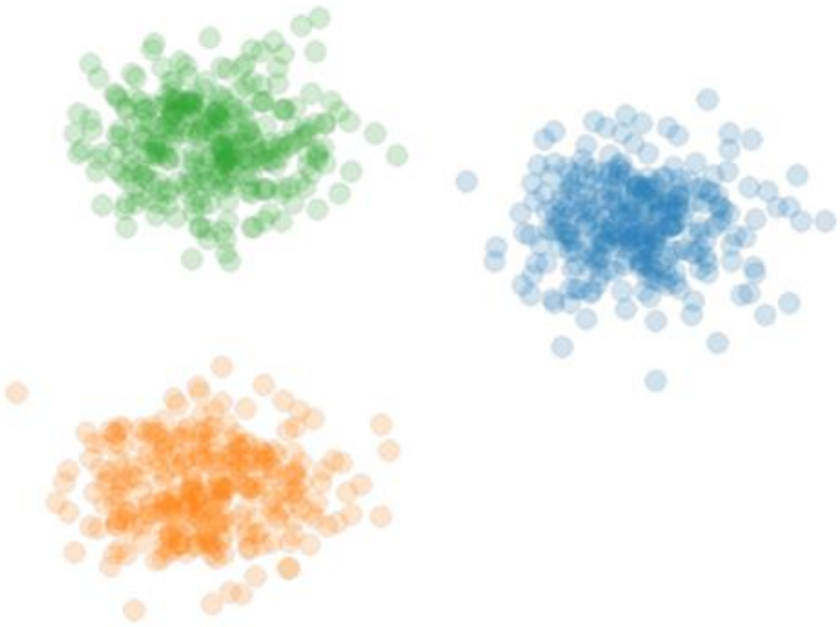
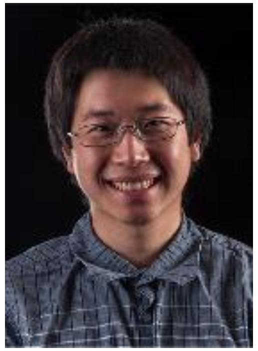
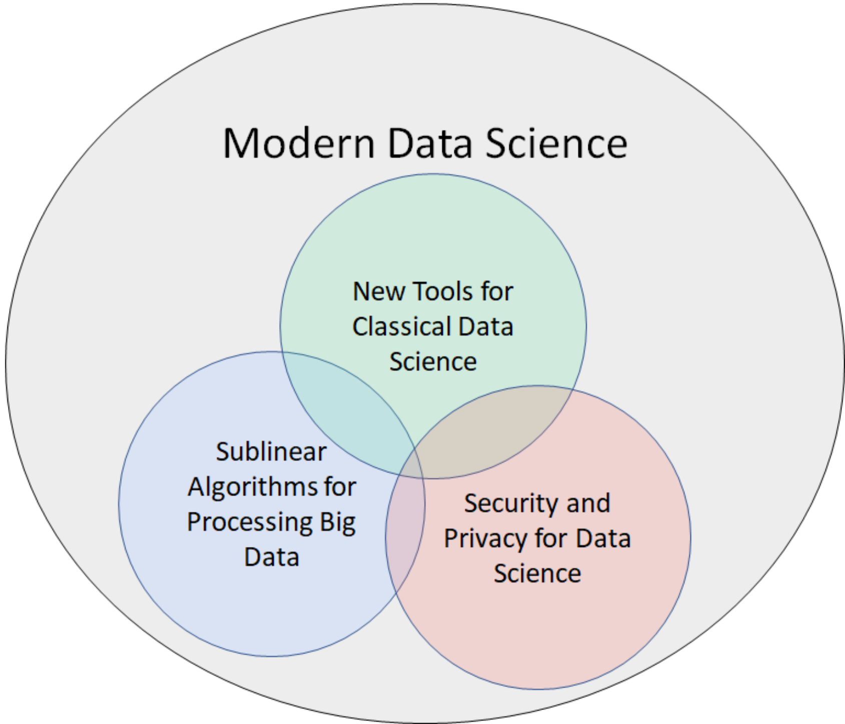
Theoretical Foundations of Modern Data Science



Samson Zhou




Modern Data Science
New Tools for Classical Data Science
Sublinear Algorithms for Processing Big Data
Security and Privacy for Data Science

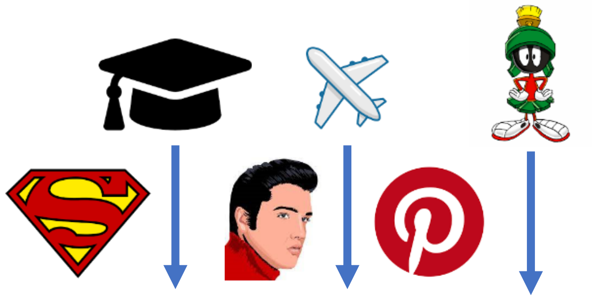
Background

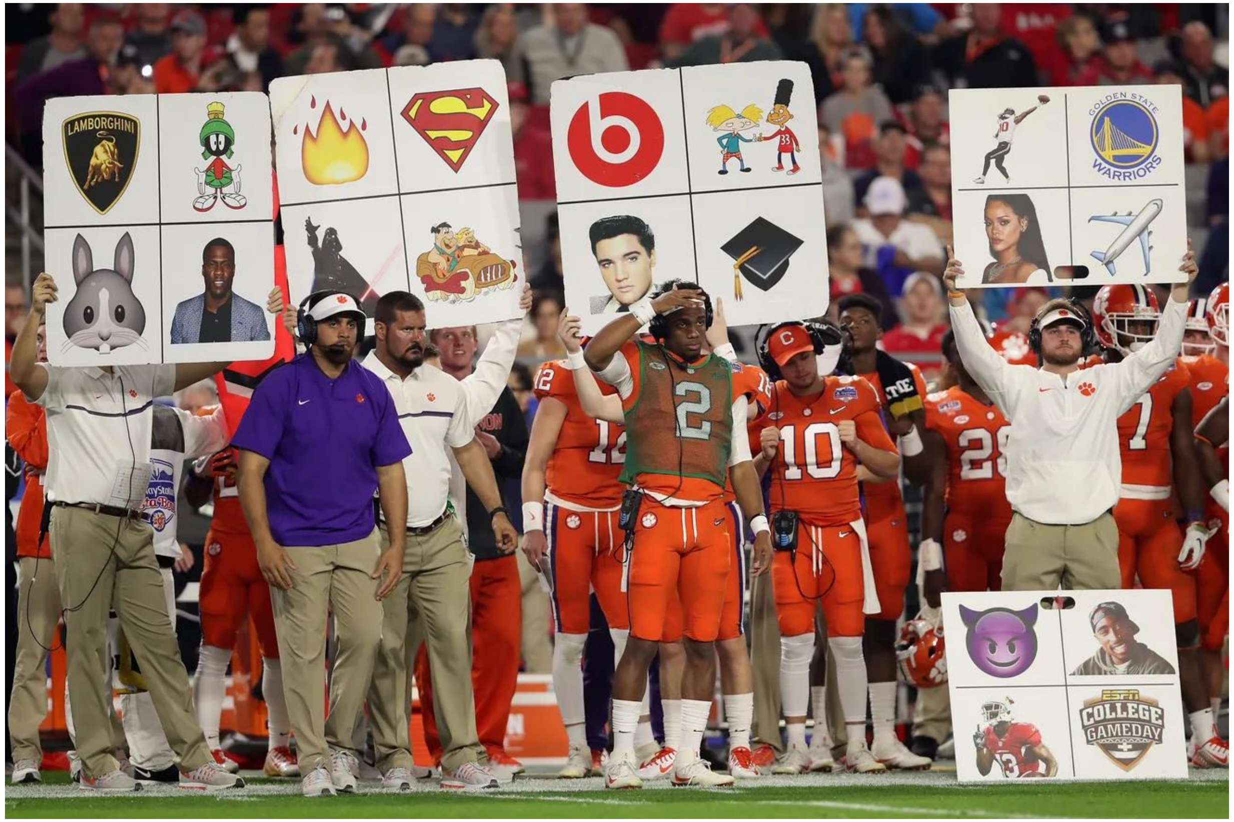
- Post-doc at UC Berkeley / Rice
- Previous: Post-doc at Carnegie Mellon
- PhD in Computer Science from Purdue
- Dual Bachelors in Math, Computer Science from MIT

- Research areas: Data science, sublinear algorithms, security and privacy

Data Science

LAMBORGHINI
GOLDEN STATE
WARRIORS
ESPN
COLLEGE
GAMEDAY

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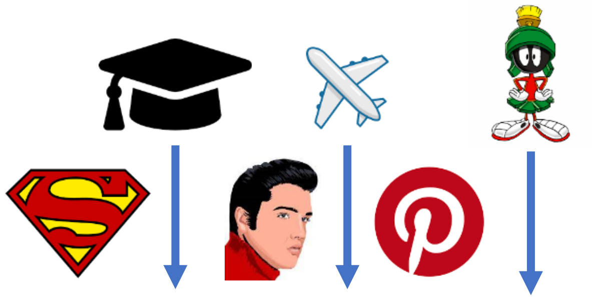

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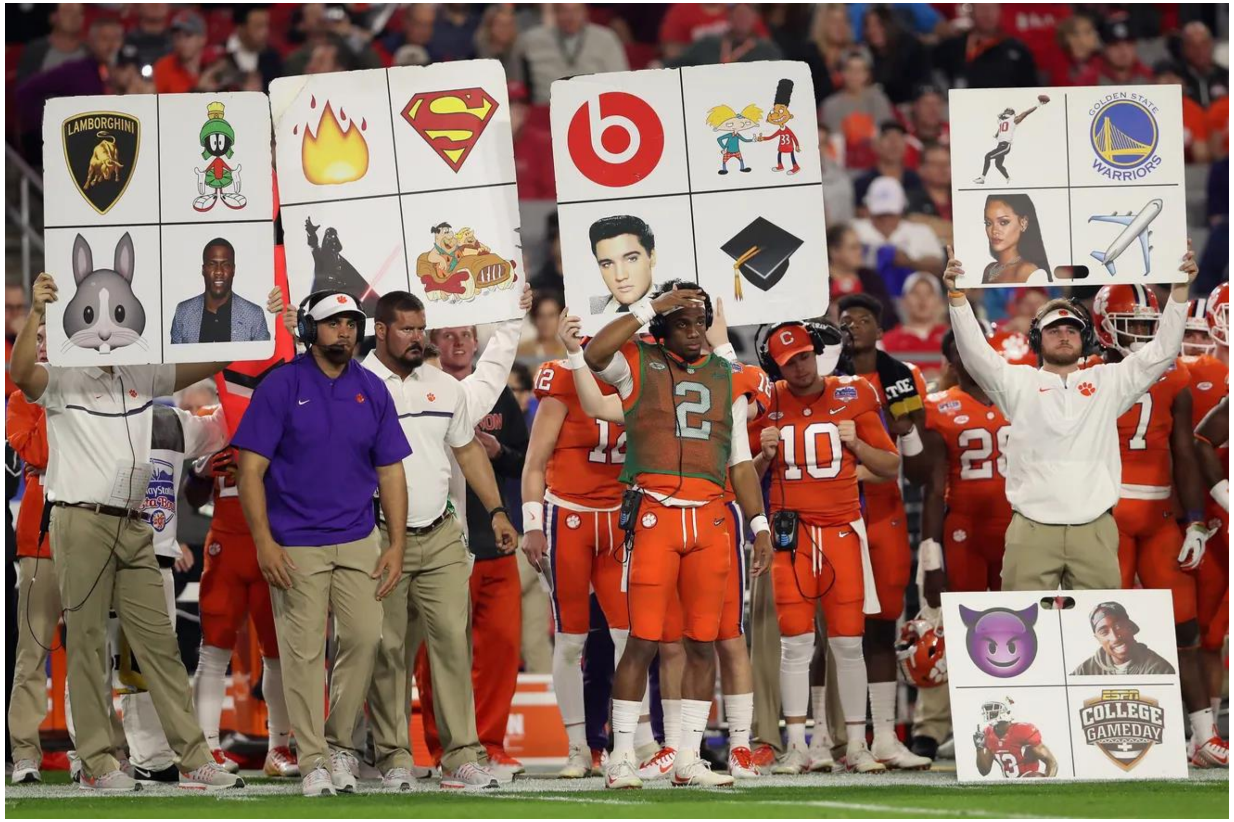
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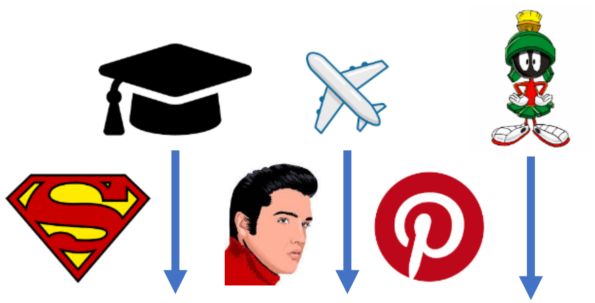
10

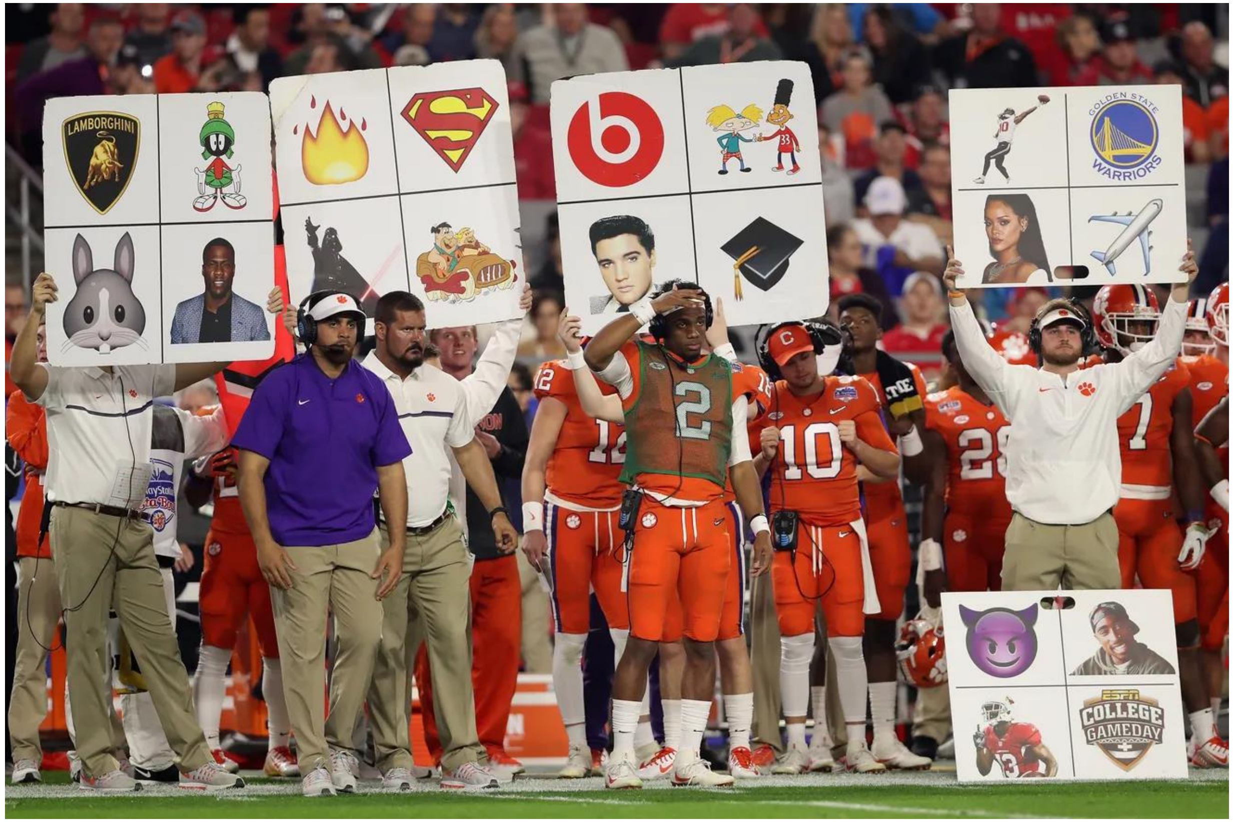


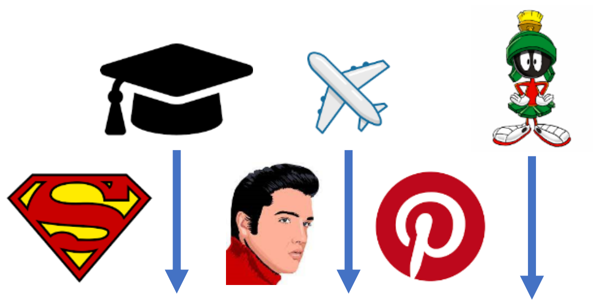
1 1 0 1 0 1

0 1 1 1 0 0

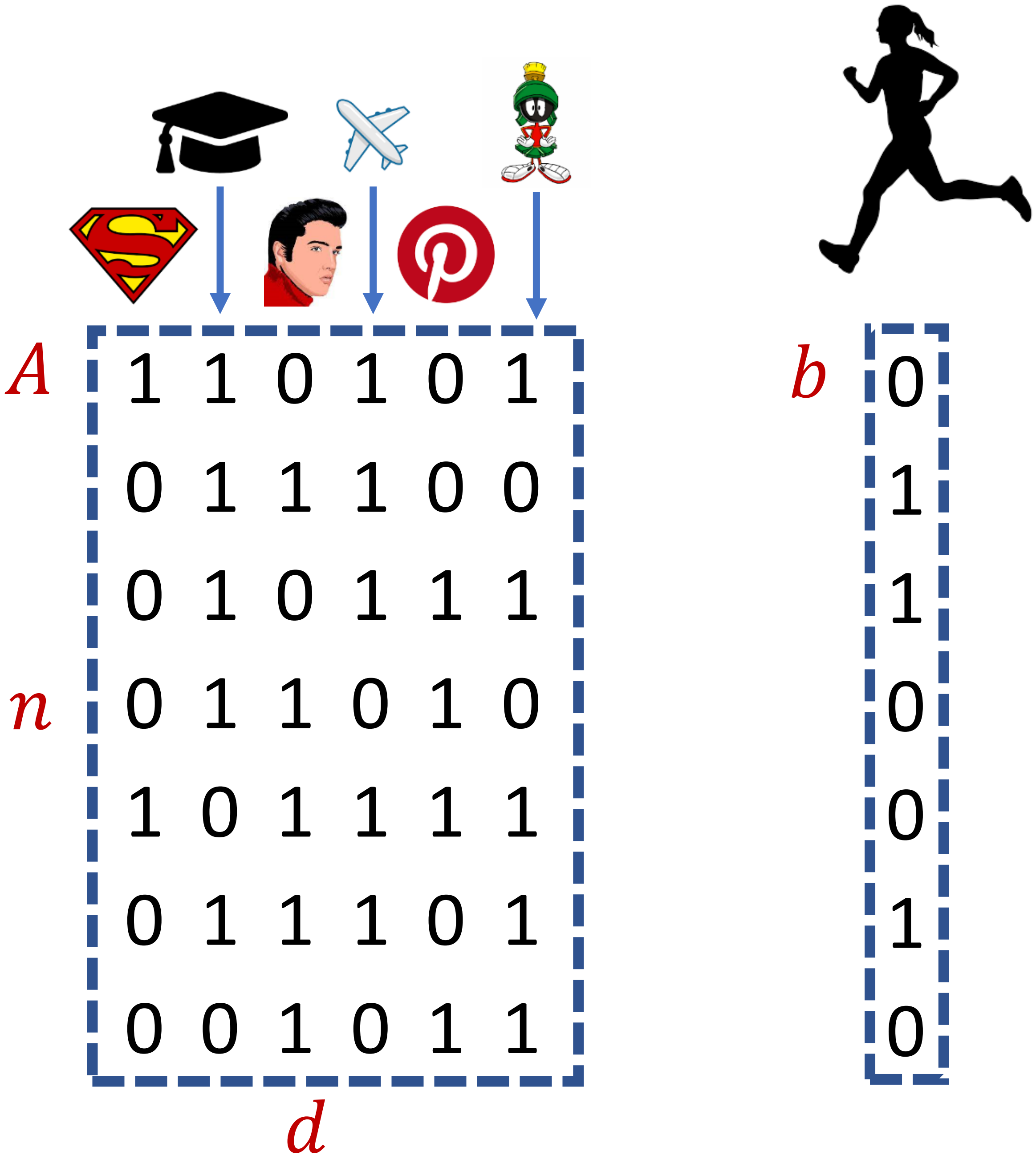
0

1

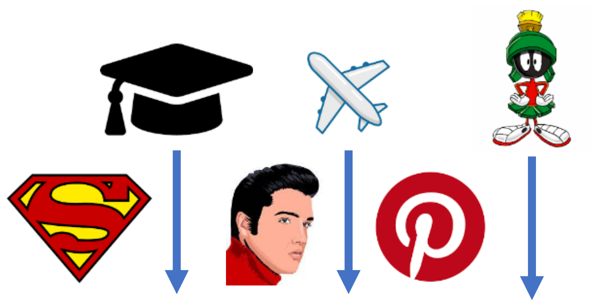




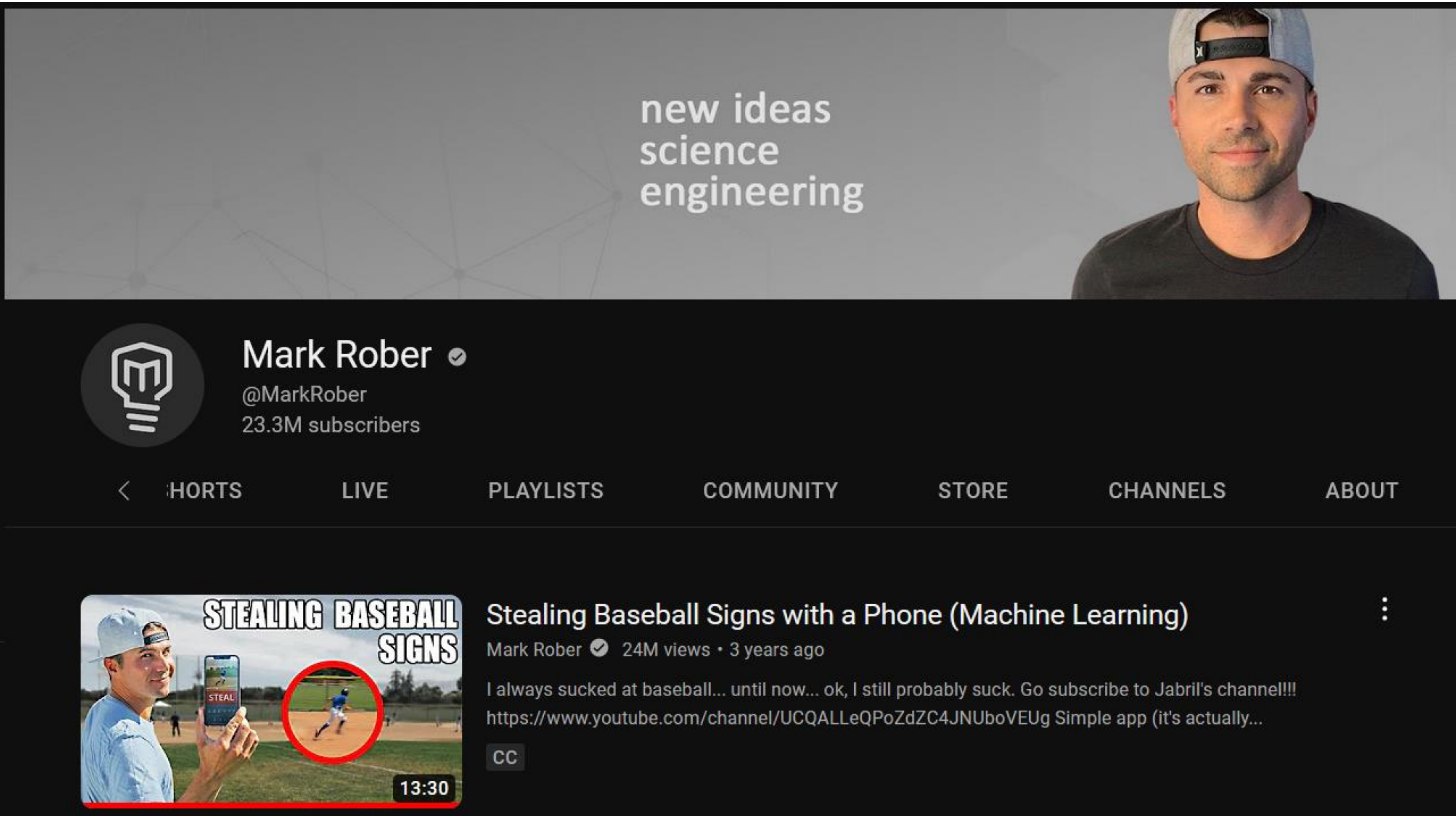
1	1	0	1	0	1	0
0	1	1	1	0	0	1
0	1	0	1	1	1	1
0	1	1	0	1	0	0
1	0	1	1	1	1	0
0	1	1	1	0	1	1
0	0	1	0	1	1	0



$$A = \begin{bmatrix} 1 & 1 & 0 & 1 & 0 & 1 \\ 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 1 & 1 \\ 0 & 1 & 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 & 1 \end{bmatrix} \qquad b = \begin{bmatrix} 0 \\ 1 \\ 1 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}$$



$$A \quad n \; \underbrace{\begin{array}{cccccc} 1 & 1 & 0 & 1 & 0 & 1 \\ 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 1 & 1 \\ 0 & 1 & 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 & 1 \end{array}}_{d} \qquad b \; \begin{array}{c} 0 \\ 1 \\ 1 \\ 0 \\ 0 \\ 1 \\ 0 \end{array}$$



Mark Rober

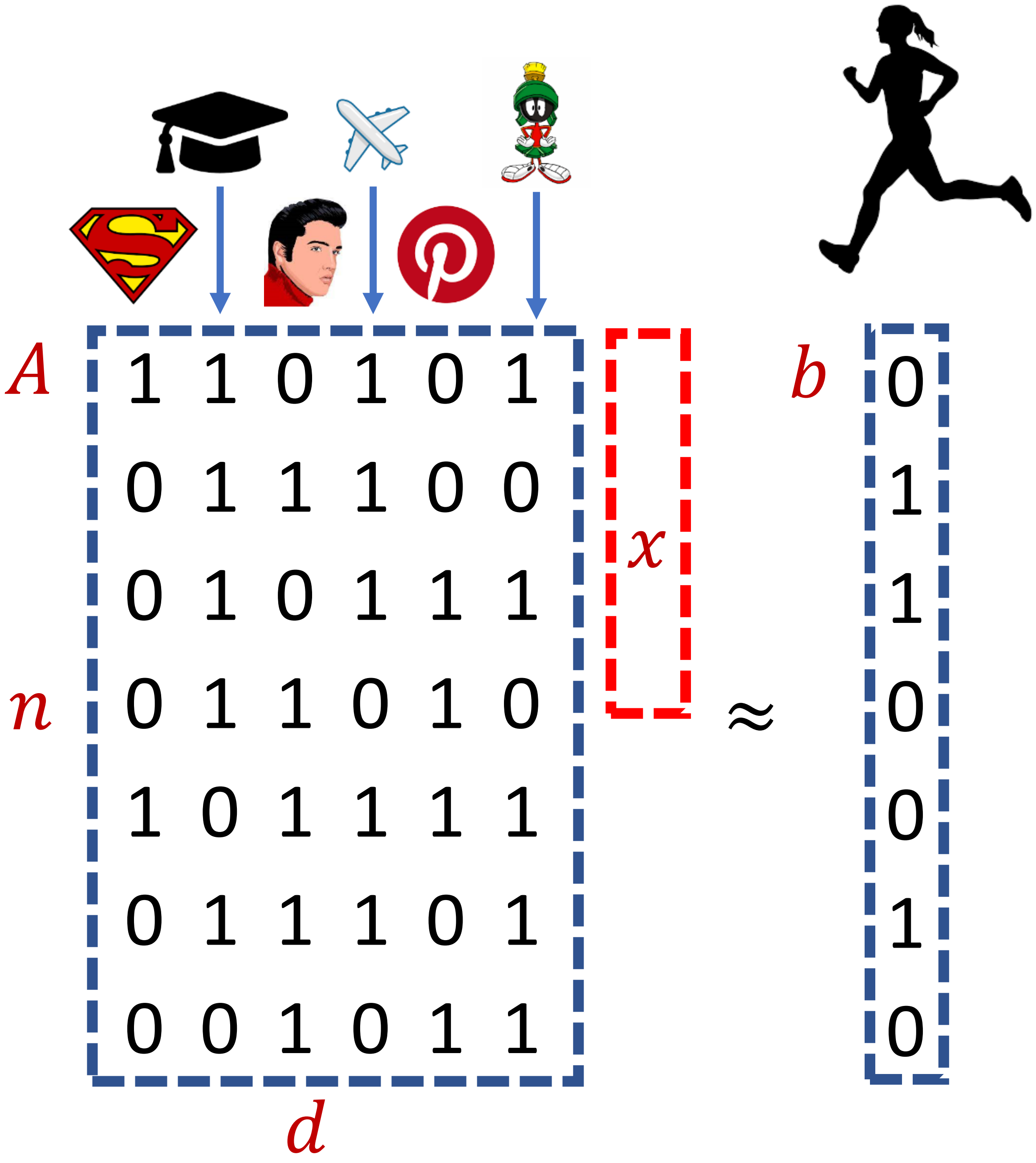
@MarkRober

23.3M subscribers

Stealing Baseball Signs with a Phone (Machine Learning)

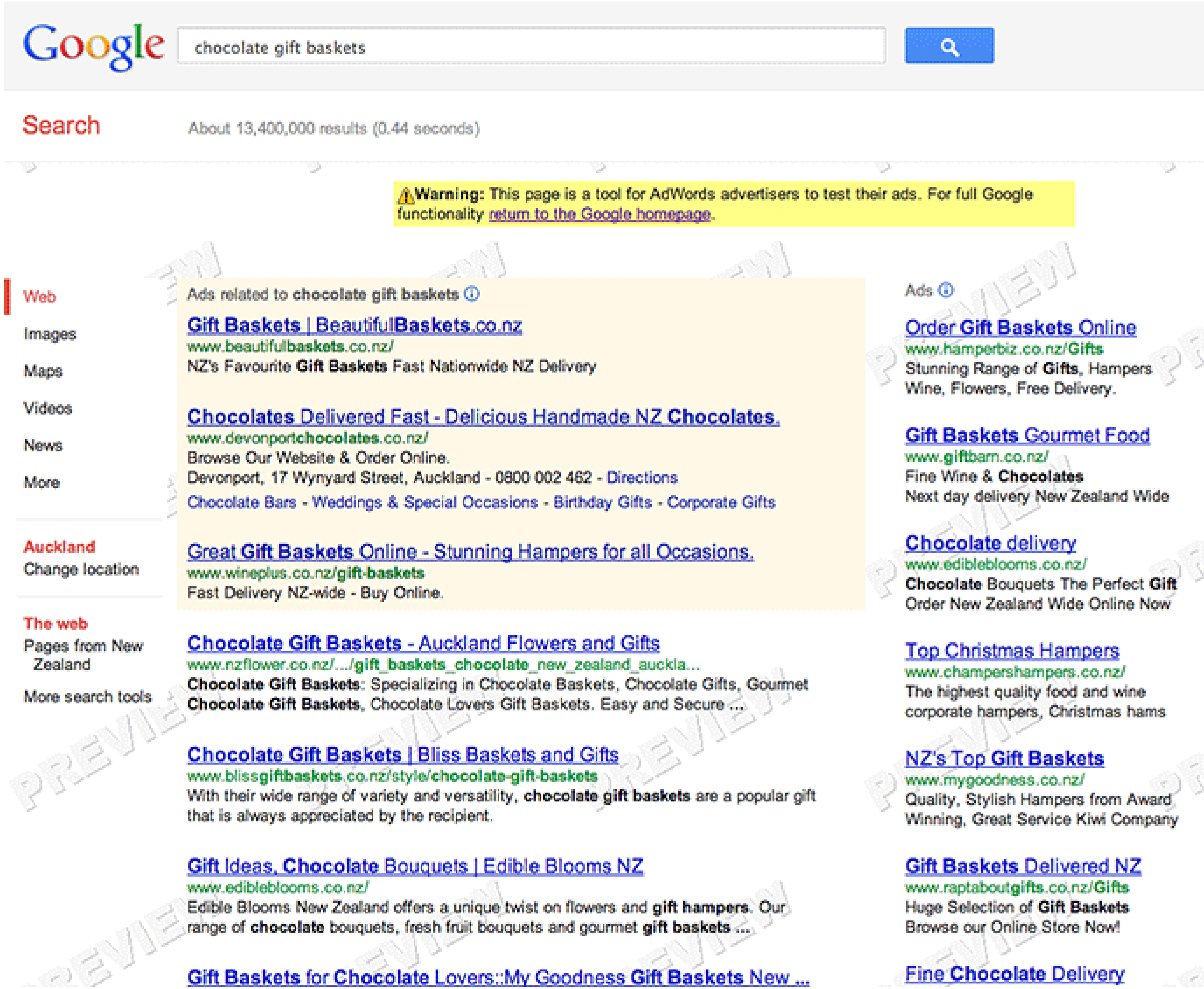
Mark Rober 24M views • 3 years ago

I always sucked at baseball... until now... ok, I still probably suck. Go subscribe to Jabril's channel!!! https://www.youtube.com/channel/UCQALLeQPoZdZC4JNUboVEUg Simple app (it's actually...



$$\overset{}{A}\;\underbrace{\begin{bmatrix}1&1&0&1&0&1\\0&1&1&1&0&0\\0&1&0&1&1&1\\0&1&1&0&1&0\\1&0&1&1&1&1\\0&1&1&1&0&1\\0&0&1&0&1&1\end{bmatrix}}_{d}\;\begin{bmatrix}\\x\\ \\\end{bmatrix}\approx b\;\begin{bmatrix}0\\1\\1\\0\\0\\1\\0\end{bmatrix}$$

n



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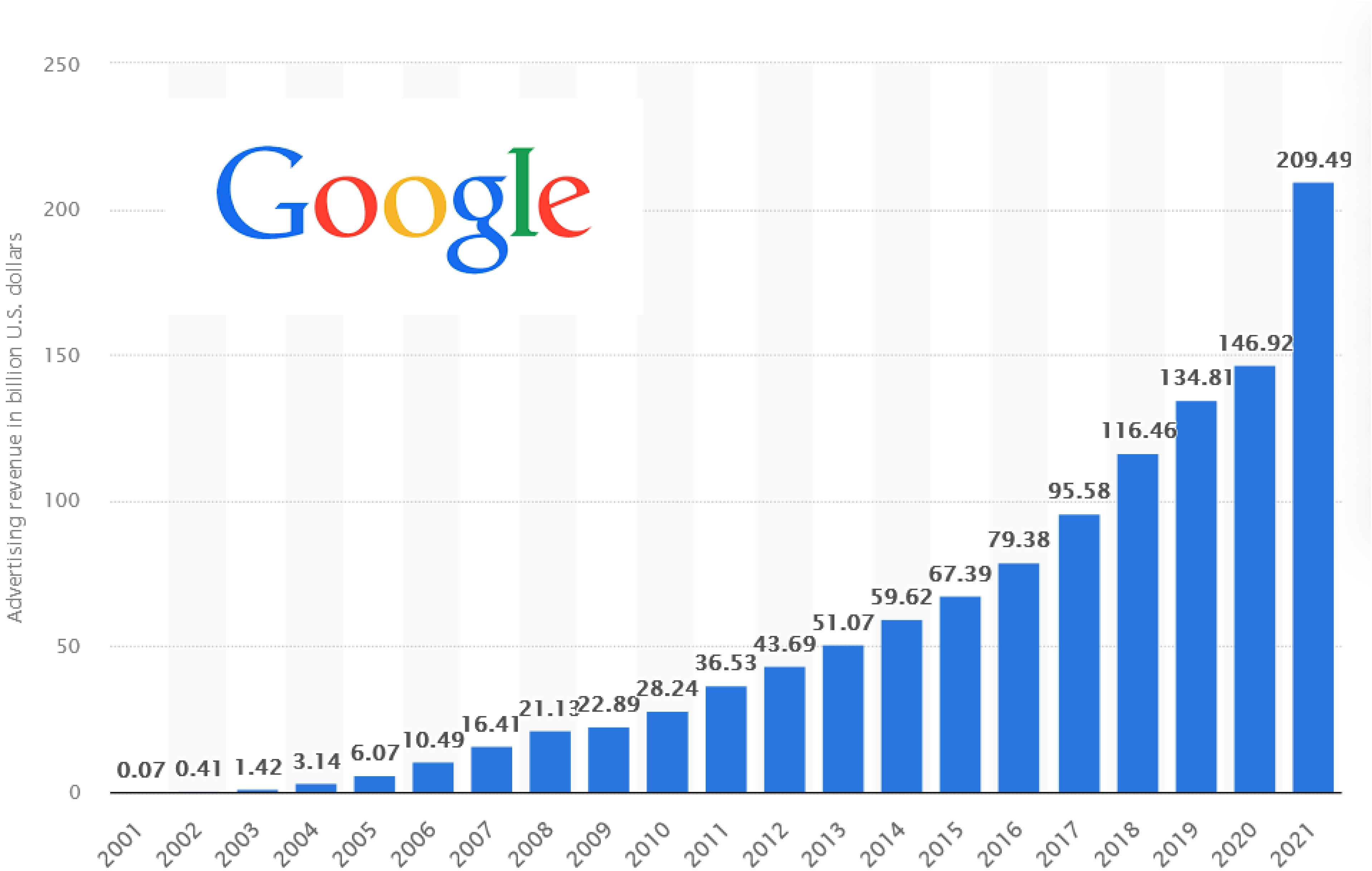
Fine **Chocolate** Delivery

Google Ad Revenue (2001-2021, billion USD)



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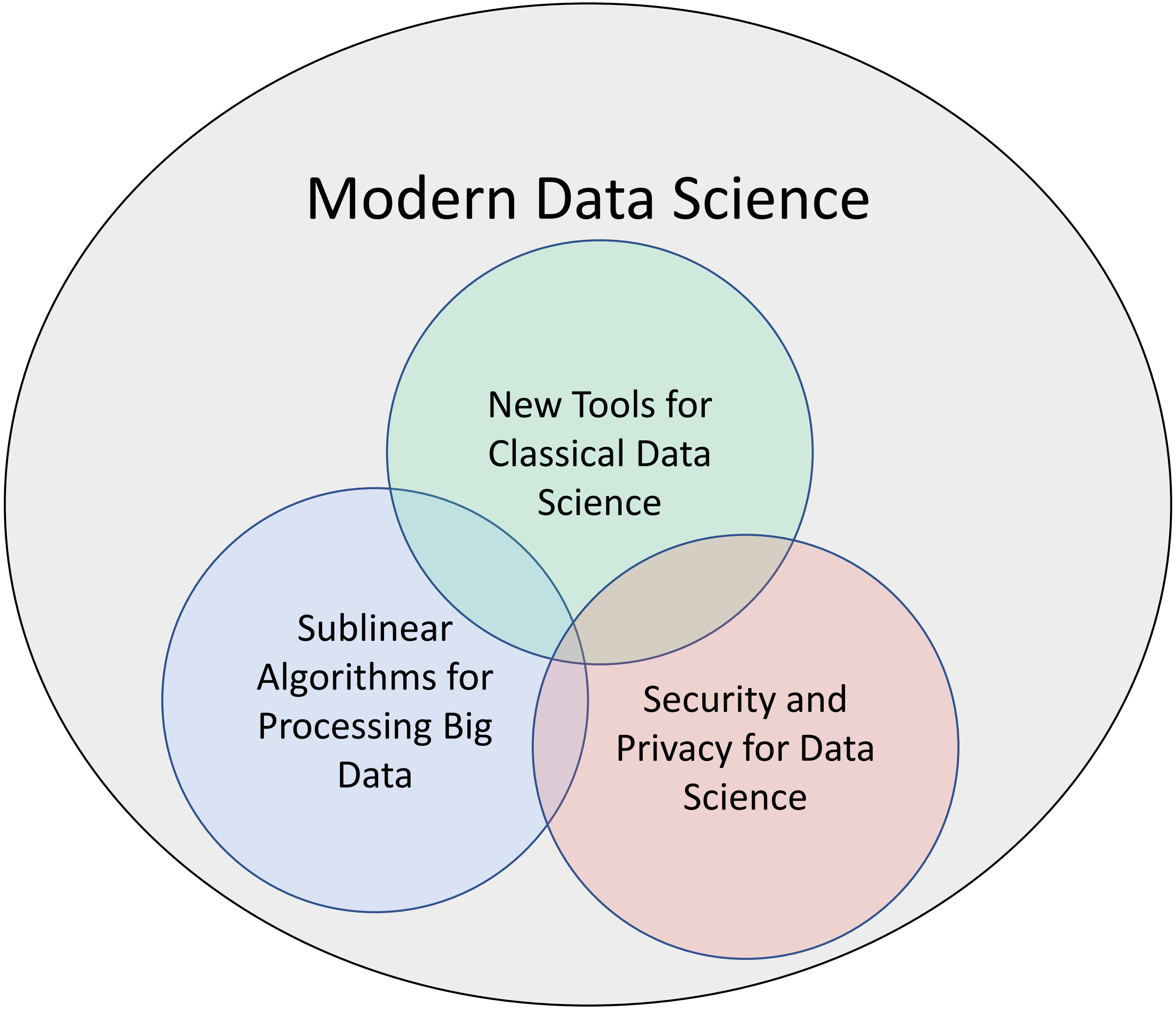
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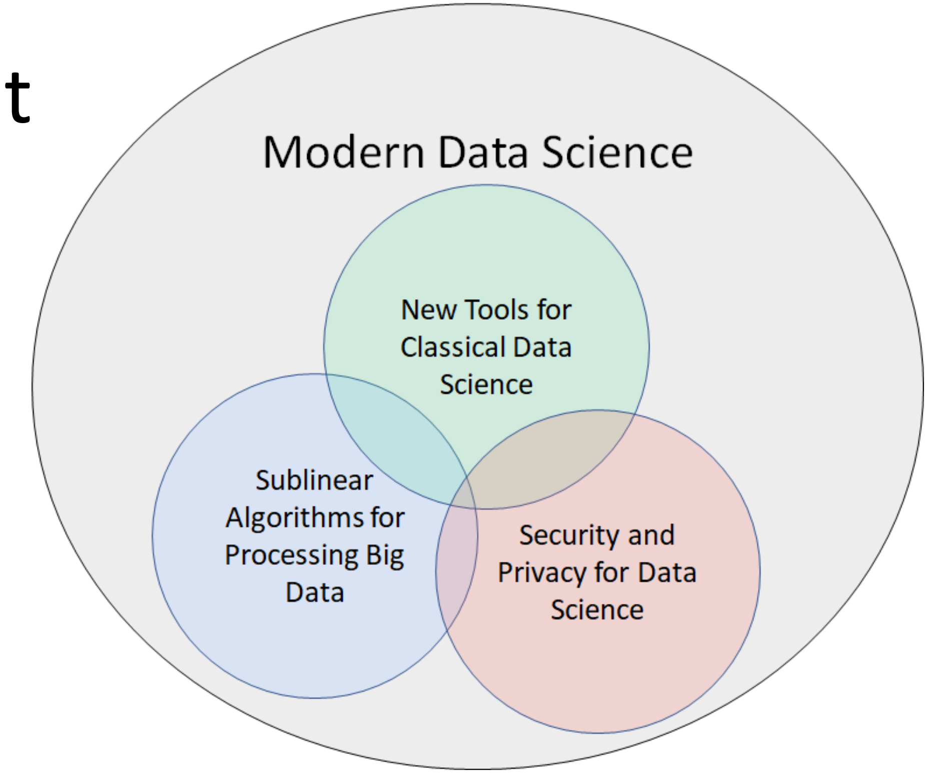
Evolving Demands

- Sublinear-time or sublinear-space algorithms
- Incorporation of advice
- Security and privacy
- Robustness to noise or adversarial input
- Ability to handle time-sensitive data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New Tools for Classical Data Science

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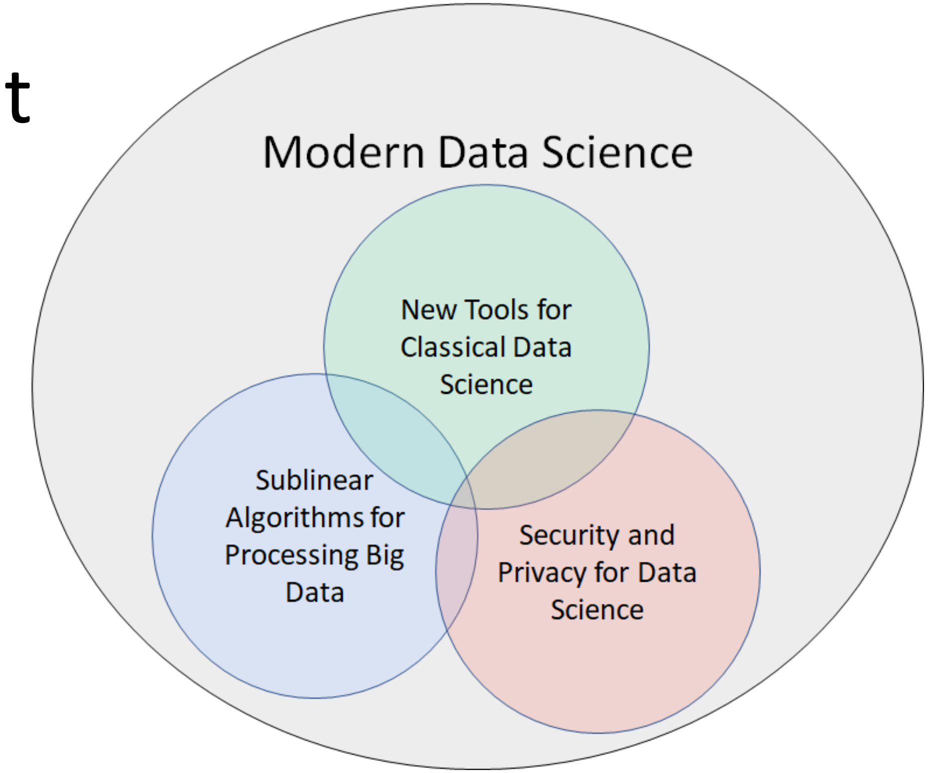

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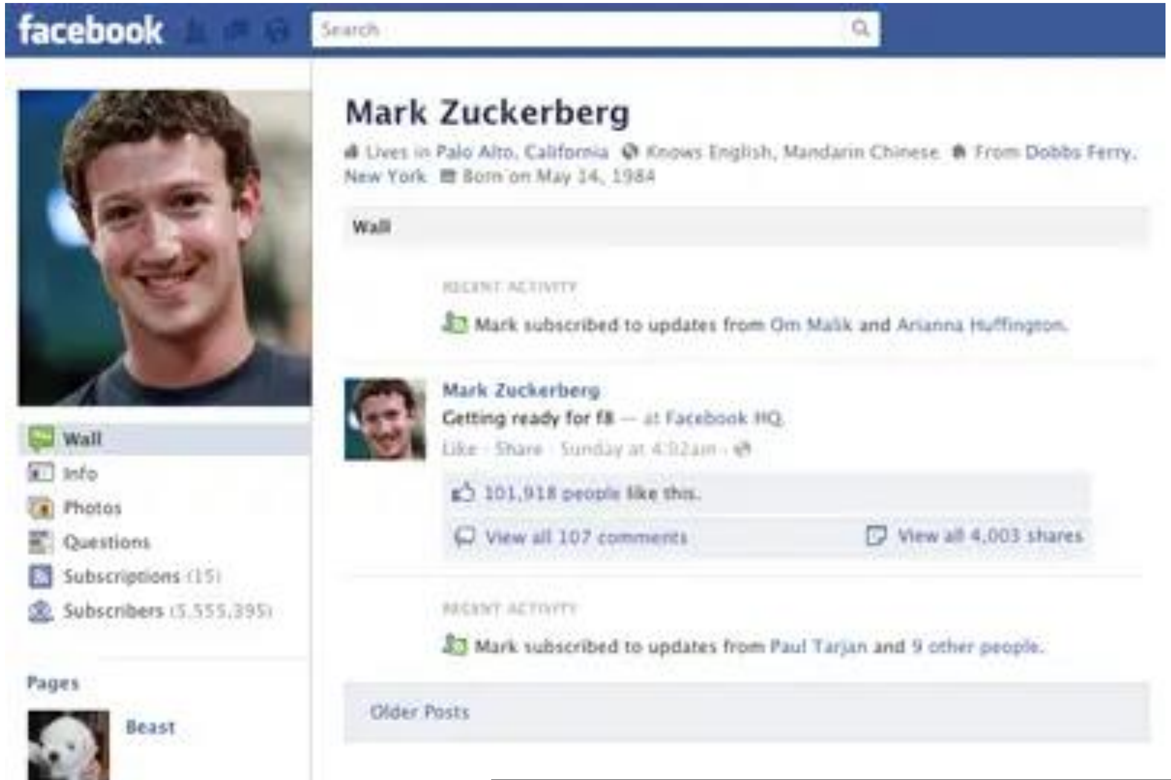


facebook Search

Mark Zuckerberg

Lives in Palo Alto, California · Knows English, Mandarin Chinese · From Dobbs Ferry, New York · Born on May 14, 1984

Wall

RECENT ACTIVITY

Mark subscribed to updates from Om Malik and Arianna Huffington.

Mark Zuckerberg
Getting ready for f8 — at Facebook HQ
Like · Share · Sunday at 4:02am ·

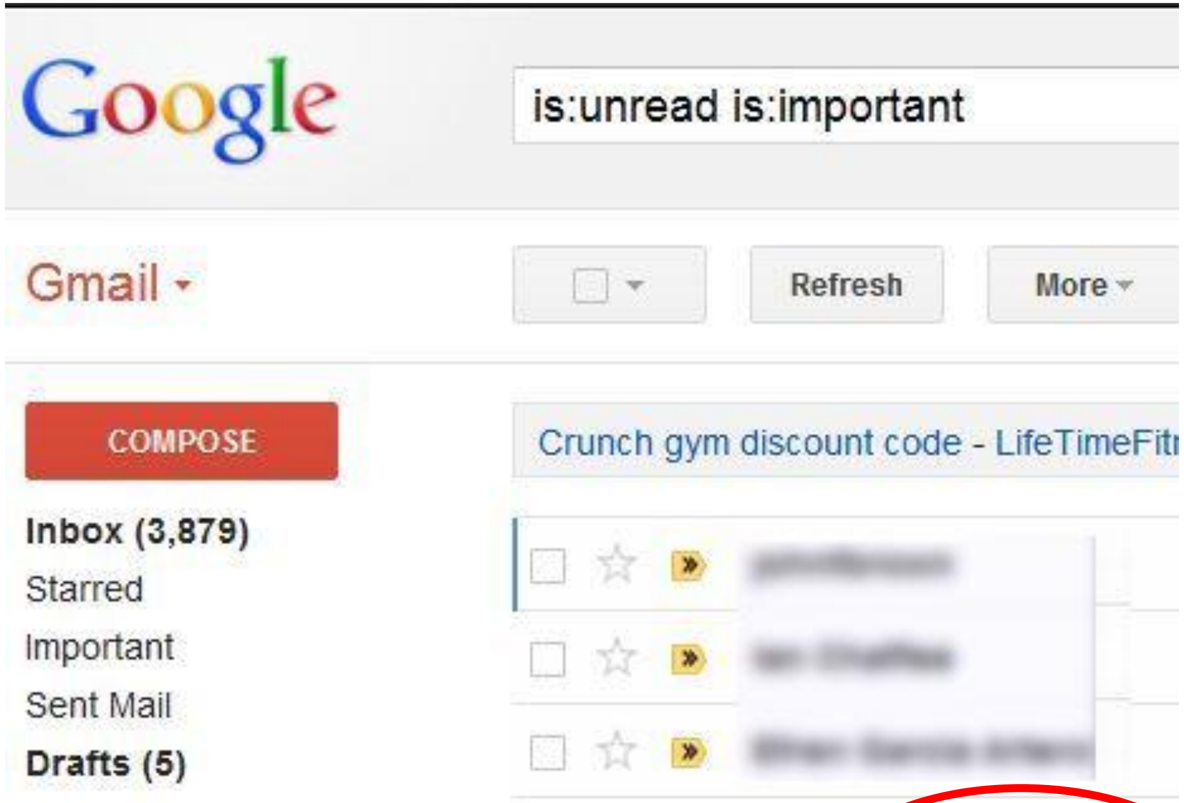
101,918 people like this.

View all 107 comments · View all 4,003 shares

RECENT ACTIVITY

Mark subscribed to updates from Paul Tarjan and 9 other people.

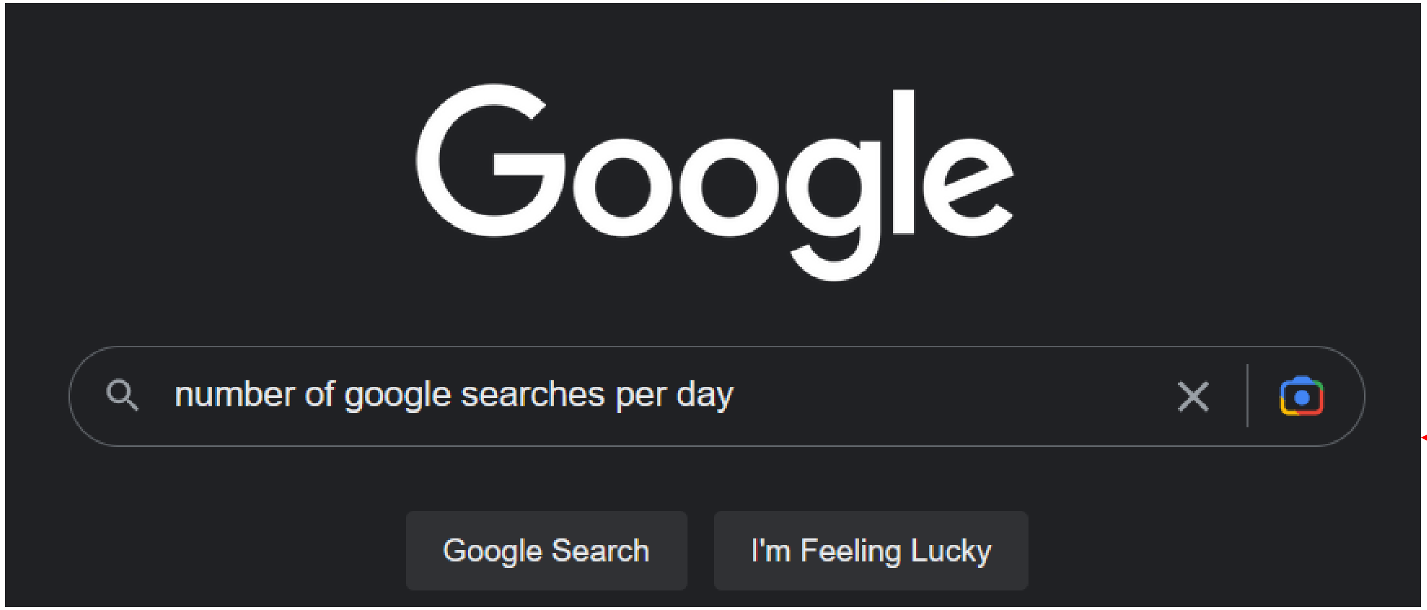
Older Posts



Google is:unread is:important

Crunch gym discount code - LifeTimeFitn

[redacted]



Google

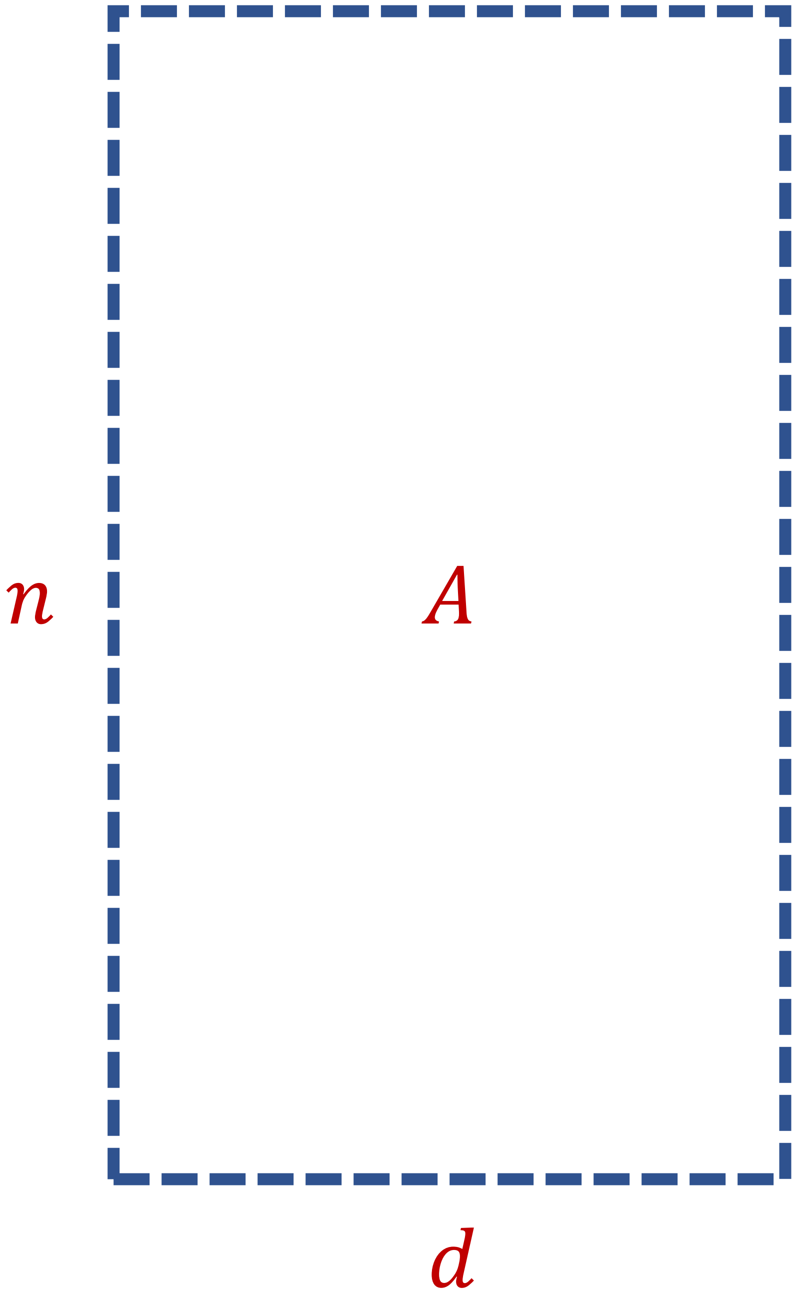
number of google searches per day

3 billion monthly active users

330 billion daily e-mails

8.5 billion daily Google searches

Dimensionality Reduction



- Reduce d
- Reduce n

Sampling, Sketching, Johnson-Lindenstrauss, IsoMap

Sampling, Sketching, Coresets

- Application depends on task!

New Dimensionality Reduction Results

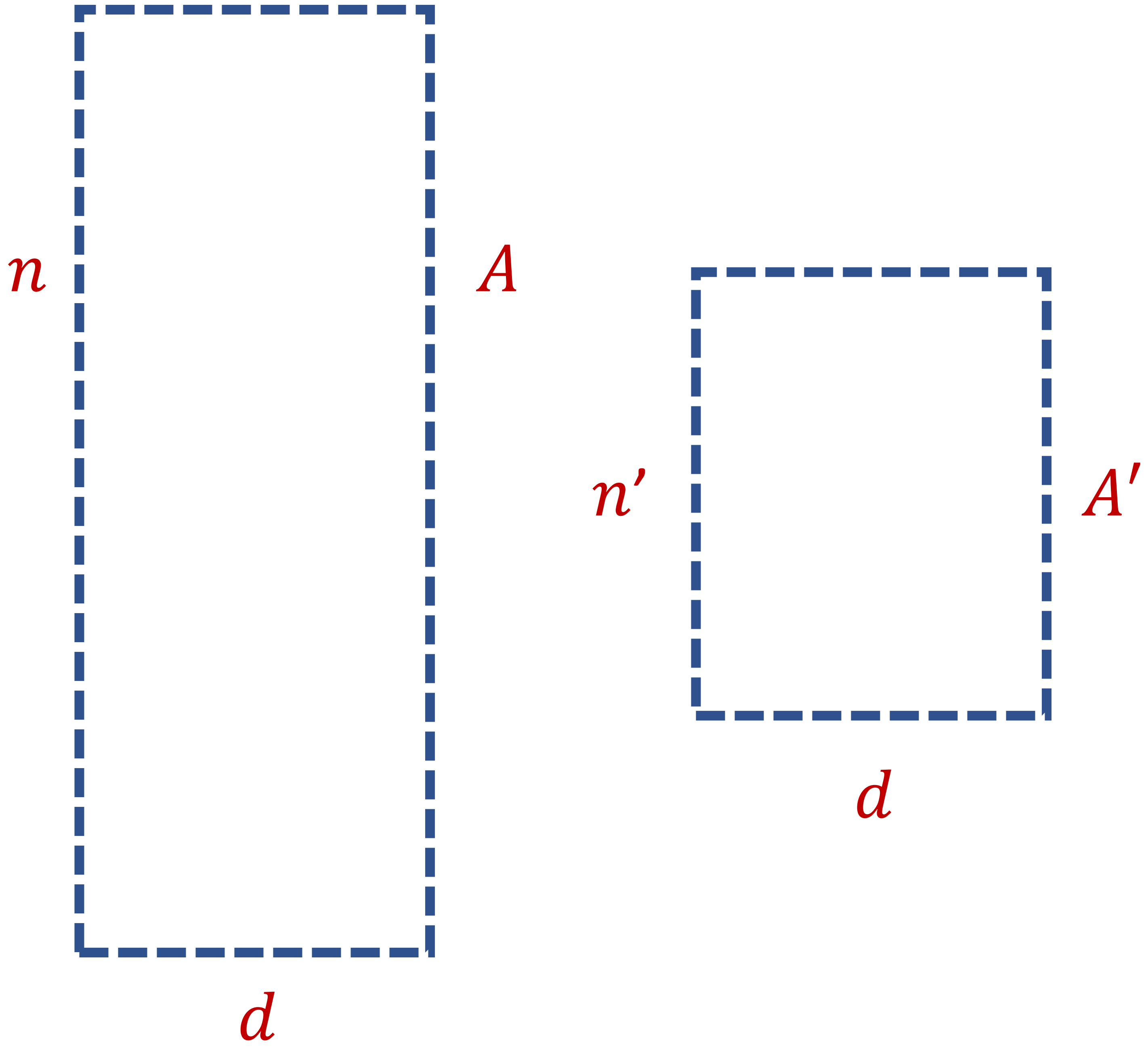
- Dimensionality reduction for Wasserstein barycenter [ISZ21]

- Sketching for valuation functions, e.g., additive, submodular, Lipschitz [YZ19]

- Kernel density estimation on kernel matrices [BKISZ22]

Coreset

- Subset A' of representative rows of A for a given task with "score" function f
- $f(A,\cdot) \approx f(A',\cdot)$

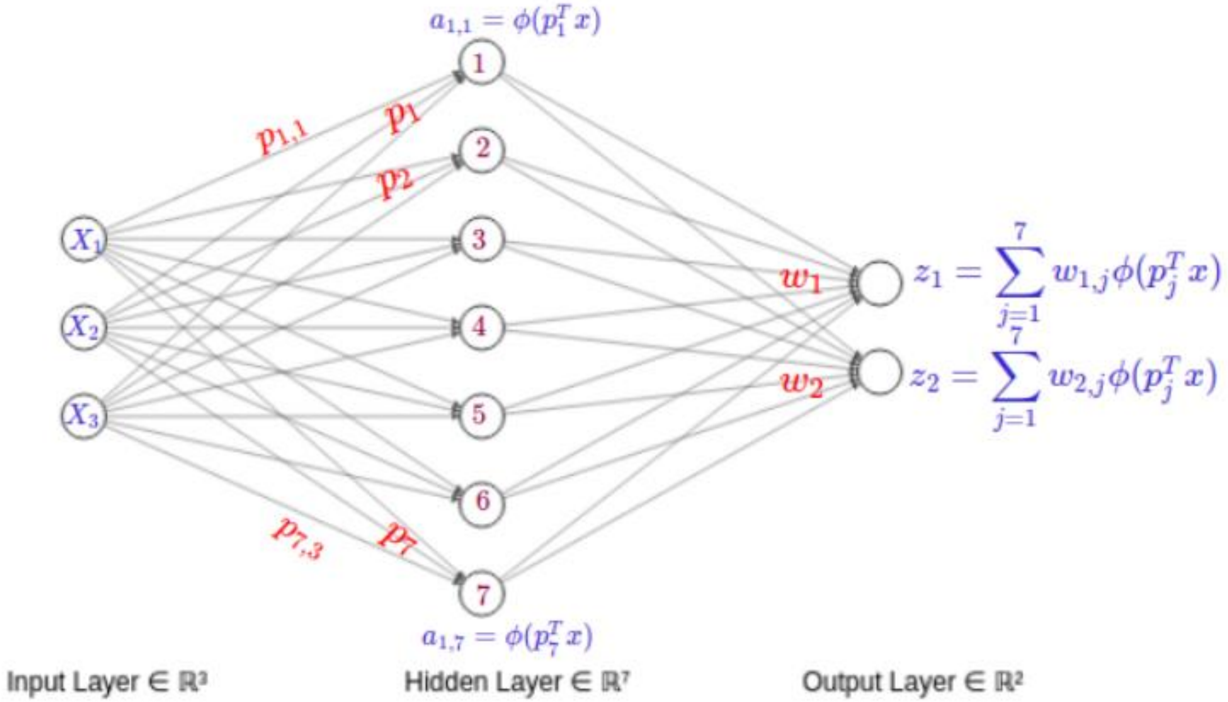


Coreset

- Lots of different constructions with various tradeoffs
  - Size n' vs. accuracy
  - Size n' vs. computation time
  - Size n' vs. interpretability
  - Average-case vs. worst-case performance

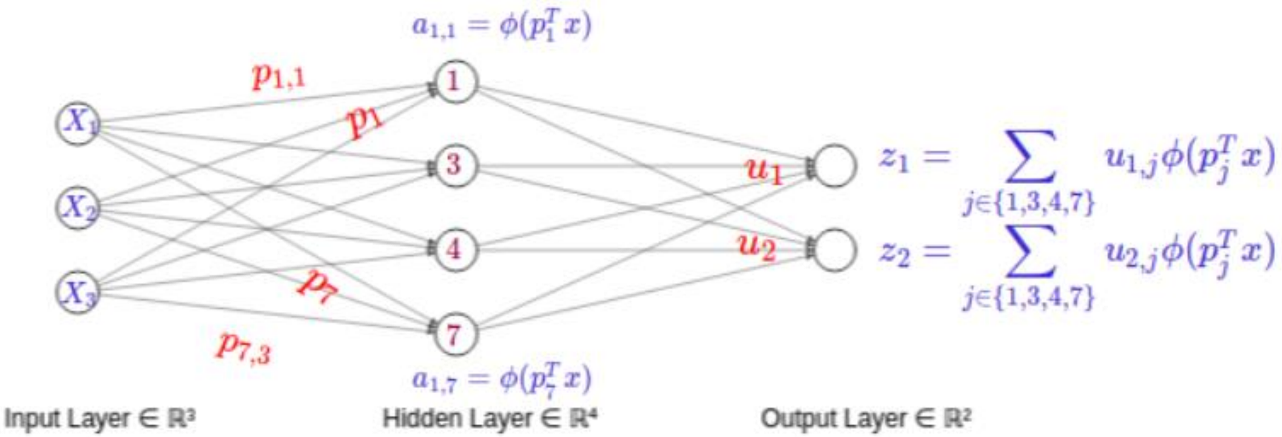
New Coreset Constructions

- Coresets for data-independent neural pruning [MOBZF20]
- Coresets for projective clustering [TWZBF22]
- Coresets for regression on structured matrices [MMMWZF22]
- Online coresets for linear algebra [BDMMUWZ20]
- General coreset construction framework through sensitivity sampling [BFLSZ21]

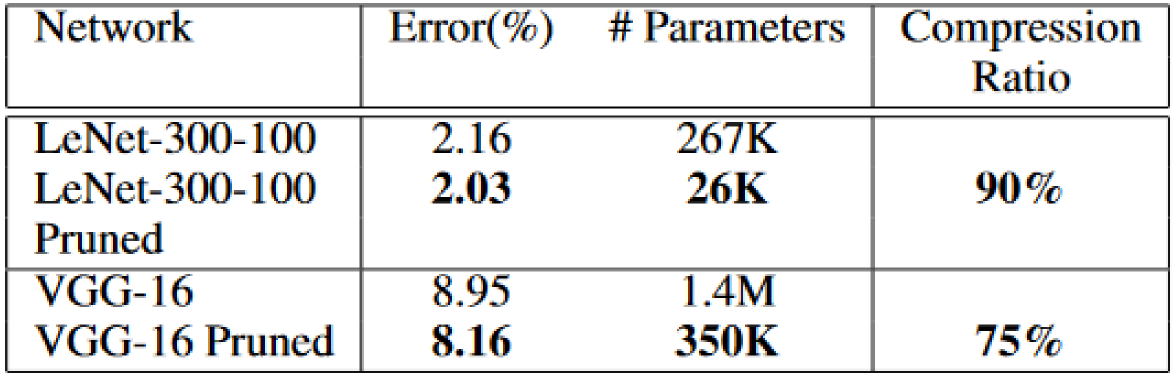

$a_{1,1} = \phi(p_1^T x)$
$p_{1,1}$
p_1
p_2
X_1
X_2
X_3
1
2
3
4
5
6
7
w_1
w_2
$z_1 = \sum_{j=1}^{7} w_{1,j}\phi(p_j^T x)$
$z_2 = \sum_{j=1}^{7} w_{2,j}\phi(p_j^T x)$
$p_{7,3}$
p_7
$a_{1,7} = \phi(p_7^T x)$
Input Layer ∈ ℝ³
Hidden Layer ∈ ℝ⁷
Output Layer ∈ ℝ²

(a)

[MOBZF20]


$a_{1,1} = \phi(p_1^T x)$
$p_{1,1}$
p_1
X_1
X_2
X_3
1
3
4
7
u_1
u_2
$z_1 = \sum_{j\in\{1,3,4,7\}} u_{1,j}\phi(p_j^T x)$
$z_2 = \sum_{j\in\{1,3,4,7\}} u_{2,j}\phi(p_j^T x)$
p_7
$p_{7,3}$
$a_{1,7} = \phi(p_7^T x)$
Input Layer ∈ ℝ³
Hidden Layer ∈ ℝ⁴
Output Layer ∈ ℝ²

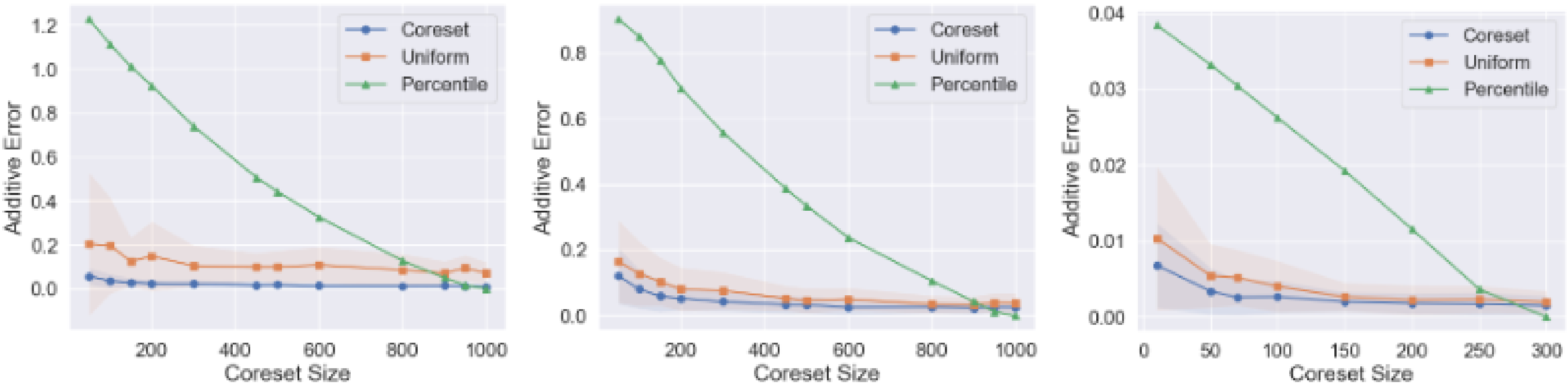
(b)



Network	Error(%)	# Parameters	Compression Ratio
LeNet-300-100	2.16	267K	
LeNet-300-100 Pruned	**2.03**	**26K**	**90%**
VGG-16	8.95	1.4M	
VGG-16 Pruned	**8.16**	**350K**	**75%**

Table 2: Empirical evaluations of our coresets on existing architectures for MNIST and CIFAR-10. Note the improvement of accuracy in both cases!

[MOBZF20]



(a) (b) (c)

Figure 2: Approximation error of a single neuron on MNIST dataset across different coreset sizes. The weights of the points in (a) are drawn from the Gaussian distribution, in (b) from the Uniform distribution and in (c) we used the trained weights from LeNet-300-100.

Evolving Demands

- Sublinear-time or sublinear-space algorithms
- Incorporation of advice
- Security and privacy
- Robustness to noise or adversarial input
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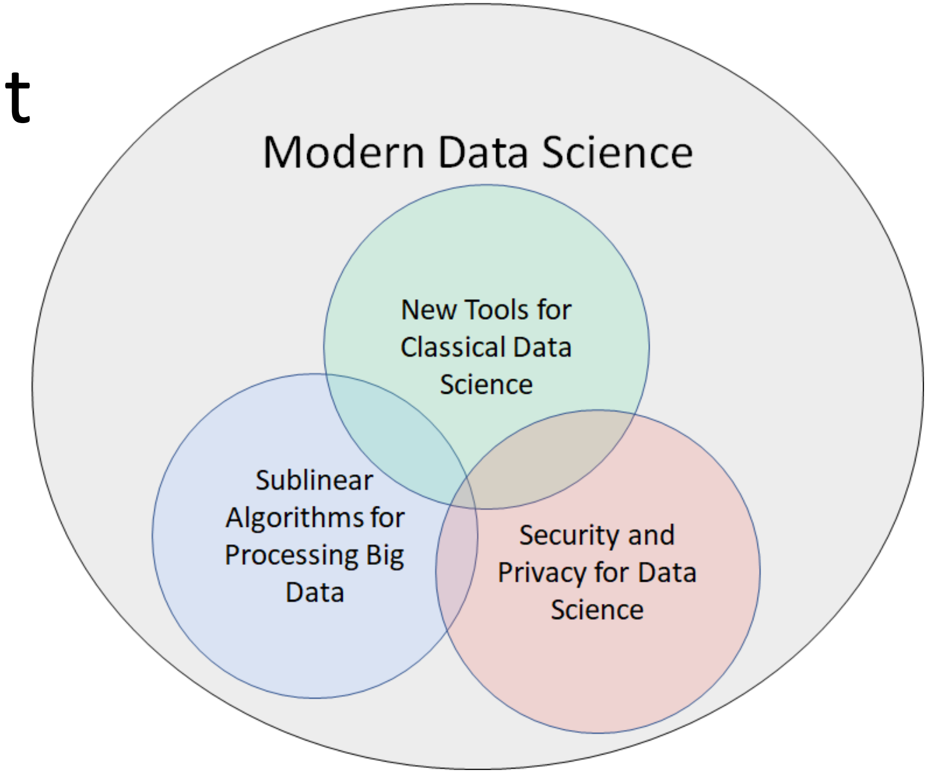
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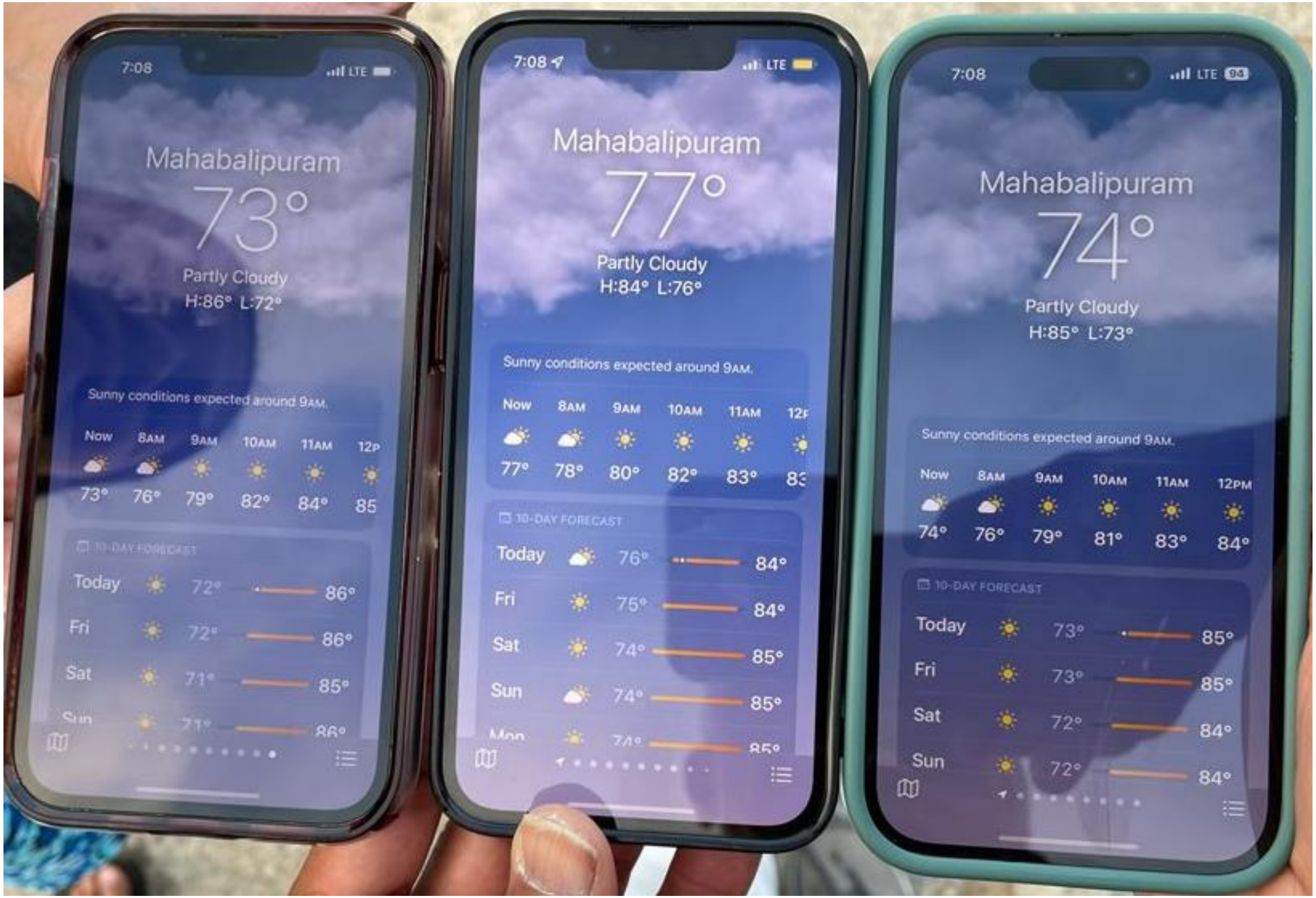


7:08 LTE

Mahabalipuram

73°

Partly Cloudy

H:86° L:72°

Sunny conditions expected around 9AM.

Now	8AM	9AM	10AM	11AM	12P
73°	76°	79°	82°	84°	85

10-DAY FORECAST

Today	72°	86°
Fri	72°	86°
Sat	71°	85°
Sun	71°	86°

7:08 LTE

Mahabalipuram

77°

Partly Cloudy

H:84° L:76°

Sunny conditions expected around 9AM.

Now	8AM	9AM	10AM	11AM	12P
77°	78°	80°	82°	83°	83

10-DAY FORECAST

Today	76°	84°
Fri	75°	84°
Sat	74°	85°
Sun	74°	85°
Mon	74°	85°

7:08 LTE 94

Mahabalipuram

74°

Partly Cloudy

H:85° L:73°

Sunny conditions expected around 9AM.

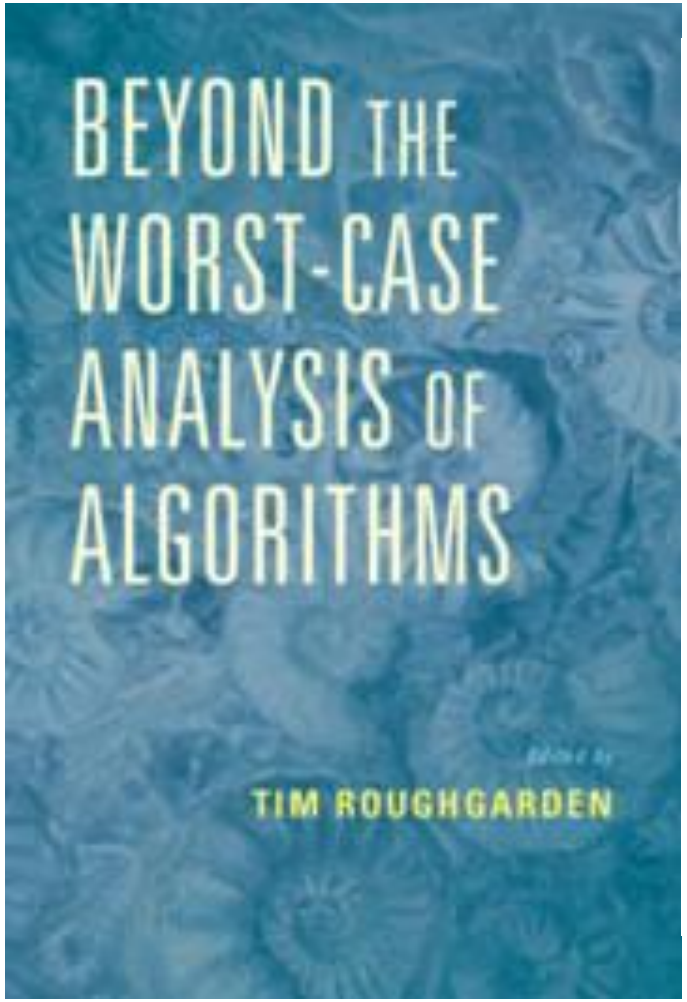
Now	8AM	9AM	10AM	11AM	12PM
74°	76°	79°	81°	83°	84°

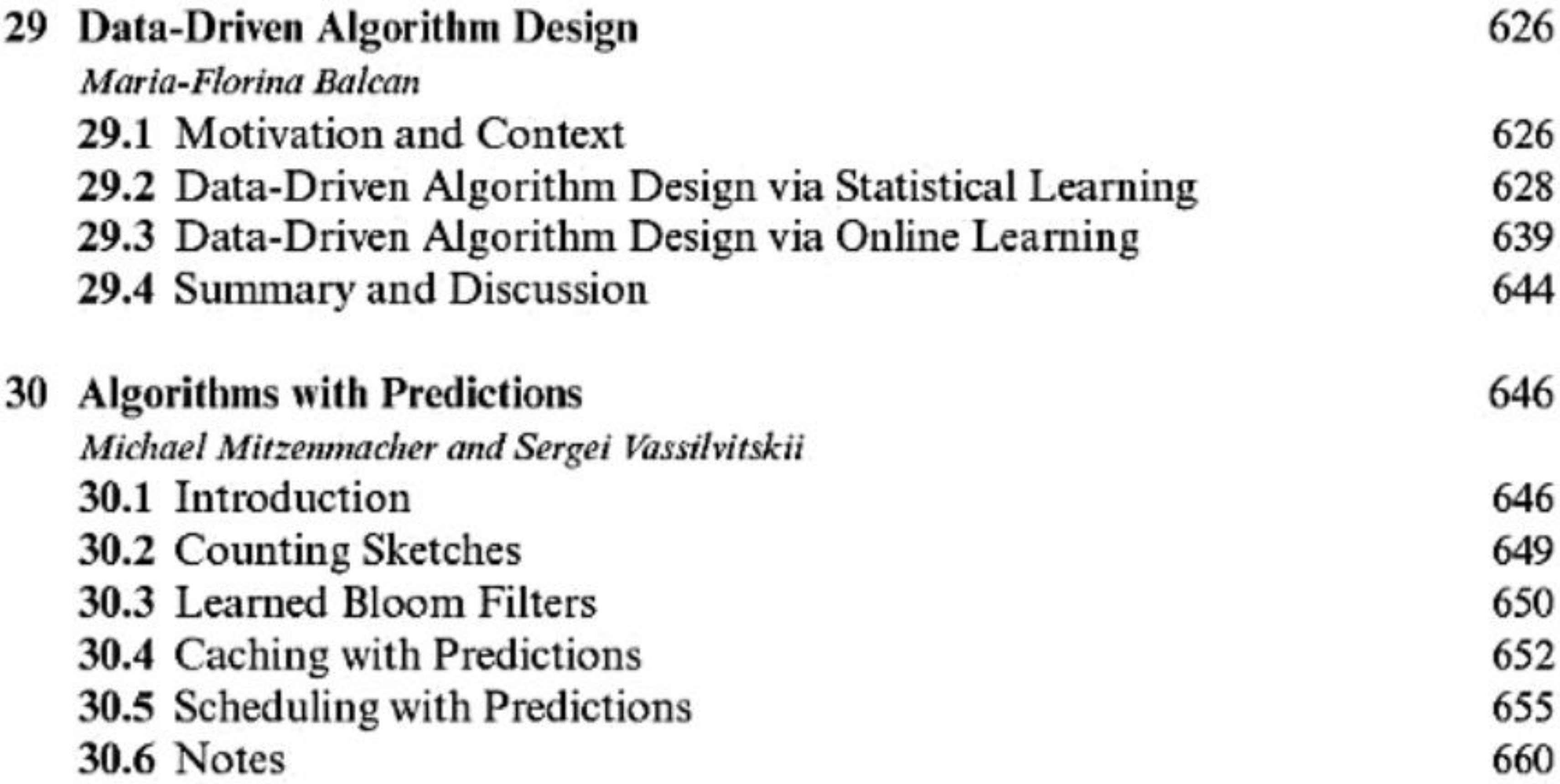
10-DAY FORECAST

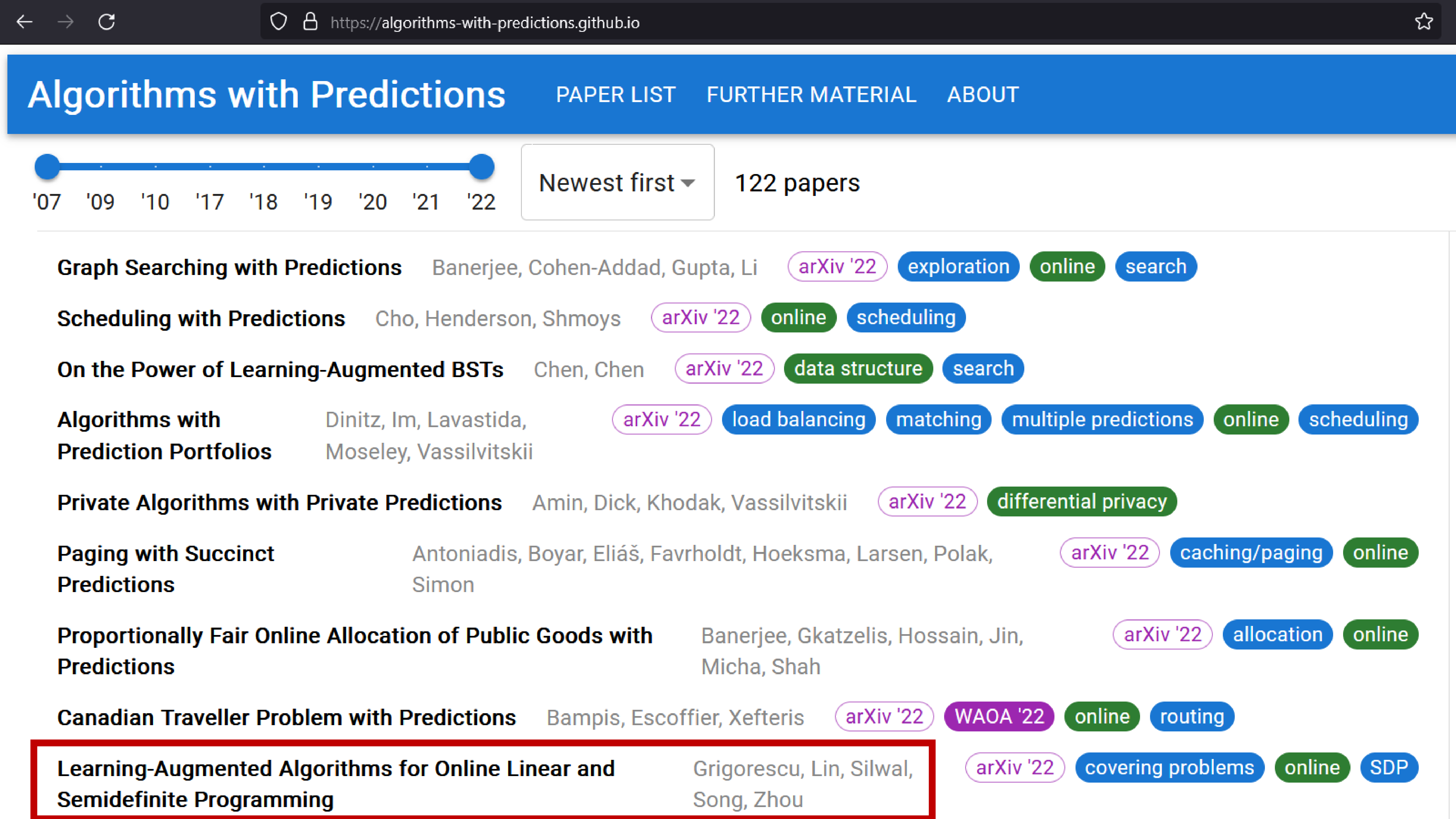
Today	73°	85°
Fri	73°	85°
Sat	72°	84°
Sun	72°	84°

6.890 Learning-Augmented Algorithms

Course : » Course 6 : » Spring 2019 : » 6.890 : »Materials







Algorithms with Predictions

Newest first

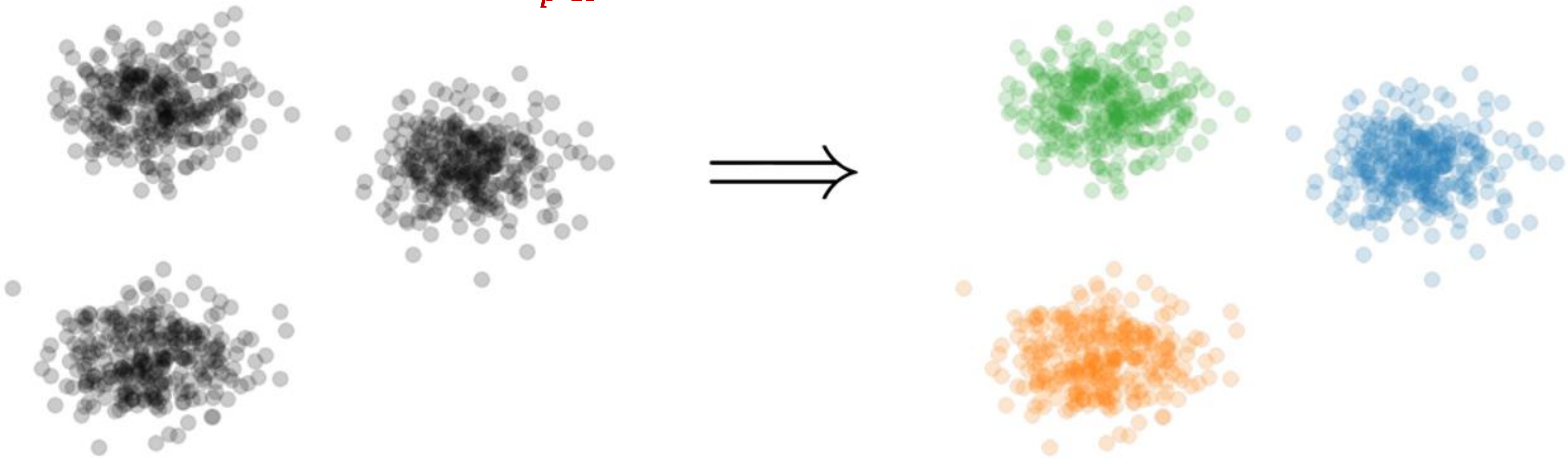
122 papers

Graph Searching with Predictions	Banerjee, Cohen-Addad, Gupta, Li	arXiv '22 exploration online search
Scheduling with Predictions	Cho, Henderson, Shmoys	arXiv '22 online scheduling
On the Power of Learning-Augmented BSTs	Chen, Chen	arXiv '22 data structure search
Algorithms with Prediction Portfolios	Dinitz, Im, Lavastida, Moseley, Vassilvitskii	arXiv '22 load balancing matching multiple predictions online scheduling
Private Algorithms with Private Predictions	Amin, Dick, Khodak, Vassilvitskii	arXiv '22 differential privacy
Paging with Succinct Predictions	Antoniadis, Boyar, Eliáš, Favrholdt, Hoeksma, Larsen, Polak, Simon	arXiv '22 caching/paging online
Proportionally Fair Online Allocation of Public Goods with Predictions	Banerjee, Gkatzelis, Hossain, Jin, Micha, Shah	arXiv '22 allocation online
Canadian Traveller Problem with Predictions	Bampis, Escoffier, Xefteris	arXiv '22 WAOA '22 online routing
Learning-Augmented Algorithms for Online Linear and Semidefinite Programming	Grigorescu, Lin, Silwal, Song, Zhou	arXiv '22 covering problems online SDP

Learning-Augmented Clustering

- Goal: Given dataset P in d dimensions, output a set C of k centers to minimize

$$\sum_{p \in P} \min_{c \in C} \|p - c\|_2^2$$



Learning-Augmented Clustering

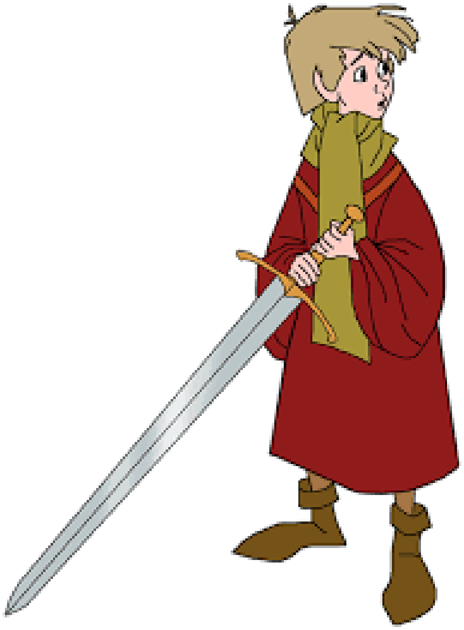
- Goal: Given dataset P in d dimensions, output a set C of k centers to minimize

$$\sum_{p \in P} \min_{c \in C} \|p - c\|_2^2$$

- NP-hard to even approximate within a factor of 1.07 [CC20, LSW17]
- Beyond worst case: Clustering on similar inputs or inputs with auxiliary information
- ML can guide the clustering!
- Our main message: We can avoid worst case with advice!

Predictor

- Suppose Π outputs noisy labels according to a $(1+\alpha)$ approximate clustering C and error rate $\lambda \leq \alpha$



What is the label of x_1?

x_1 belongs to cluster 3

What is the label of x_2?

x_2 belongs to cluster 7

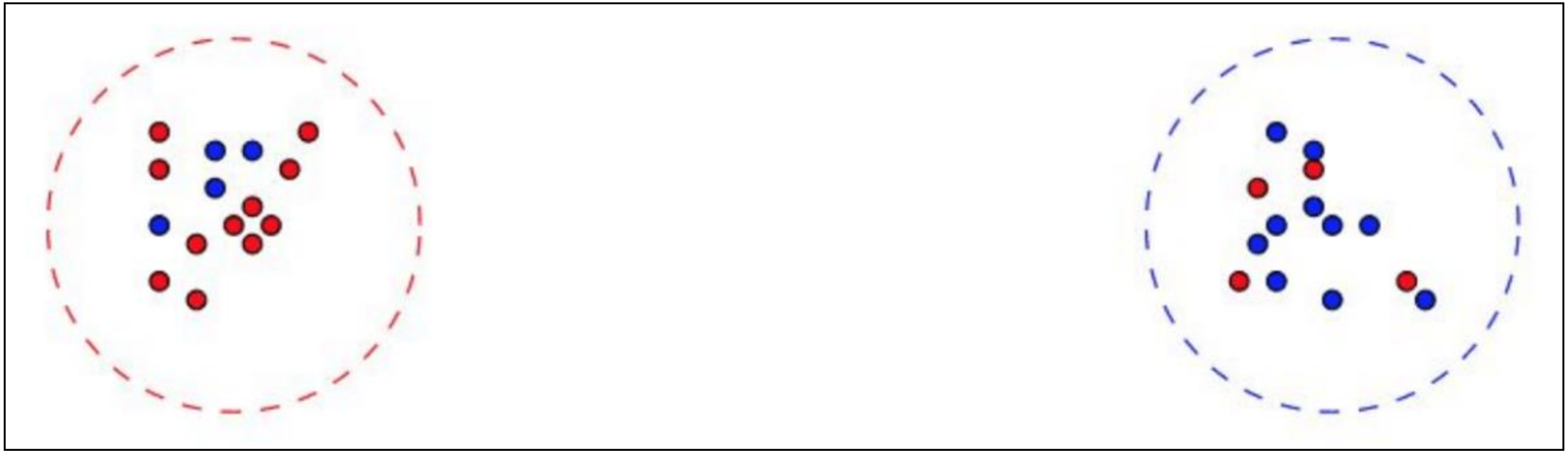
Theoretical Guarantee

- Suppose Π outputs noisy labels according to a $(1+\alpha)$ approximate clustering C and error rate $\lambda \leq \alpha$
- Main result [EFSWZ22]: Algorithm that outputs a $(1+O(\alpha))$ approximate k-means clustering in nearly linear time

- “Predictions can overcome complexity hardness barriers!”

Algorithmic Intuition

- Not enough to blindly follow predictions!



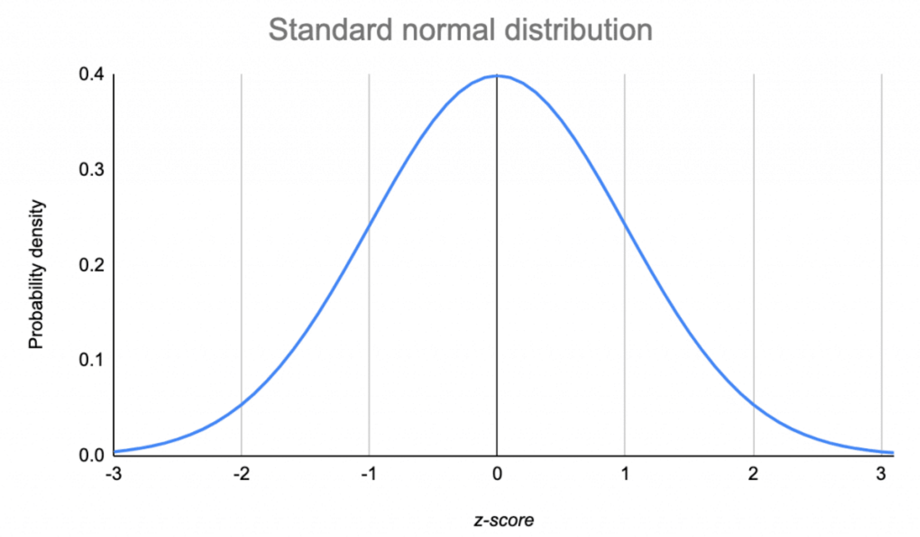
- Optimal cost ≈ 0
- Predictor with arbitrary small error has large cost!

Algorithmic Intuition

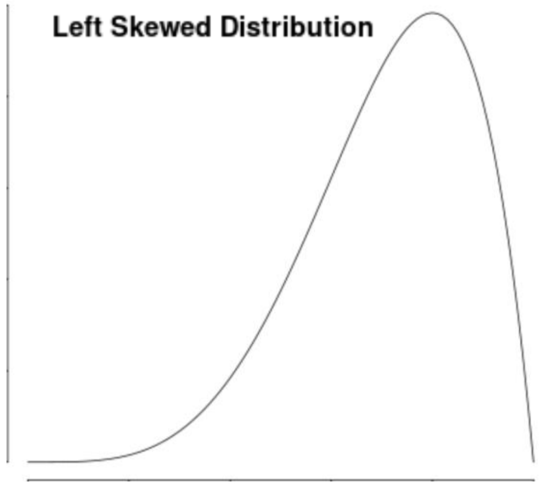
- Not enough to blindly follow predictions!

- Our approach: Use ideas from robust mean estimation

$(1-\varepsilon)P$



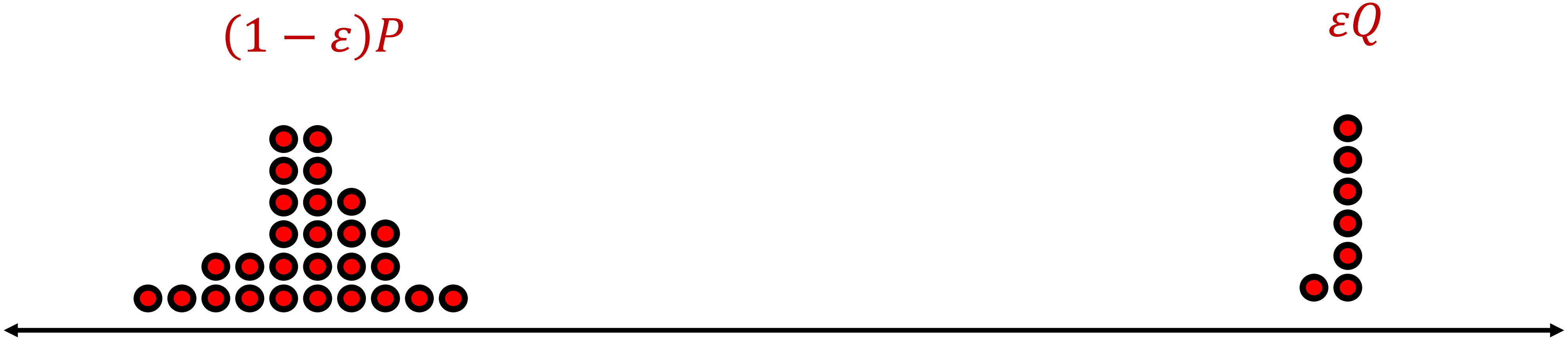
εQ



Algorithmic Intuition

- Not enough to blindly follow predictions!

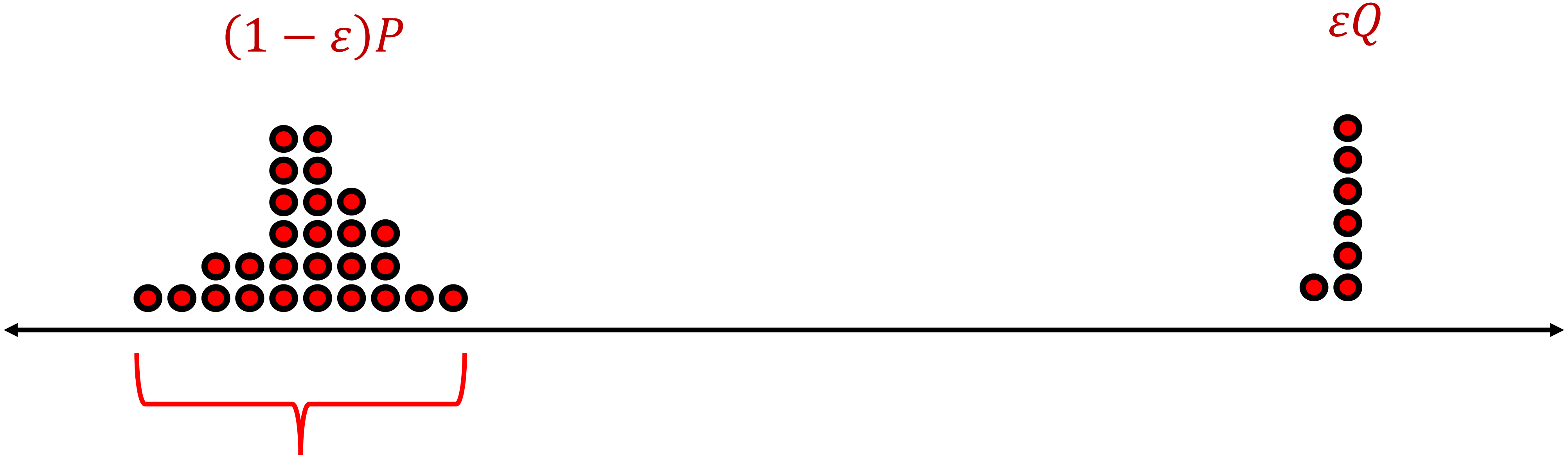
- Our approach: Use robust mean estimation



Algorithmic Intuition

- Not enough to blindly follow predictions!

- Our approach: Use robust mean estimation



Algorithmic Intuition

- Not enough to blindly follow predictions!

- Our approach: Use robust mean estimation

- We exploit the fact that cluster centers are means of points!

Algorithmic Intuition

- Not enough to blindly follow predictions!
- Our approach: Use robust mean estimation
- We exploit the fact that cluster centers are means of points!
- Introduces a new set of tools for k-means clustering

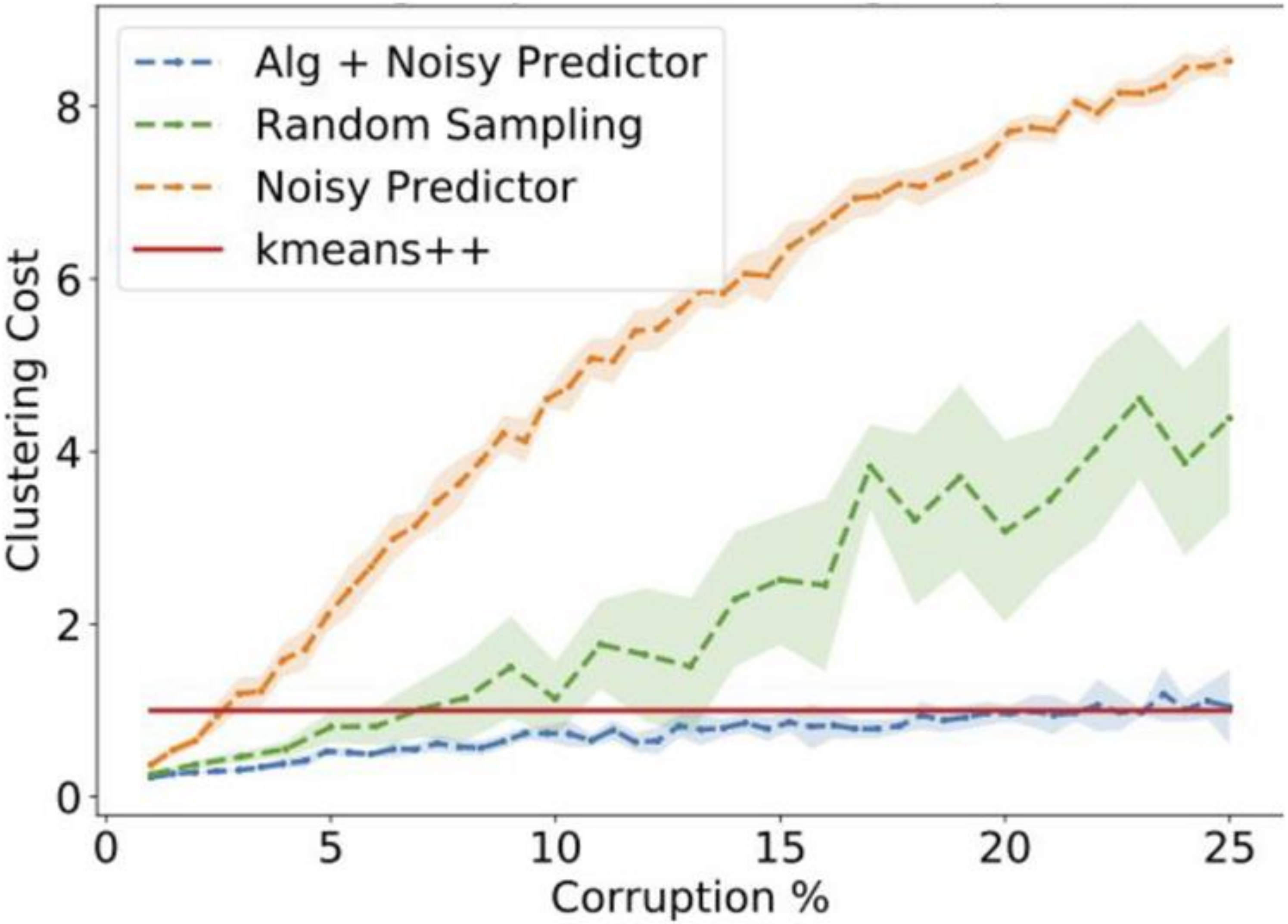
Experimental Results

- Case Study: Spectral clustering on graphs varying over time

- Dataset: Internet router graph varying over the course of a year

- Methodology: Compare to standard benchmarks while using various natural predictors, i.e., noisily perturb true labels and compare to baselines as function of error

Dataset: Internet router graph varying over the course of a year, $k = 10$



Conclusion: Our algorithm (using predictor) outperforms benchmarks such as k-means ++ for low error while staying competitive with high corruptions

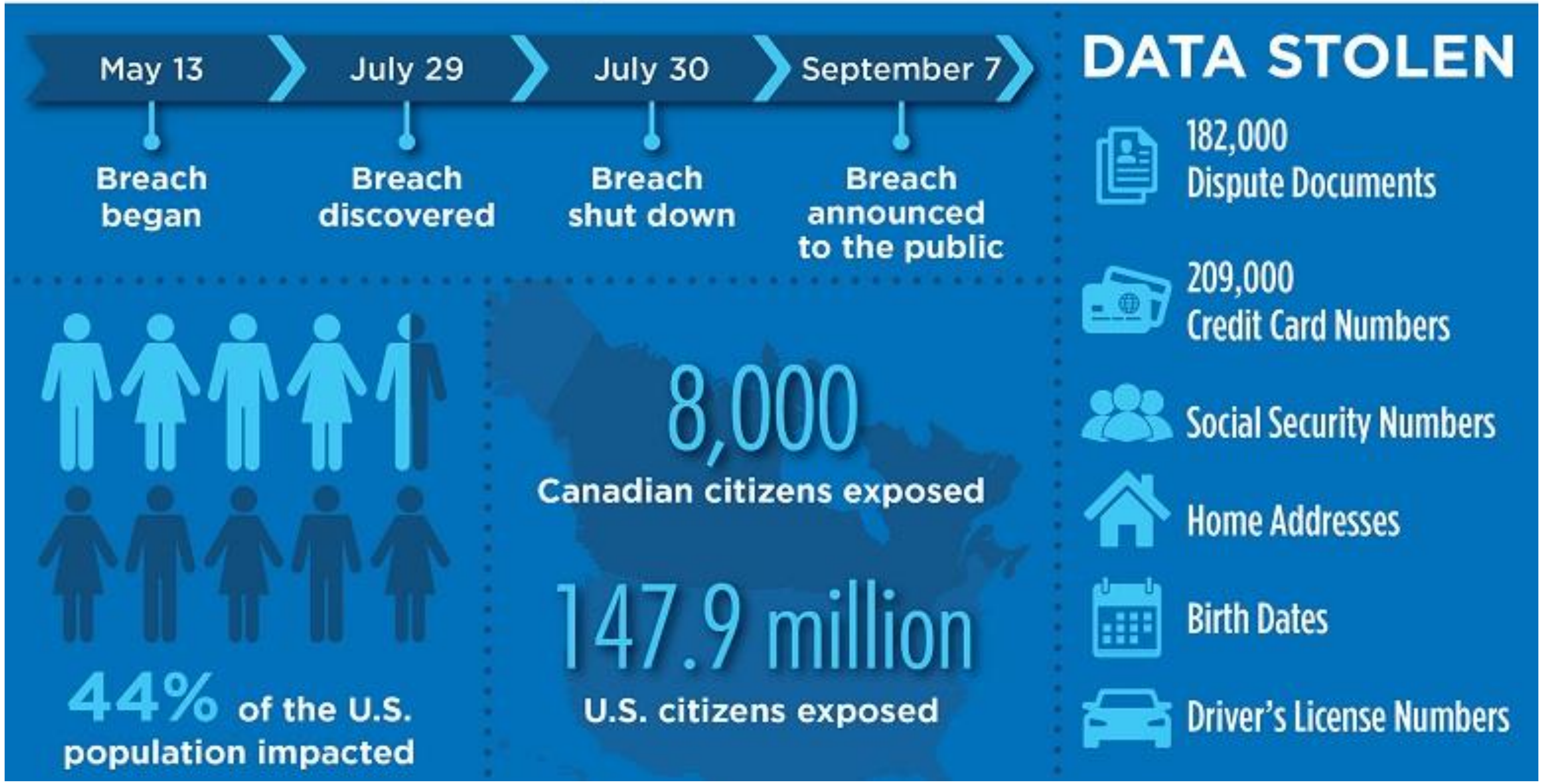
My Recent Work on Data Science

- Learning-Augmented k-means Clustering (ICLR 2022)
- Fast Regression for Structured Inputs (ICLR 2022)
- New Coresets for Projective Clustering and Applications (AISTATS 2022)
- Dimensionality Reduction for Wasserstein Barycenter (NeurIPS 2021)
- Learning a Latent Simplex in Input Sparsity Time (ICLR 2021)
- Near Optimal Linear Algebra in the Online and Sliding Window Models (FOCS 2020)
- Data-Independent Neural Pruning via Coresets (ICLR 2020)
- Adversarially Robust Submodular Maximization under Knapsack Constraints (KDD 2019)

Questions?

Security and Privacy for Big Data

2017 Equifax Data Breach

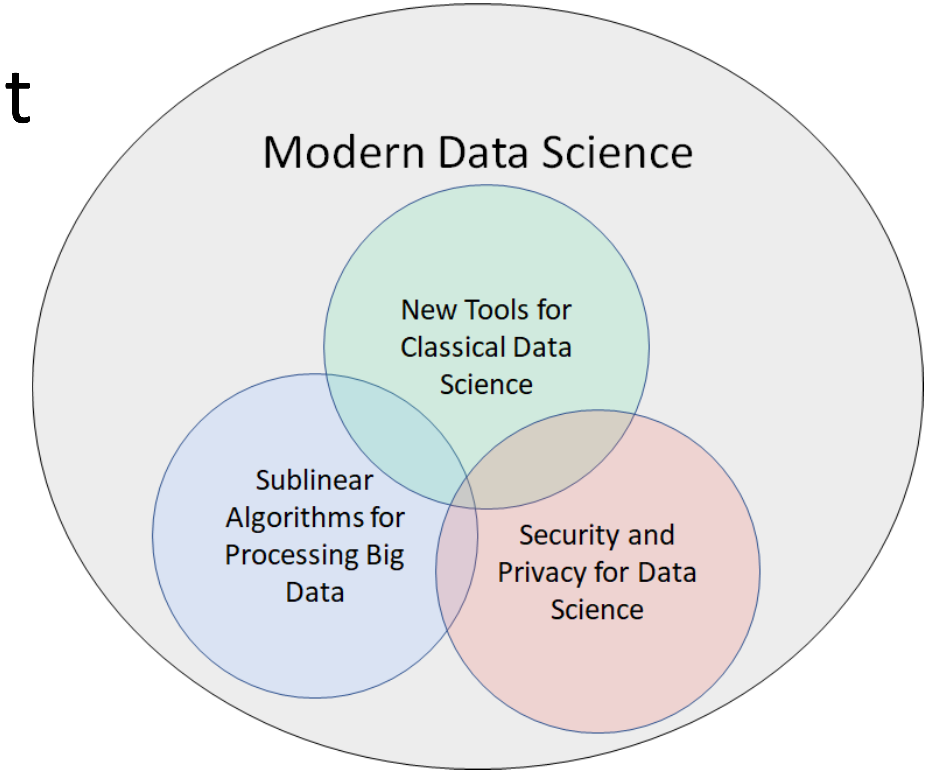


“Equifax agreed to a $700 million settlement over the privacy breach, but $425 million of that was set aside to repay consumers as a restitution fund.”

YAHOO!
UBER
Gmail
by Google
Adobe
BLIZZARD
ENTERTAINMENT
eHarmony
AMERICA
Online
U.S. DEPARTMENT OF HOMELAND SECURITY
LastPass
****
ebay
Dropbox
LinkedIn
PlayStation

Evolving Demands

- Sublinear-time or sublinear-space algorithms
- Incorporation of advice
- Security and privacy
- Robustness to noise or adversarial input
- Ability to handle time-sensitive data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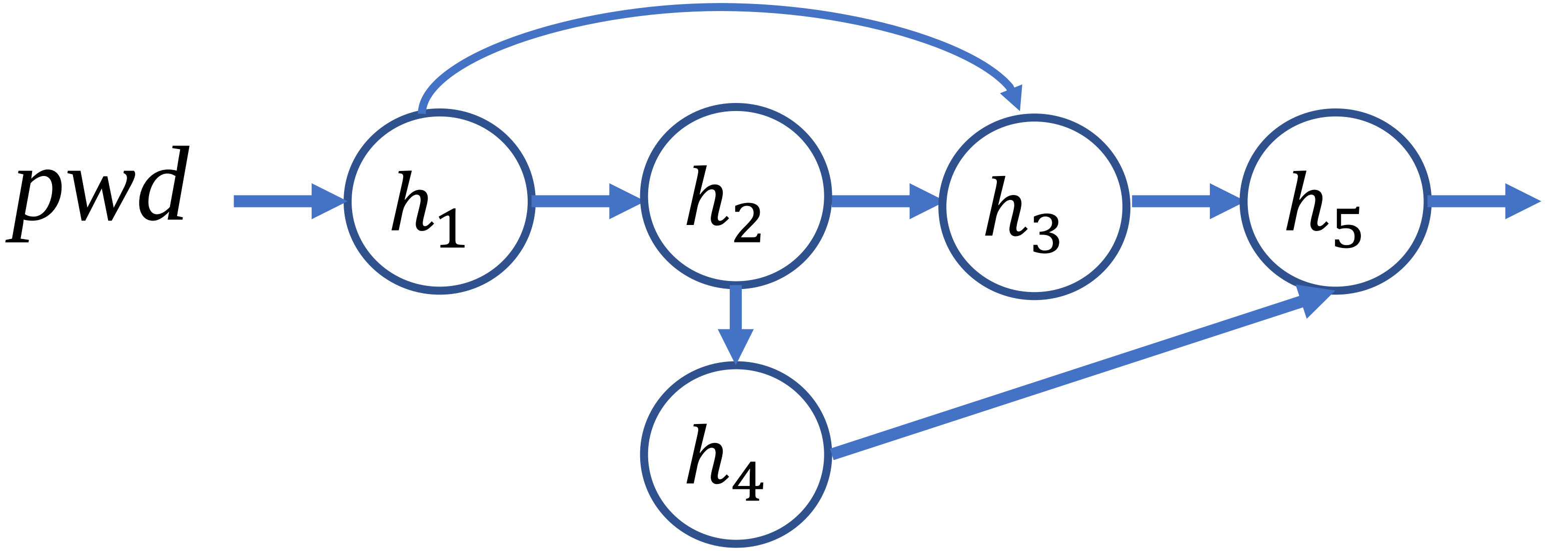
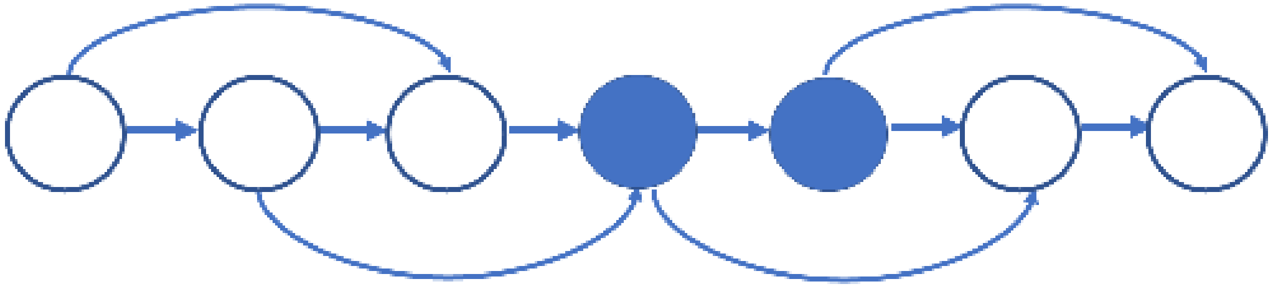
Graph Theory for Memory Hard Functions

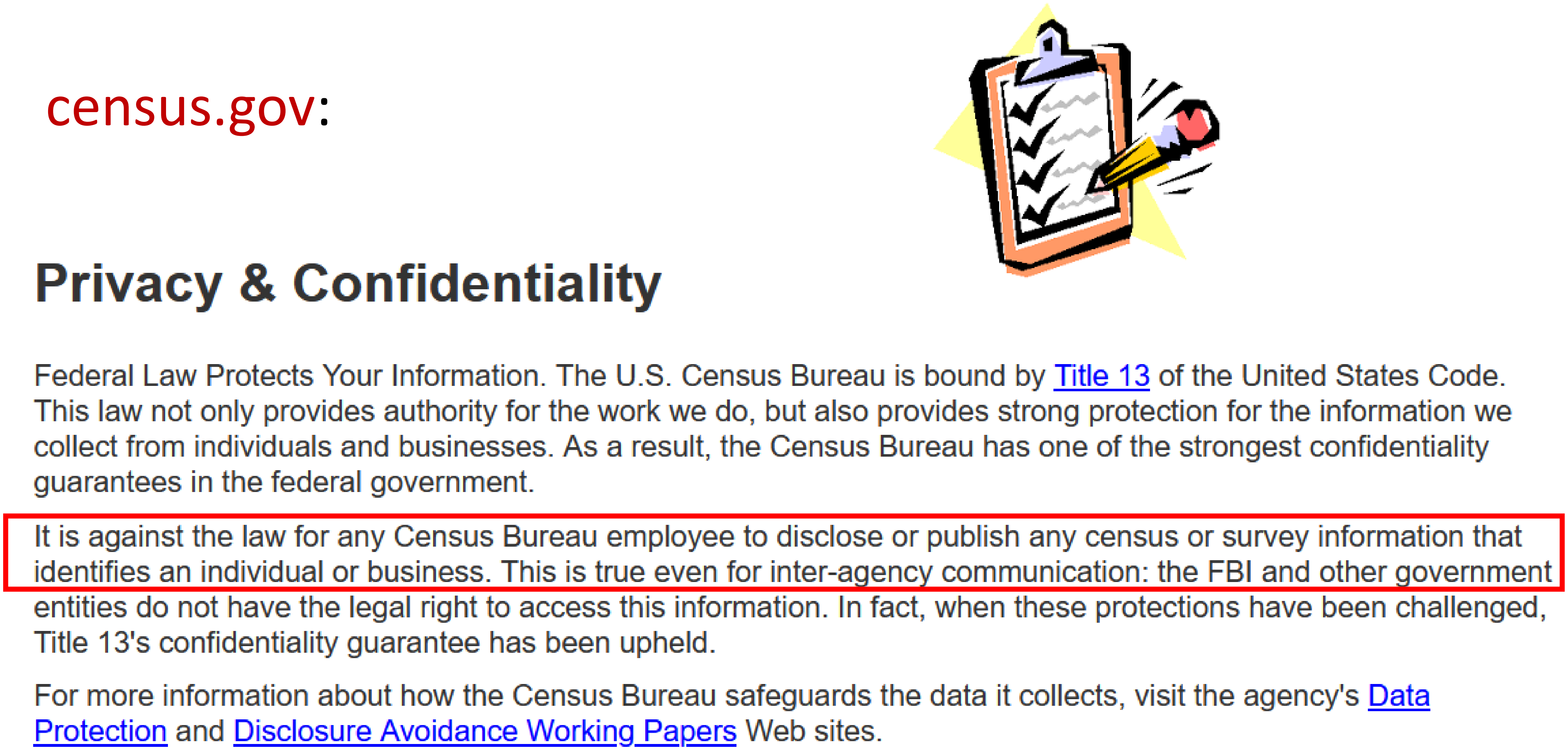


Graph Theory for Memory Hard Functions

- Proved the security benefits of memory-hard functions using an economic marginal cost-revenue analysis [BHZ18]
- Showed the hardness of computing [BZ18] and approximating the computational cost [BLZ20] of graph pebbling
- Applied graph theory to cryptanalyze the computational complexity of memory-hard functions [BZ18, BRZ18]



census.gov:



Privacy & Confidentiality

Federal Law Protects Your Information. The U.S. Census Bureau is bound by Title 13 of the United States Code. This law not only provides authority for the work we do, but also provides strong protection for the information we collect from individuals and businesses. As a result, the Census Bureau has one of the strongest confidentiality guarantees in the federal government.

It is against the law for any Census Bureau employee to disclose or publish any census or survey information that identifies an individual or business. This is true even for inter-agency communication: the FBI and other government entities do not have the legal right to access this information. In fact, when these protections have been challenged, Title 13's confidentiality guarantee has been upheld.

For more information about how the Census Bureau safeguards the data it collects, visit the agency's Data Protection and Disclosure Avoidance Working Papers Web sites.

Anonymizing Data

Age	Zip Code	Employer	Has Pet
56	77005	Apple	Yes
32	77005	Microsoft	No
71	77005	Amazon	Yes
44	77005	Petsmart	Yes
25	77005	Netflix	No
61	77005	Google	No

Anonymizing Data

Age	Zip Code	Employer	Has Pet
56	77005	Apple	Yes
32	77005	Microsoft	No
71	77005	Amazon	Yes
44	77005	Petsmart	Yes
25	77005	Netflix	No
61	77005	Google	No

Name	Age	Gender	Employer
Alice	56	Female	Apple
Bob	32	Male	Microsoft
Carol	71	Female	Amazon
Dale	44	Male	Petsmart
Erin	25	Female	Netflix
Fred	61	Male	Google

Reconstruction Attack

Name	Age	Zip Code	Gender	Employer	Has Pet
Alice	56	77005	Female	Apple	Yes
Bob	32	77005	Male	Microsoft	No
Carol	71	77005	Female	Amazon	Yes
Dale	44	77005	Male	Petsmart	Yes
Erin	25	77005	Female	Netflix	No
Fred	61	77005	Male	Google	No

Implications of the simulated attack

The Census Bureau believed in 2010 that it was necessary to coarsen geographic identifiers in microdata such that the minimum population in any published geography was at least 100,000 persons (Public-Use Microdata Areas).

Our simulated reconstruction-abetted re-identification attack demonstrated that the tabular summaries from the 2010 Census can be converted into a 100% microdata file with geographic precision to the census block-level.

Our simulated attack demonstrated that, depending on the quality of the external data used, between 52 and 179 million respondents to the 2010 Census can be correctly re-identified from the reconstructed microdata.

Stronger privacy protections, such as those in the 2020 Census Disclosure Avoidance System, are necessary to protect against reconstruction-abetted attacks.

Differential Privacy

- [DMNS06] Given $\varepsilon > 0$ and $\delta \in (0,1)$, a randomized algorithm $A: U^* \rightarrow Y$ is (ε, δ)-differentially private if, for every neighboring frequency vectors f and f' and for all $E \subseteq Y$,

$$\Pr[A(f) \in E] \leq e^{\varepsilon} \Pr[A(f') \in E] + \delta$$

$A($ $) \approx A($ $)$

Differential Privacy Result Highlights

- Framework for converting FPTAS/FPRAS algorithms to private FPTAS/FPRAS algorithms [BGMZ22]

- Privacy has a price in memory cost [DSWZ23]

- No overhead in communication cost for summation in the differentially oblivious shuffle model [GKNMZ22]

My Recent Work on Security and Privacy

- Private Data Stream Analysis for Universal Symmetric Norm Estimation (FORC 2022)
- On the Security of Proofs of Sequential Work in a Post-Quantum World (ITC 2021)
- Approximating Cumulative Pebbling Cost is Unique Games Hard (ITCS 2020)
- Computationally Data-Independent Memory Hard Functions (ITCS 2020)
- Data-Independent Memory Hard Functions: New Attacks and Stronger Constructions (CRYPTO 2019)
- Bandwidth-Hard Functions: Reductions and Lower Bounds (CCS 2018)
- On the Economics of Offline Password Cracking (Security and Privacy 2018)

Questions?

Sublinear Algorithms for Processing Big Data

Model #1: Streaming Model

- Input: Elements of an underlying data set S, which arrives sequentially
- Output: Evaluation (or approximation) of a given function
- Goal: Use space *sublinear* in the size m of the input S

1 0 1 1 1 0 0 1

Frequency Vector

- Given a set S of m elements from $[n]$, let f_i be the frequency of element i. (How often it appears)

$$1\ 1\ 2\ 1\ 2\ 1\ 1\ 2\ 3 \rightarrow [5, 3, 1, 0] \coloneqq f$$

Heavy-Hitters (Frequent Items)

- Given a set S of m elements from $[n]$, let f_i be the frequency of element i. (How often it appears)
- Let L_2 be the norm of the frequency vector:

$$L_2 = \sqrt{f_1^2 + f_2^2 + \cdots + f_n^2}$$

- Goal: Given a set S of m elements from $[n]$ and a threshold ε, output the elements i such that $f_i > \varepsilon\, L_2$...and no elements j such that $f_j < \frac{\varepsilon}{16}\, L_2$
- Motivation: DDoS prevention, iceberg queries

Frequency Moments (L_p Norm)

- Given a set S of m elements from $[n]$, let f_i be the frequency of element i. (How often it appears)
- Let F_p be the frequency moment of the vector:

$$F_p = f_1^p + f_2^p + \cdots + f_n^p$$

- Goal: Given a set S of m elements from $[n]$ and an accuracy parameter ε, output a $(1 + \varepsilon)$-approximation to F_p
- Motivation: Entropy estimation, linear regression

Distinct Elements (F_0 Estimation)

- Given a set S of m elements from $[n]$, let f_i be the frequency of element i. (How often it appears)
- Let F_0 be the frequency moment of the vector:

$$F_0 = |\{i : f_i \neq 0\}|$$

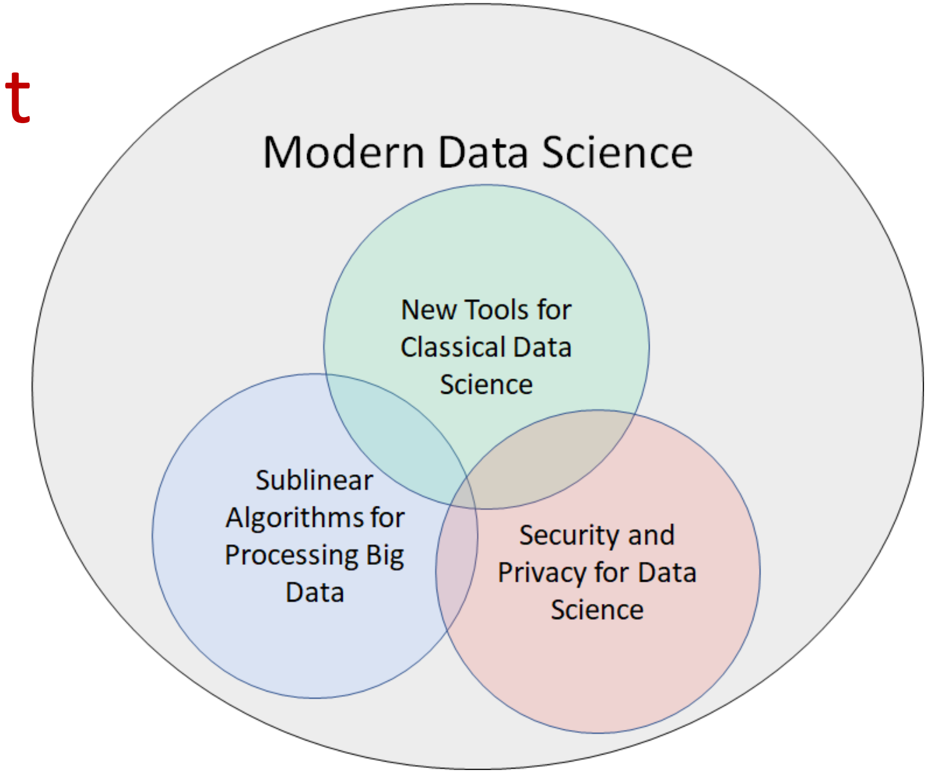
- Goal: Given a set S of m elements from $[n]$ and an accuracy parameter ε, output a $(1+\varepsilon)$-approximation to F_0
- Motivation: Traffic monitoring

$(1+\varepsilon)$-Approximation Streaming Algorithms

- $\Theta\left(\frac{1}{\varepsilon^2}\right)$ space-accuracy tradeoff for distinct elements, i.e., F_0 [KNW10, Blasiok20]
- $\Theta\left(\frac{1}{\varepsilon^2}\right)$ space-accuracy tradeoff for F_p with $p \in (0,2]$ [BDN17]
- $\Theta\left(\frac{1}{\varepsilon^2}\right)$ space-accuracy tradeoff for F_p with $p > 2$ [Ganguly11, GW18]
- $\Theta\left(\frac{1}{\varepsilon^2}\right)$ space-accuracy tradeoff for L_2-heavy hitters [BCINWW17]

Evolving Demands

- Sublinear-time or sublinear-space algorithms
- Incorporation of advice
- Security and privacy
- Robustness to noise or adversarial input
- Ability to handle time-sensitive data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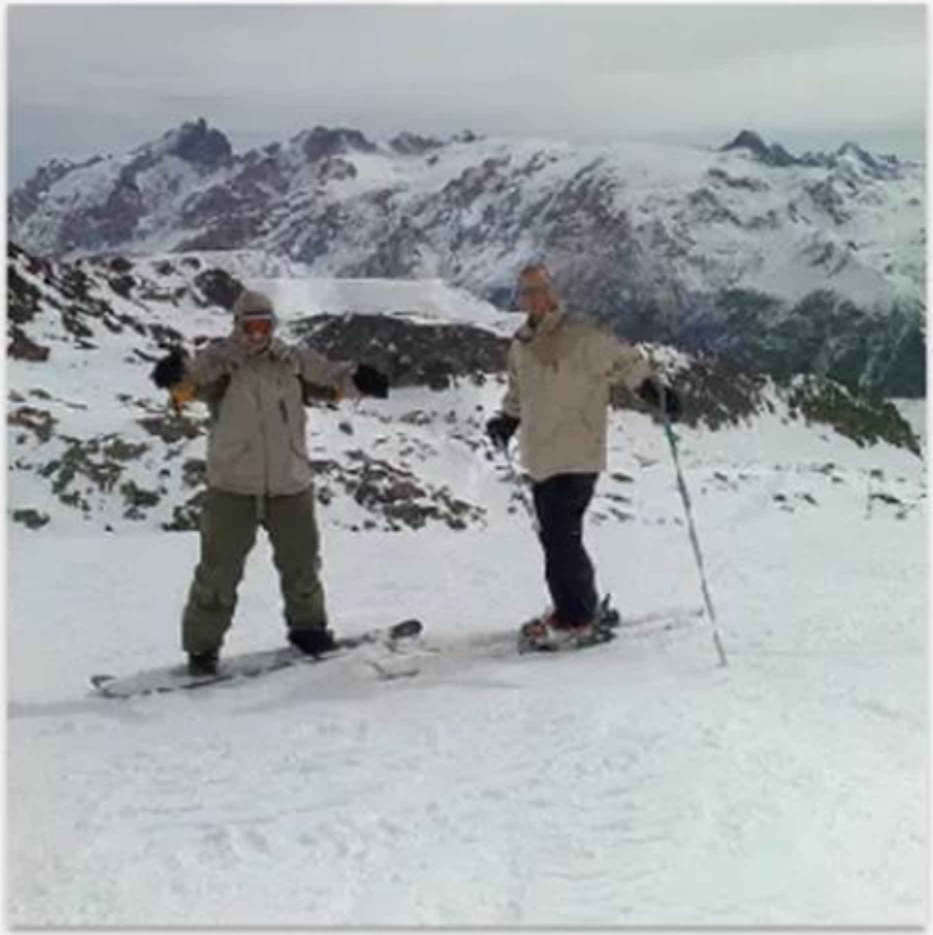
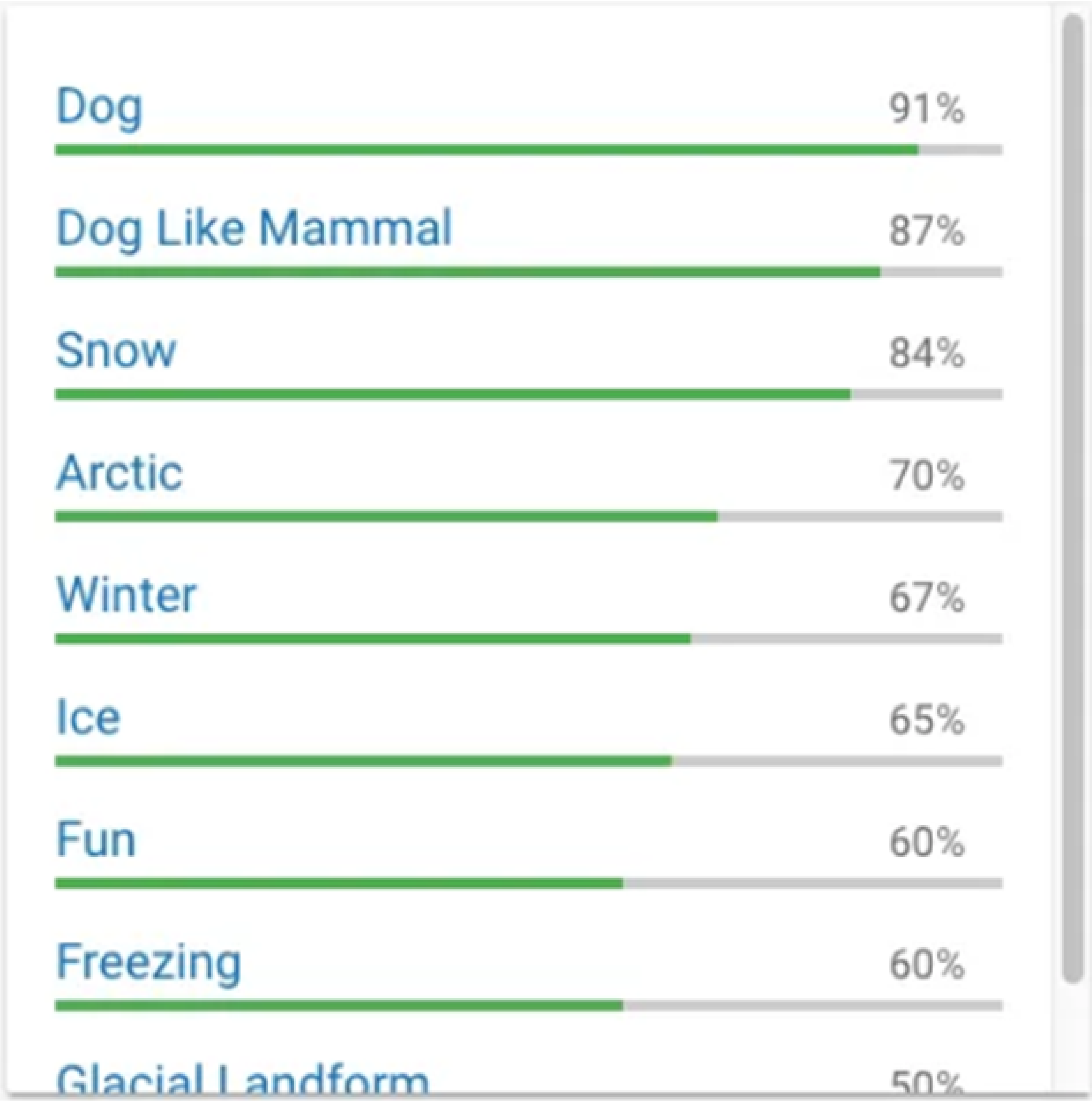


skier_adv.png

Human readers will easily identify the image as showing two men on skis. Google's Cloud Vision service reported being 91 percent certain it saw a dog. Other stunts have shown how to make stop signs invisible, or audio that sounds benign to humans but is transcribed by software as "OK Google browse to evil dot com."

LABSIX



Dog	91%
Dog Like Mammal	87%
Snow	84%
Arctic	70%
Winter	67%
Ice	65%
Fun	60%
Freezing	60%
Glacial Landform	50%

Model #2: Adversarially Robust Streaming

- Input: Elements of an underlying data set S, which arrives sequentially and *adversarially*
- Output: Evaluation (or approximation) of a given function
- Goal: Use space *sublinear* in the size m of the input S

1

1

Model #2: Adversarially Robust Streaming

- Input: Elements of an underlying data set S, which arrives sequentially and *adversarially*
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10

1

Model #2: Adversarially Robust Streaming

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- Goal: Use space *sublinear* in the size m of the input S

101

2

Model #2: Adversarially Robust Streaming

- Input: Elements of an underlying data set S, which arrives sequentially and *adversarially*
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- Goal: Use space *sublinear* in the size m of the input S

1010

3

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1010

3

$(1+\varepsilon)$-Robust Algorithms [WZ21]

- $\tilde{\Theta}\left(\frac{1}{\varepsilon^2}\right)$ space-accuracy tradeoff for distinct elements, i.e., F_0
- $\tilde{\Theta}\left(\frac{1}{\varepsilon^2}\right)$ space-accuracy tradeoff for F_p with $p \in (0,2]$
- $\tilde{\Theta}\left(\frac{1}{\varepsilon^2}\right)$ space-accuracy tradeoff for F_p with integer $p > 2$
- $\tilde{\Theta}\left(\frac{1}{\varepsilon^2}\right)$ space-accuracy tradeoff for L_2-heavy hitters

“No losses* are necessary!”

15-859 Algorithms for Big Data — Fall 2022

Problem Set 3

Due: Tuesday, November 8, 11:59pm

Problem 2: F_2-Difference Estimator in a Stream (25 points)
In this problem we consider insertion-only streams, meaning that we just see positive updates to an underlying vector $x \in \{0, 1, 2, \ldots, M\}^n$ for some $M = \mathrm{poly}(n)$. That is, no negative changes to coordinates of x are allowed. We will consider estimating $\|x\|_2^2$ up to a $(1+\epsilon)$-multiplicative factor.

Often x is *slowly-changing*, meaning that at some point in the stream $x = u$ and then at some later point in the stream $x = u + v$ for some $v \in \{0, 1, 2, \ldots, M\}^n$, and we have $\|u+v\|_2^2 - \|u\|_2^2 \leq \gamma\|u\|_2^2$ and $\|v\|_2^2 \leq \gamma\|u\|_2^2$ for some $0 < \gamma < 1$. You would like to estimate $\|u+v\|_2^2$ using your previous estimate $\|u\|_2^2$ and using very little space. Show how to estimate $\|u+v\|_2^2$ up to a $(1 \pm \epsilon)$-multiplicative factor with probability at least 9/10, given a $(1 \pm \epsilon/2)$-approximation to $\|u\|_2^2$ and a sketch which uses space $O(\gamma\epsilon^{-2}\log n)$ bits. You can assume that you initialize $x = 0$ and after processing some number of updates you will have $x = u$ at which point you are given a $1 \pm \epsilon/2$ approximation to $\|u\|_2^2$. Then you start processing the rest of the updates and finally end up setting $x = u + v$ and at the end of the stream you want to output a $1 \pm \epsilon$ approximation to $\|u+v\|_2^2$.

Note that if $\gamma = \Theta(1)$, then there is no improvement over just estimating $\|u+v\|_2^2$ directly using the sketch from class. However, if for example, $\gamma = \Theta(\epsilon)$, then the memory is only $O(\epsilon^{-1}\log n)$ bits, which is a significant savings.

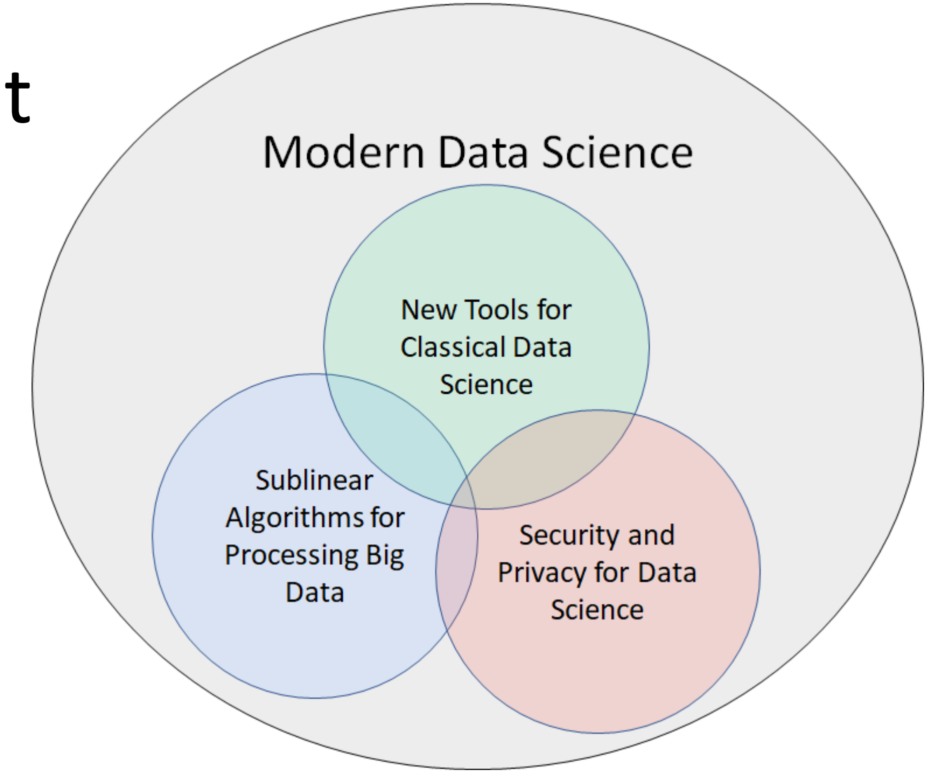
Additional Work

- [BHMSSZ22] showed that "sampling-based" algorithms achieve adversarial robustness "for-free"
- [ABJSSWZ22] showed impossibility results for many natural problems for "white-box" adversaries
- [ABJSSWZ22] gave a sublinear-space algorithm for estimating F_0 when the white-box adversary has polynomial computation time

- Open Questions: 1) Is anything non-trivial possible for "black-box" adversaries that are allowed to delete elements? 2) Can lattice-based crypto be used for other algorithms robust to white-box adversaries?

Evolving Demands

- Sublinear-time or sublinear-space algorithms
- Incorporation of advice
- Security and privacy
- Robustness to noise or adversarial input
- Ability to handle time-sensitive data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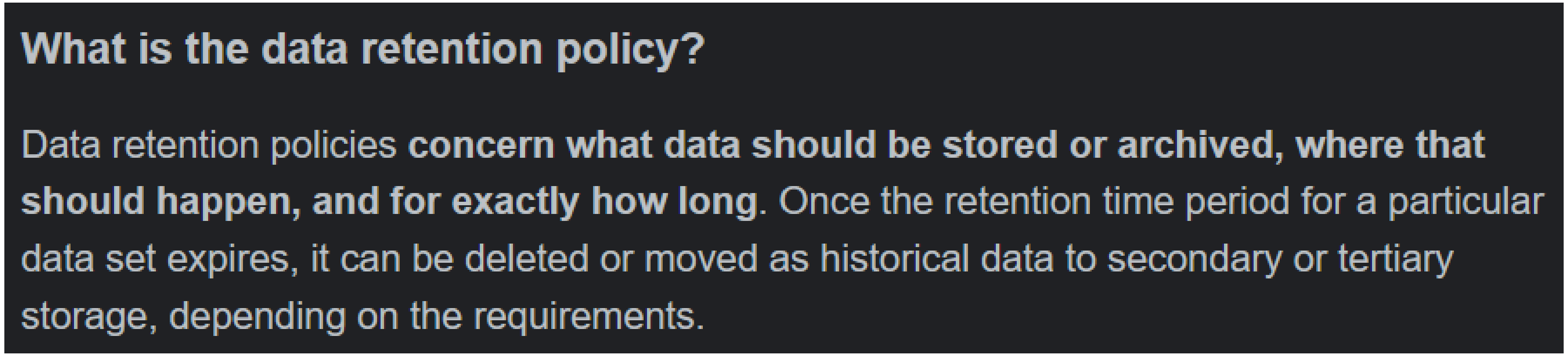
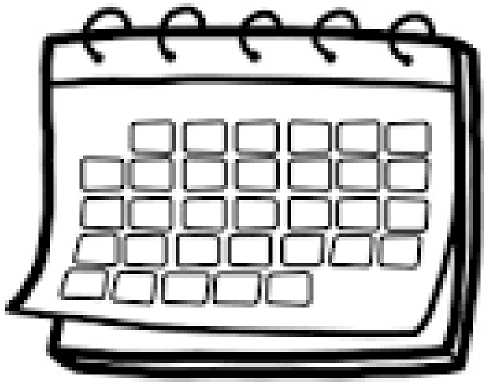
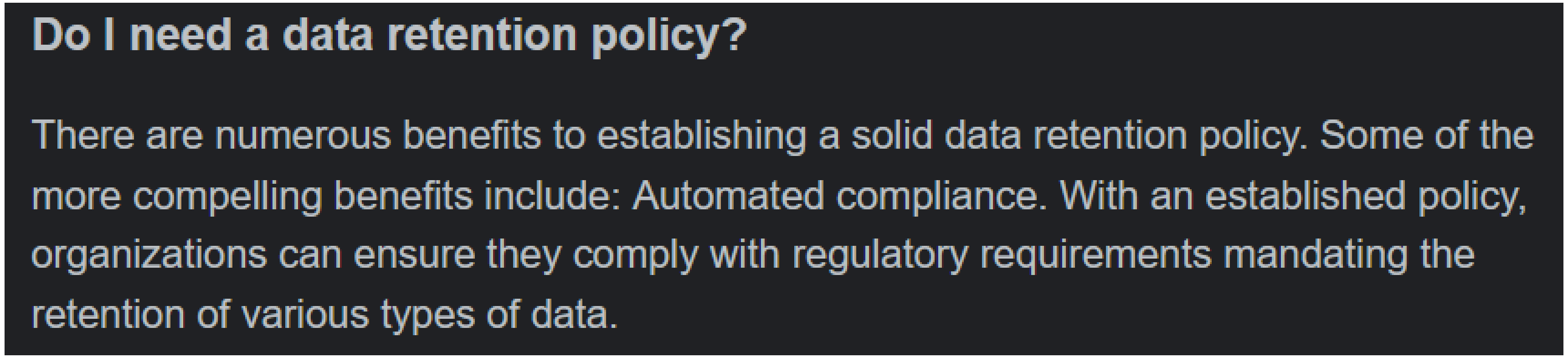
"Facebook data policy retains user search histories for 6 months, the Apple differential privacy overview states that collected data is retained for 3 months, the Google data retention policy states that browser information may be stored for up to 9 months"



What is the data retention policy?

Data retention policies **concern what data should be stored or archived, where that should happen, and for exactly how long**. Once the retention time period for a particular data set expires, it can be deleted or moved as historical data to secondary or tertiary storage, depending on the requirements.





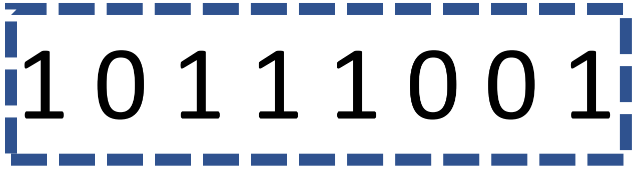
Do I need a data retention policy?

There are numerous benefits to establishing a solid data retention policy. Some of the more compelling benefits include: Automated compliance. With an established policy, organizations can ensure they comply with regulatory requirements mandating the retention of various types of data.

Model #3: Sliding Window Model

- Input: Elements of an underlying data set S, which arrives sequentially
- Output: Evaluation (or approximation) of a given function
- Goal: Use space *sublinear* in the size m of the input S

- Sliding Window: "Only the m most recent updates form the underlying data set S"



1 0 1 1 1 0 0 1

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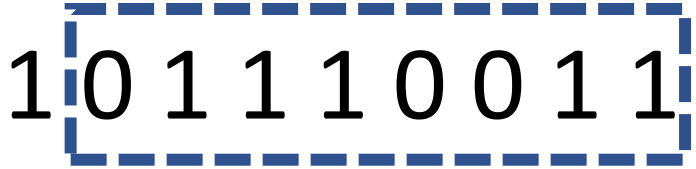

1 0 1 1 1 0 0 1 1

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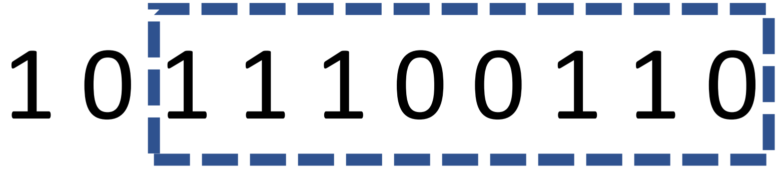

1 0 1 1 1 0 0 1 1 0

Model #3: Sliding Window Model

- Input: Elements of an underlying data set S, which arrives sequentially
- Output: Evaluation (or approximation) of a given function
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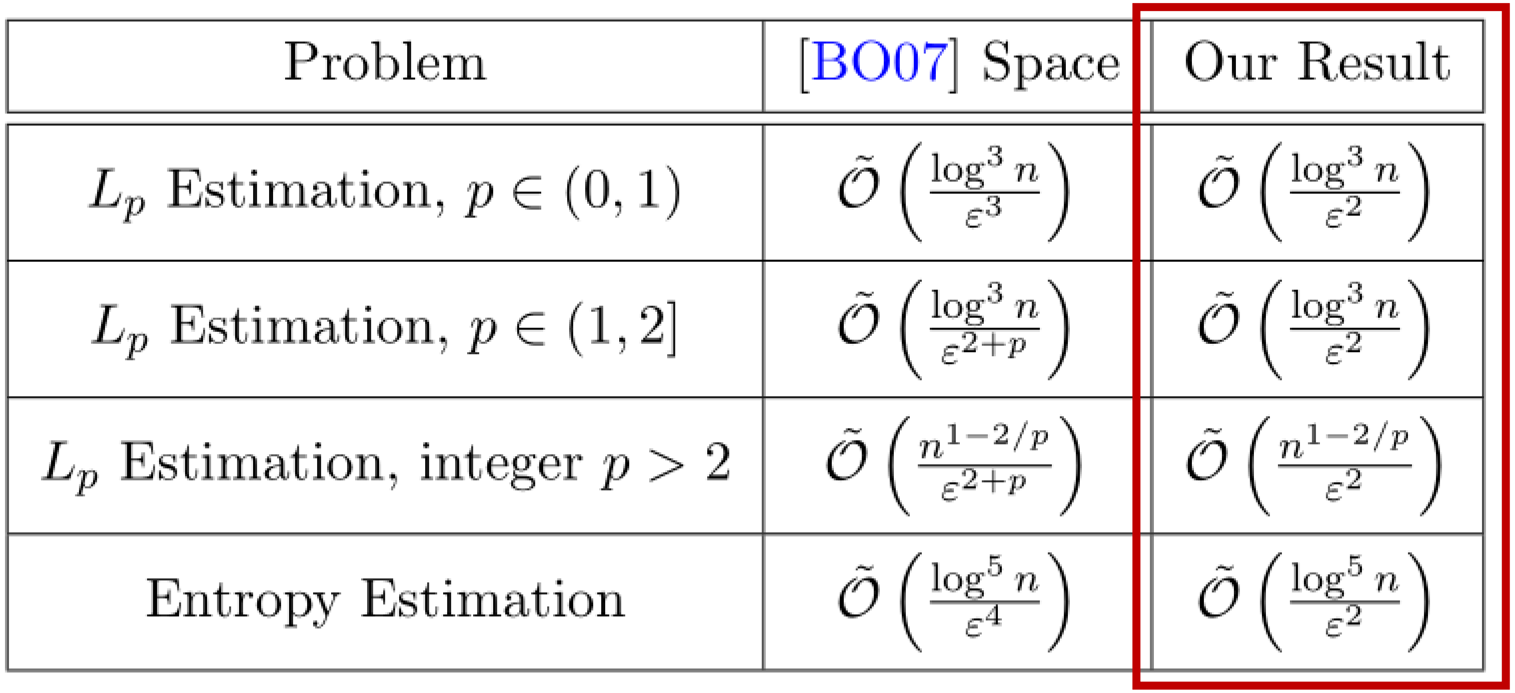
- Sliding Window: “Only the m most recent updates form the underlying data set S”
  - Emphasizes recent interactions, appropriate for time sensitive settings

$$1\ 0\ 1\ \boxed{1\ 1\ 0\ 0\ 1\ 1\ 0\ 1}$$

$(1+\varepsilon)$-Approximation Sliding Window Algorithms [WZ21]

- Space $\tilde{\Theta}\left(\frac{1}{\varepsilon^2}\right)$ algorithm for F_p with $p \in (0,2]$ [WZ21]



Problem	[BO07] Space	Our Result
L_p Estimation, $p \in (0,1)$	$\tilde{\mathcal{O}}\left(\frac{\log^3 n}{\varepsilon^3}\right)$	$\tilde{\mathcal{O}}\left(\frac{\log^3 n}{\varepsilon^2}\right)$
L_p Estimation, $p \in (1,2]$	$\tilde{\mathcal{O}}\left(\frac{\log^3 n}{\varepsilon^{2+p}}\right)$	$\tilde{\mathcal{O}}\left(\frac{\log^3 n}{\varepsilon^2}\right)$
L_p Estimation, integer $p > 2$	$\tilde{\mathcal{O}}\left(\frac{n^{1-2/p}}{\varepsilon^{2+p}}\right)$	$\tilde{\mathcal{O}}\left(\frac{n^{1-2/p}}{\varepsilon^2}\right)$
Entropy Estimation	$\tilde{\mathcal{O}}\left(\frac{\log^5 n}{\varepsilon^4}\right)$	$\tilde{\mathcal{O}}\left(\frac{\log^5 n}{\varepsilon^2}\right)$

"No losses* are necessary!"

$(1+\varepsilon)$-Approximation Sliding Window Algorithms [BGLWZ18]

- $\tilde{\Theta}\left(\frac{1}{\varepsilon^2}\right)$ space-accuracy tradeoff for F_0, i.e., distinct elements
- $\tilde{\Theta}\left(\frac{1}{\varepsilon^2}\right)$ space-accuracy tradeoff for L_2-heavy hitters

- We give nearly tight new upper and lower bounds for these problems!

RandNLA in the Sliding Window Model

- First algorithms for problems in numerical linear algebra in the sliding window model [BDMMUWZ20]

- $O(d^2)$ space randomized sliding window algorithm for spectral sparsification (space optimal, up to lower order terms)
- $O(dk)$ space randomized sliding window algorithm for low-rank approximation (space optimal, up to lower order terms)
- $O(d^3)$ space randomized sliding window algorithm for ℓ_1 subspace embedding

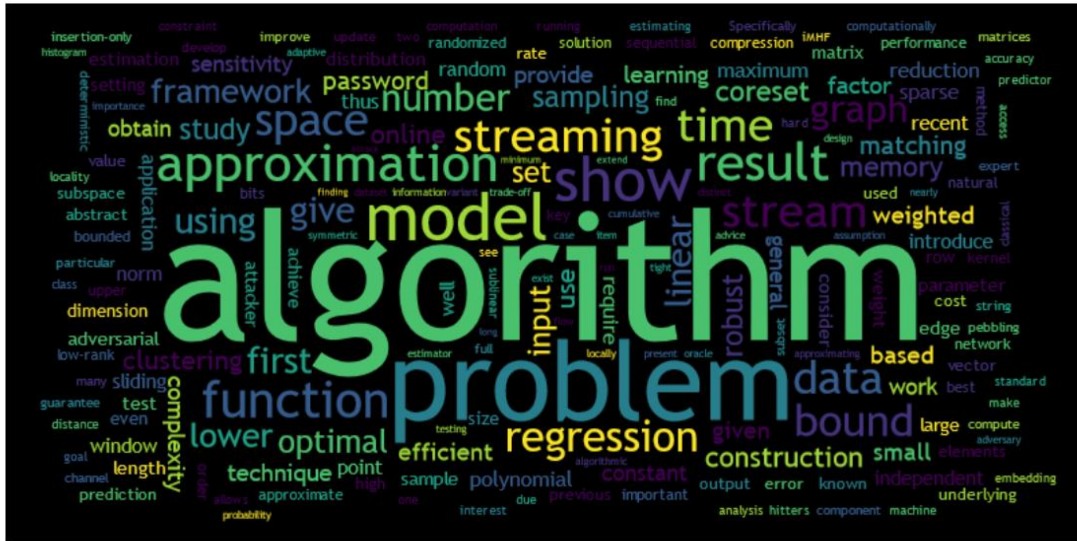
My Recent Work on Sublinear Algorithms

- Memory Bounds for the Experts Problem (STOC 2022)
- The White-Box Adversarial Data Stream Model (PODS 2022)
- Truly Perfect Samplers for Data Streams and Sliding Windows (PODS 2022)
- Noisy Boolean Hidden Matching with Applications (ITCS 2022)
- Adversarial Robustness of Streaming Algorithms through Importance Sampling (NeurIPS 2021)
- Tight Bounds for Adversarially Robust Streams and Sliding Windows via Difference Estimators (FOCS 2021)
- Separations for Estimating Large Frequency Moments on Data Streams (ICALP 2021)
- Non-Adaptive Adaptive Sampling on Turnstile Streams (STOC 2020)

Future Research Directions

- Adversarial robustness for data science/ML
- Limits of learning-augmented algorithms, beyond NP-hardness, better utility bounds for DP
- Data science with fairness considerations

- Evolving demands of the future!

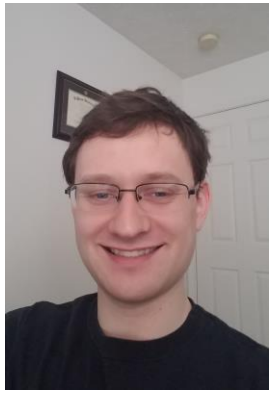


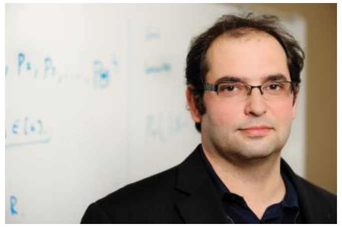
Future Agenda

- Department research: interdisciplinary collaborations
- Department activities: social hour, reading group, lunch seminar
- Regional activities: Texas Area Theory Day, Texas Area Data Science Day

- Teaching: Randomized algorithms / mathematical toolkit (hashing, concentration inequalities, linear programming, convex optimization), "modern" data science (dimensionality reduction, clustering, sublinear algorithms, differential privacy)
- Funding?: NSF, NIH, DARPA, Apple, Google, Meta, Microsoft

Thank You!





Thank You!