LAMDA
Learning And Mining from DatA
http://lamda.nju.edu.cn

南京大學
NANJING UNIVERSITY
1902

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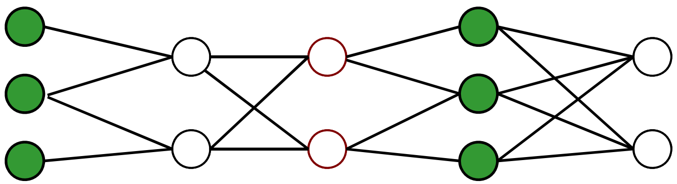
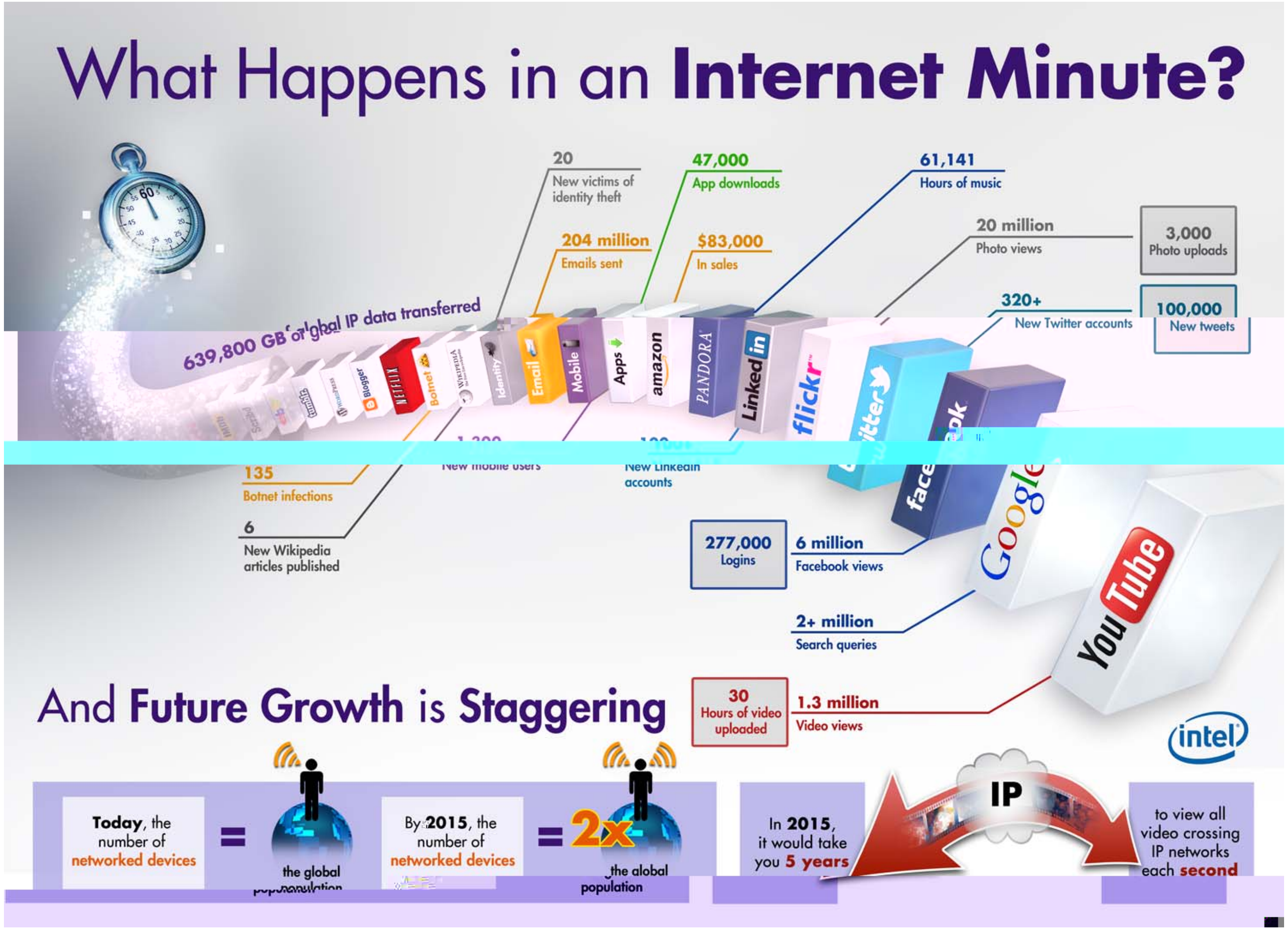



40 ZETTABYTES
[43 TRILLION GIGABYTES]
2005
2020
It's estimated that
2.5 QUINTILLION BYTES
As of 2011, the global size of data in healthcare was estimated to be
By 2014, it's anticipated there will be
420 MILLION
The FOUR V's of Big Data
Volume
SCALE OF DATA
Variety
DIFFERENT FORMS OF DATA
100 TERABYTES
Velocity
Veracity


What Happens in an Internet Minute?
639,800 GB of global IP data transferred
20
New victims of identity theft
204 million
Emails sent
47,000
App downloads
$83,000
In sales
61,141
Hours of music
20 million
Photo views
3,000
Photo uploads
320+
New Twitter accounts
100,000
New tweets
135
Botnet infections
New mobile users
New LinkedIn accounts
6
New Wikipedia articles published
277,000
Logins
6 million
Facebook views
2+ million
Search queries
30
Hours of video uploaded
1.3 million
Video views
And Future Growth is Staggering
Today, the number of networked devices
=
the global population
By 2015, the number of networked devices
= 2x
the global population
In 2015, it would take you 5 years
IP
to view all video crossing IP networks each second
intel

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TXHVWLRQV JLYHQ NQRZOHGJH RI DQVZH
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2QOLQH OHDUQLQJ LV WKH SURFHVV RI

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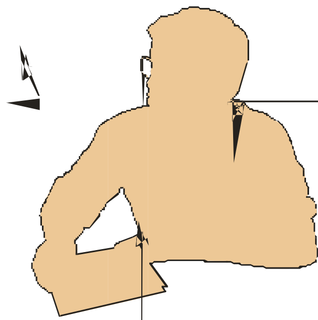

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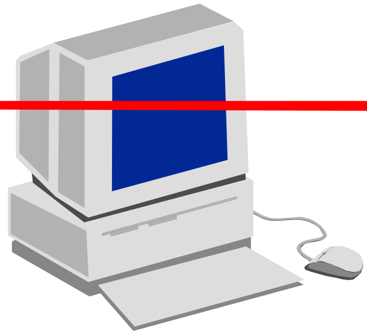

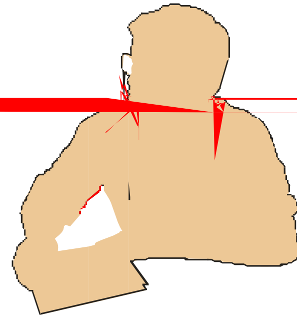

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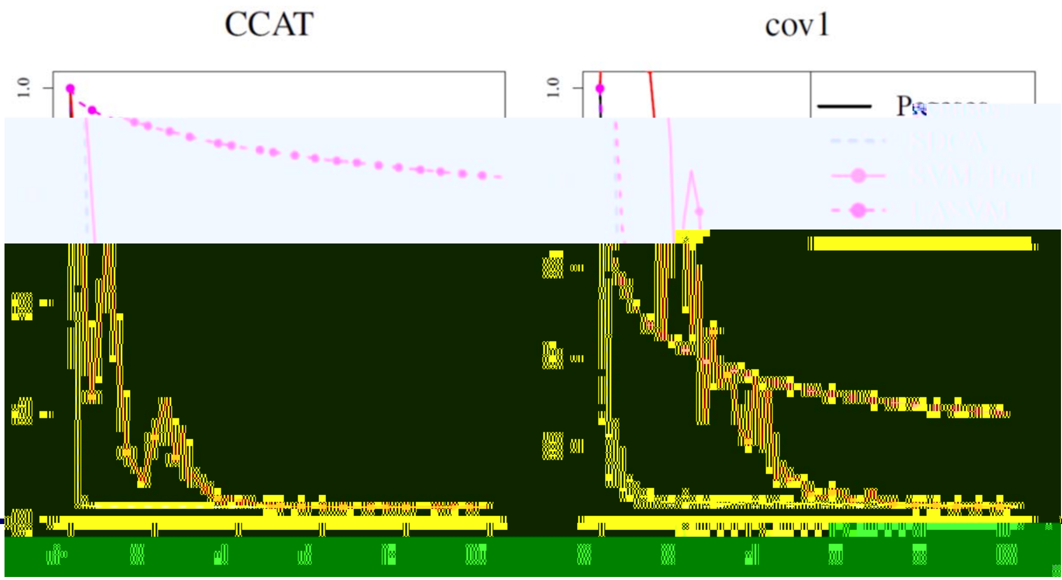

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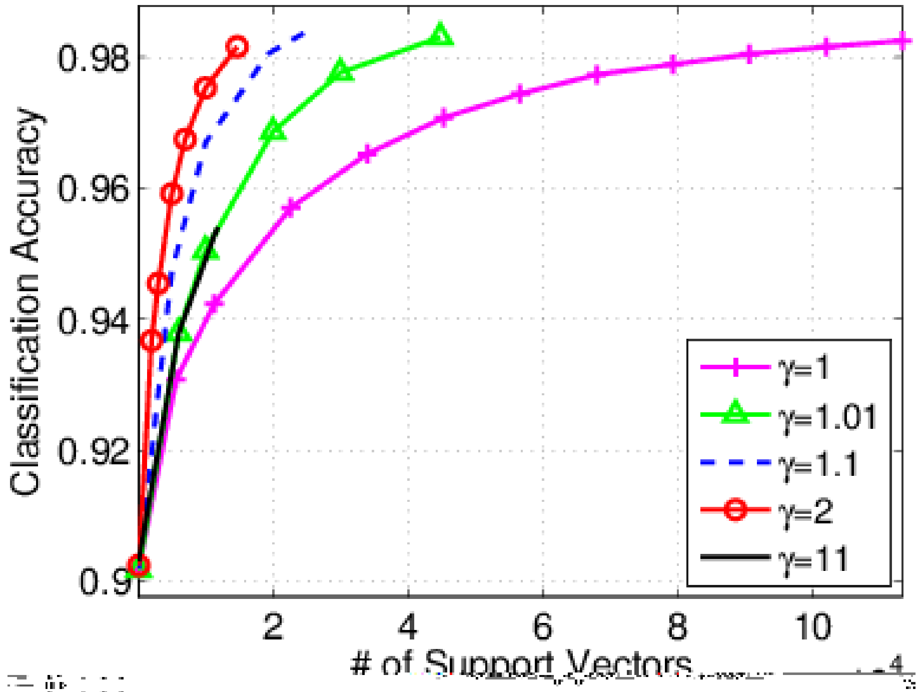

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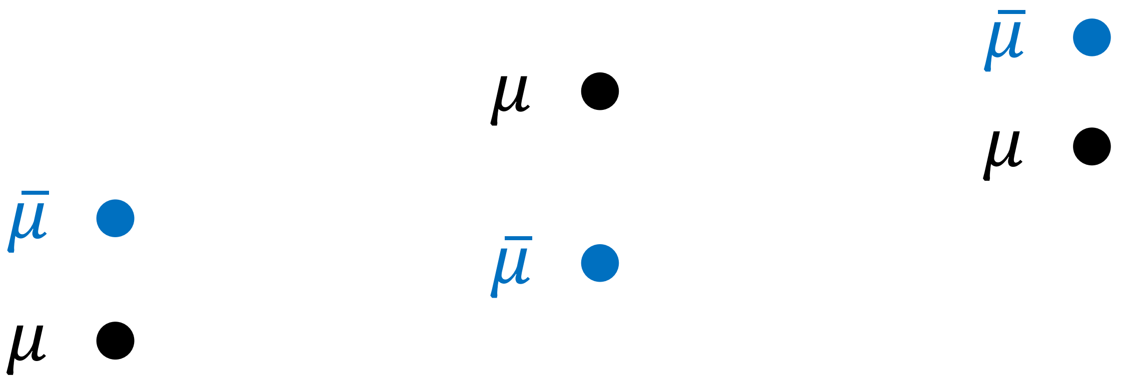

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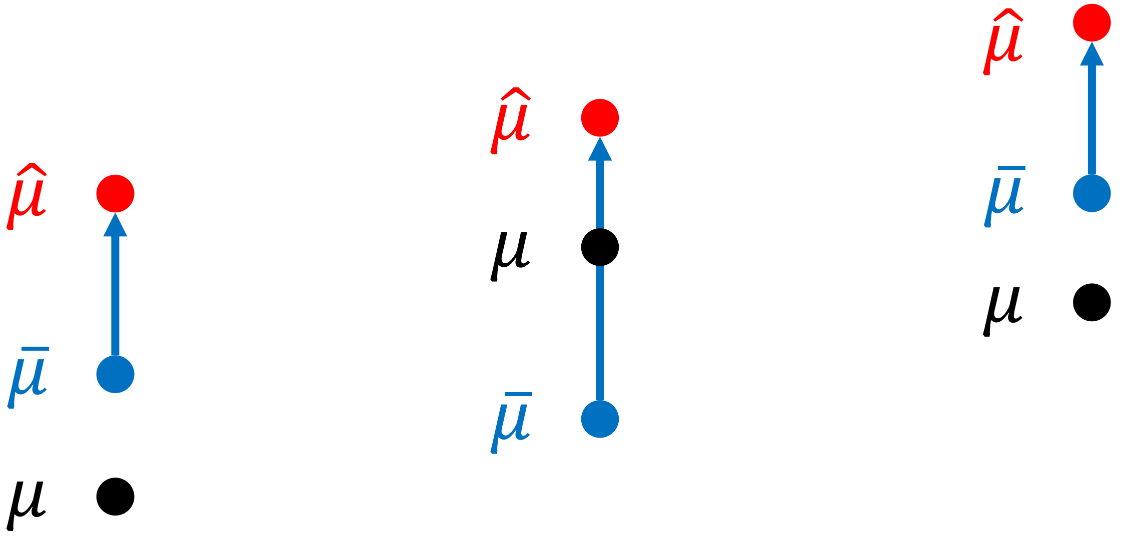

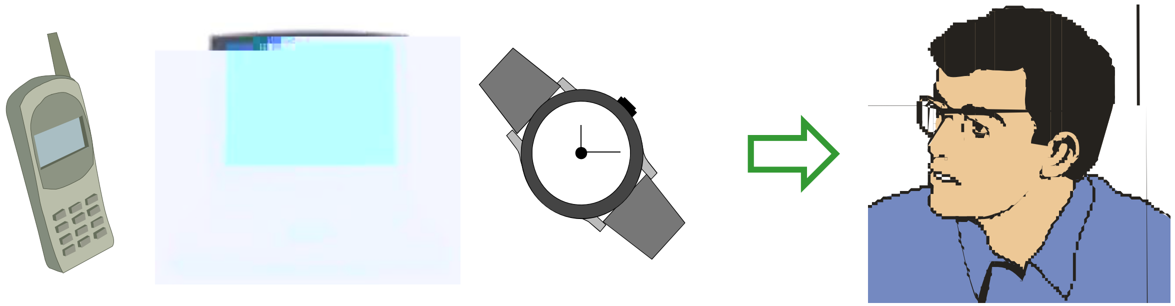

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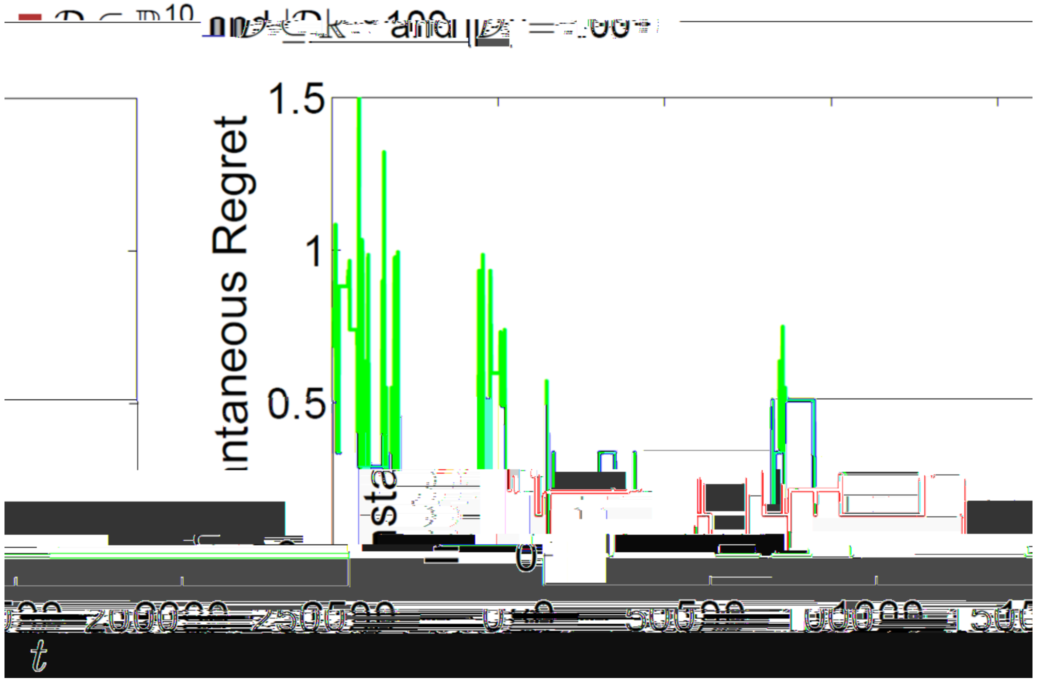

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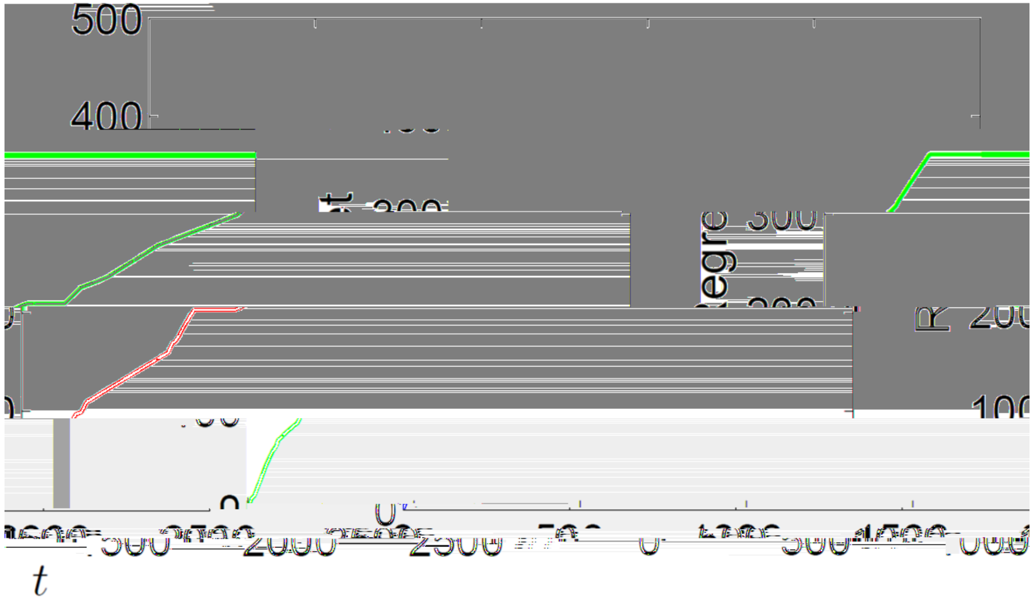
- $\mathcal{D} \subseteq \mathbb{R}^{10}$ and $|\mathcal{D}| = 100$



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Efficient online learning for large-scale sparse kernel logistic regression.
*In Proceedings of the 26th AAAI Conference on Artificial Intelligence (*AAAI*).*

=KDQJ </L - -LQ 5 /LQ 0 DQG +H ;
Online kernel learning with a near optimal sparsity bound.
*In Proceedings of the 30th International Conference on Machine Learning (*ICML*).*

=KDQJ </DQJ 7 -LQ 5 DQG =KRX = +
Online bandit learning for a special class of non-convex losses.
*In Proceedings of the 29th AAAI Conference on Artificial Intelligence (*AAAI*).*

=KDQJ </DQJ 7 -LQ 5 ;LDR < DQG =KRX =
Online stochastic linear optimization under one-bit feedback.
*In Proceedings of the 33rd International Conference on Machine Learning (*ICML*).*

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Improved dynamic regret for non-degenerate functions.

*In Advances in Neural Information Processing Systems 30 (*NIPS*).*

+RX % =K-DQJ / DQG =KRX = +

Learning with Feature Evolvable Streams.

*In Advances in Neural Information Processing Systems 30 (*NIPS*).*

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The perceptron: a probabilistic model for information storage and organization in the brain.

Psychological Review, 65:386–407.

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Online convex programming and generalized infinitesimal gradient ascent.

*In Proceedings of the 20th International Conference on Machine Learning (*ICML*).*

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Pegasos: primal estimated sub-gradient solver for SVM.

*In Proceedings of the 24th International Conference on Machine Learning (*ICML*).*

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Online learning and online convex optimization.

Foundations and Trends in Machine Learning, 4(2):107–194.

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Finite-time analysis of the multiarmed bandit problem.

Machine Learning, 47(2-3):235–256.

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Stochastic linear optimization under bandit feedback.

In Proceedings of the 21st Annual Conference on Learning (COLT).