.PR)

Journal reference: SIAM Rev., Survey and Review section, Vol. 53, num. 2, pp. 217-288, June 2011

Cite as: arXiv:0909.4061 [math.NA]  
(or arXiv:0909.4061v2 [math.NA] for this version)

☀ Randomized Matrix Decompositions using R, Aug 2016, N. Benjamin Erichson, Sergey Voronin, Steven L. Brunton, J. Nathan Kutz





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