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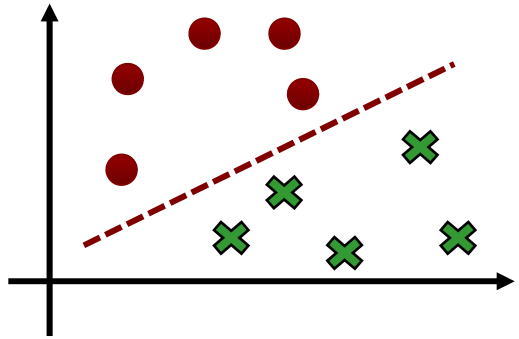
$$(\mathbf{x}\ ,y\ )$$
$$\dots$$
$$(\mathbf{x}\ ,y\ )$$

$$\Rightarrow \quad y \approx h(\mathbf{x})$$



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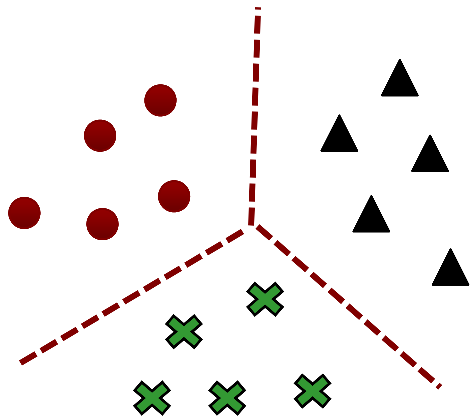
$$\mathbf{x}$$
$$\dots$$
$$\mathbf{x}$$

$$\Rightarrow \quad h(\mathbf{x})$$



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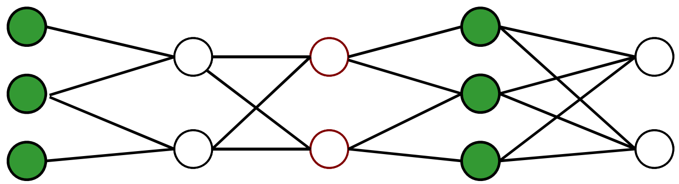
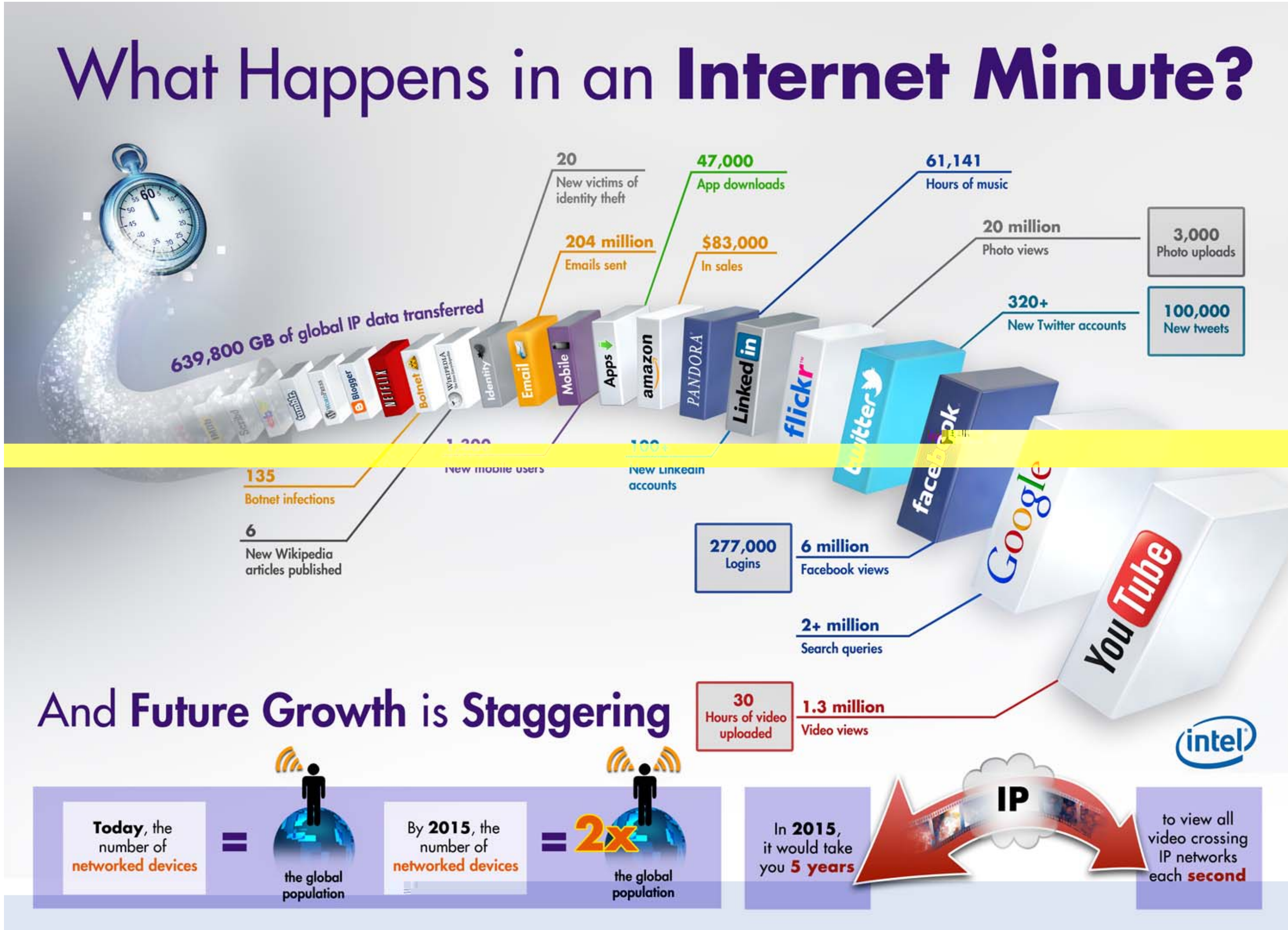



40 ZETTABYTES
[43 TRILLION GIGABYTES]
of data will be created by 2020, an increase of 300 times from 2005
2020
2005
6 BILLION PEOPLE
have cell phones
Volume
SCALE OF DATA
It's estimated that
2.5 QUINTILLION BYTES
[2.3 TRILLION GIGABYTES]
of data are created each day
The FOUR V's of Big Data
As of 2011, the global size of data in healthcare was estimated to be
150 EXABYTES
[161 BILLION GIGABYTES]
By 2014, it's anticipated there will be
420 MILLION WEARABLE, WIRELESS HEALTH MONITORS
Variety
DIFFERENT FORMS OF DATA
4 BILLION+ HOURS OF VIDEO
are watched on YouTube each month
WORLD POPULATION: 7 BILLION
Most companies in the U.S. have at least
100 TERABYTES
From traffic patterns and music downloads to web history and medical records, data is recorded, stored, and analyzed to enable the technology and services that the world relies on every day. But what exactly is big data, and how can these massive amounts of data be used?
30 BILLION PIECES OF CONTENT
are shared on Facebook every month
400 MILLION TWEETS
are sent per day by about 200 million monthly active users


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
6
New Wikipedia articles published
New mobile users
New Linkedin accounts
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

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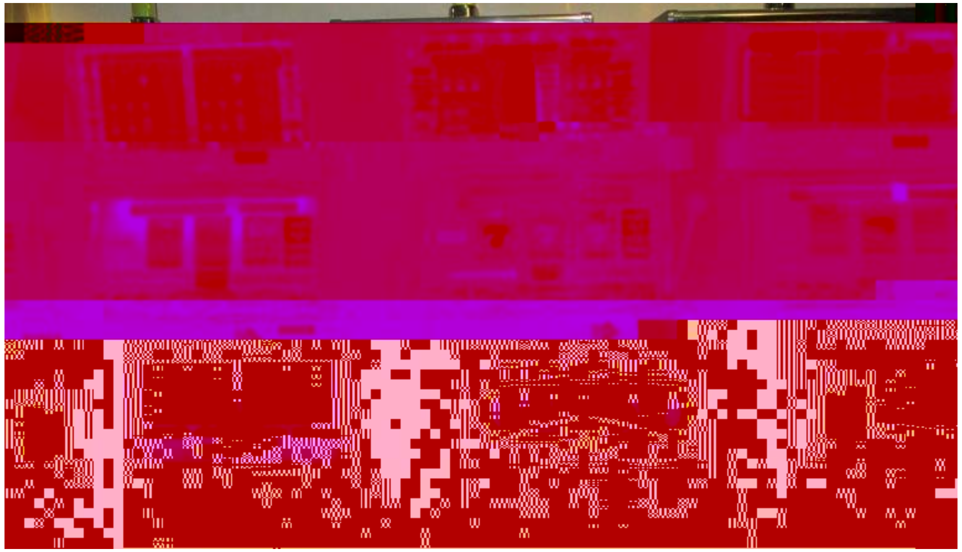

Learning And Mining from DatA
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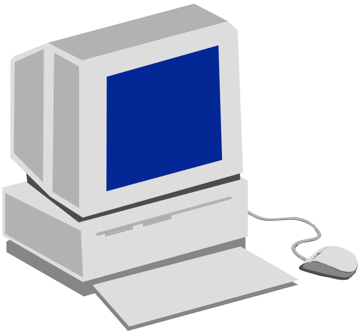

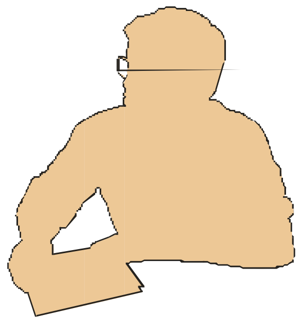

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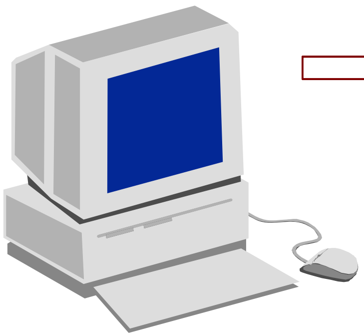

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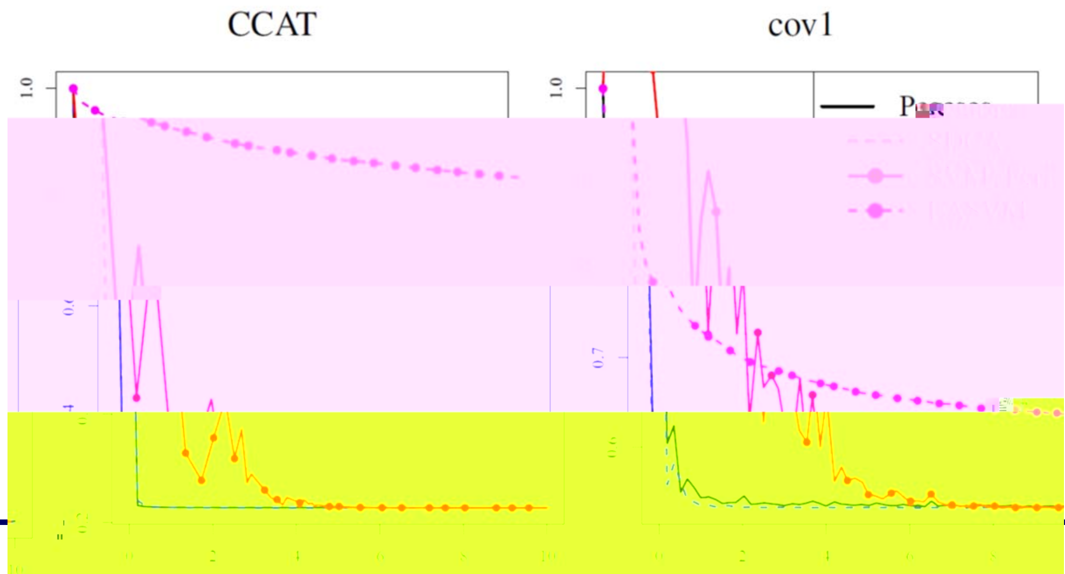

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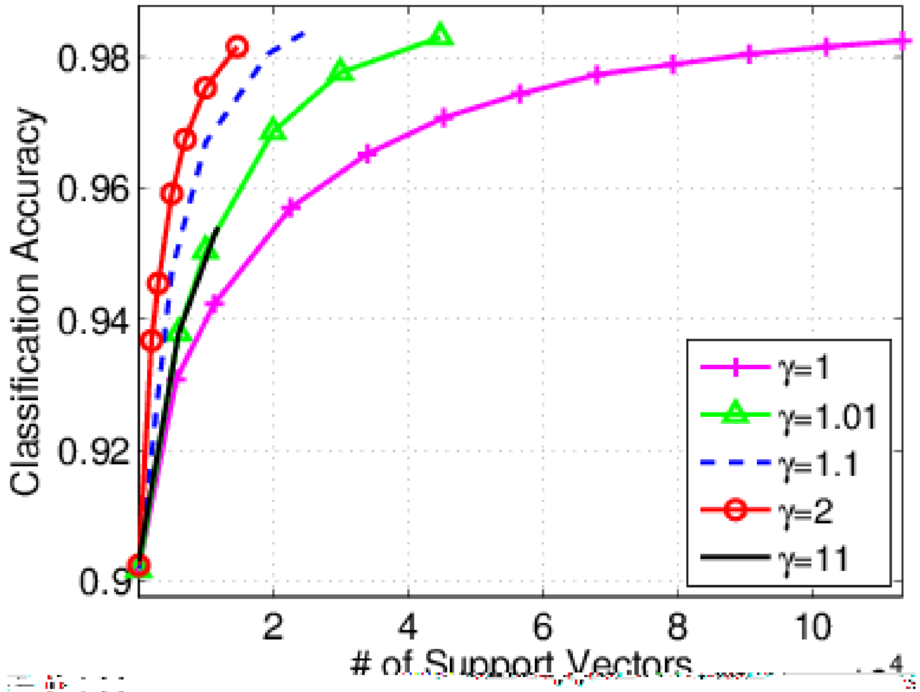

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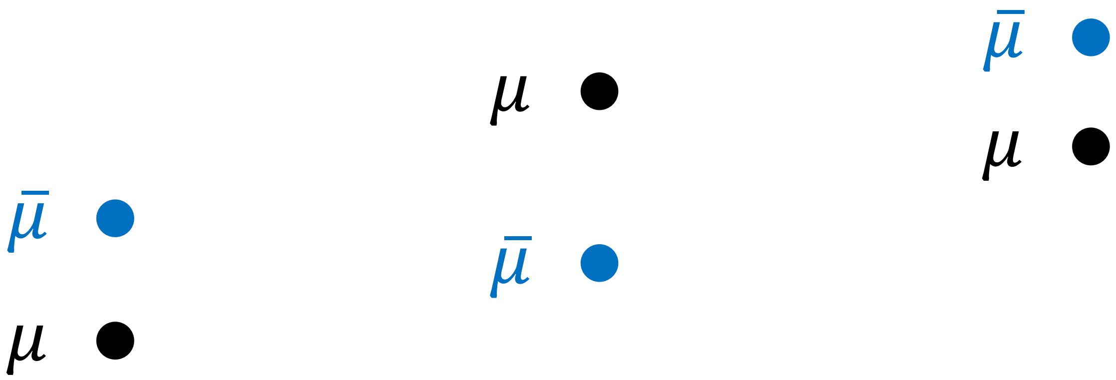

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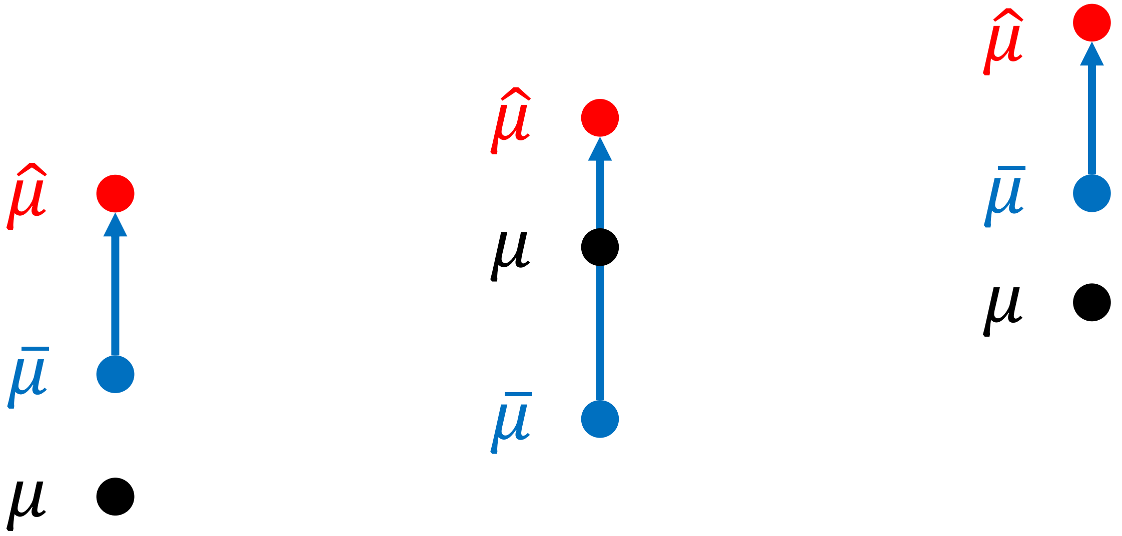

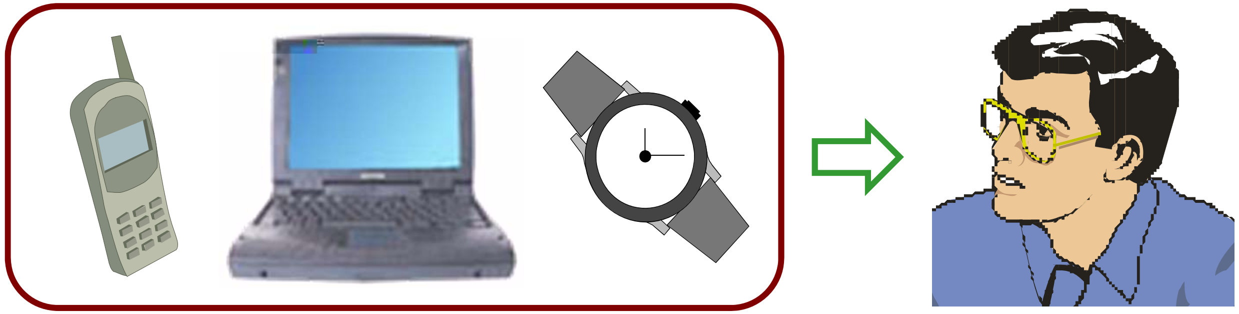

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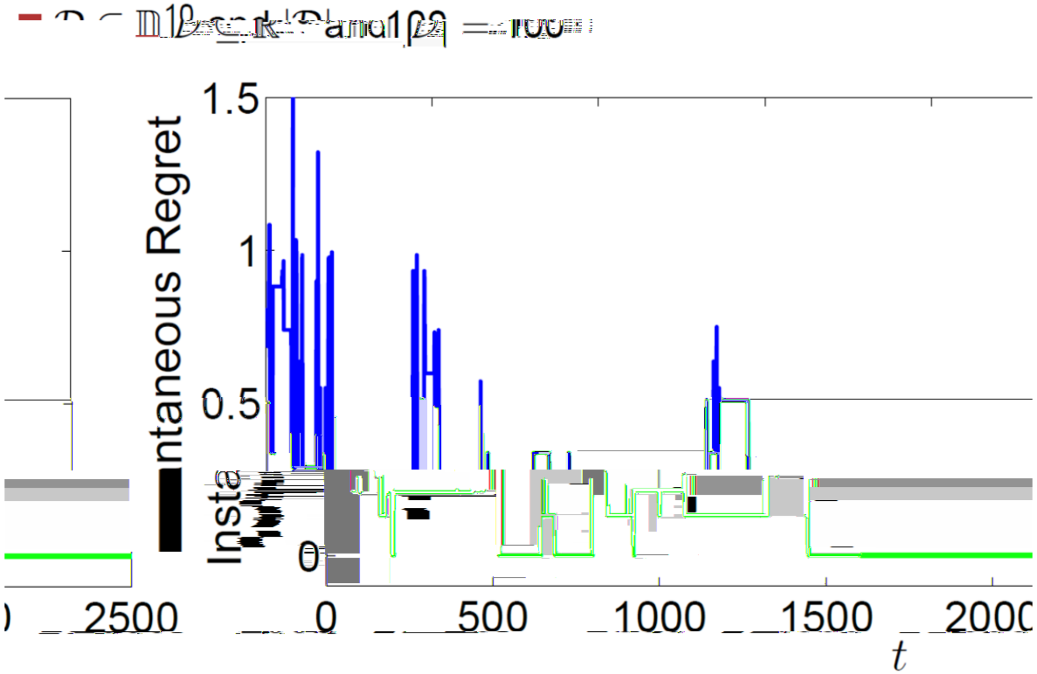

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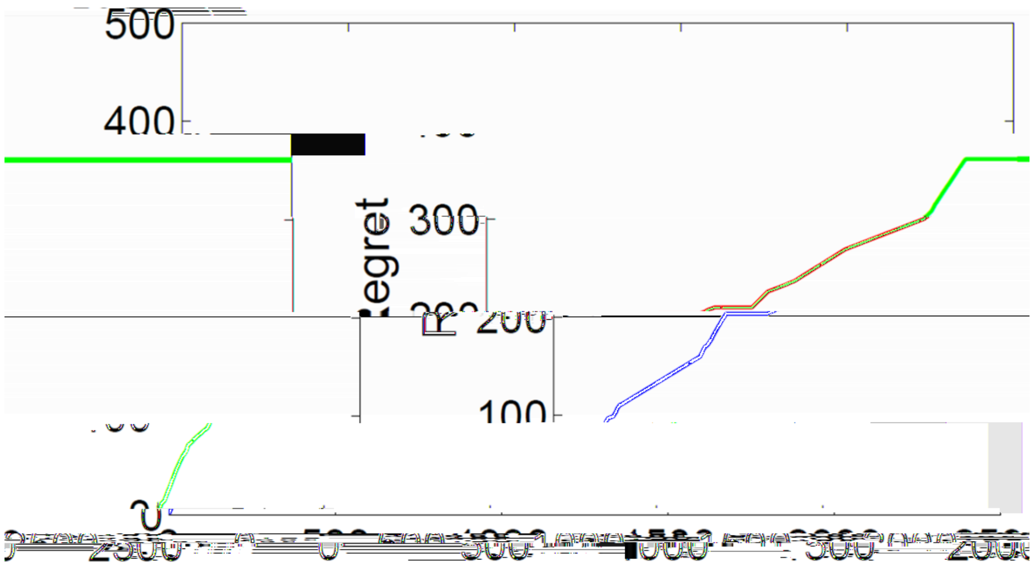
■ $\mathcal{D} \subseteq \mathbb{R}^{10}$ and $|\mathcal{D}| = 100$



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- =KDQJ -/LQ 5 &KHQ & %X - DQG +H ;
  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*).*

- =KDQJ / <DQJ 7 <L - -LQ 5 DQG =KRX = +
  Improved dynamic regret for non-degenerate functions.
  *In Advances in Neural Information Processing Systems 30 (*NIPS*).*
- +RX % =KDQJ / DQG =KRX = +
  Learning with Feature Evolvable Streams.
  *In Advances in Neural Information Processing Systems 30 (*NIPS*).*
- 5RVHQEODWW)
  The perceptron: a probabilistic model for information storage and organization in the brain.
  Psychological Review, 65:386–407.
- =LQNHYLFK 0
  Online convex programming and generalized infinitesimal gradient ascent.
  *In Proceedings of the 20th International Conference on Machine Learning (*ICML*).*
- 6KDOHY 6KZDUW] 6 6LQJHU < DQG 6UHERU
  Pegasos: primal estimated sub-gradient solver for SVM.
  *In Proceedings of the 24th International Conference on Machine Learning (*ICML*).*

- 6KDOHY 6KZDUW] 6
  Online learning and online convex optimization.
  Foundations and Trends in Machine Learning, 4(2):107–194.
- $XHU 3 &HVD %LDQFKL 1 DQG)LVFKHU 3
  Finite-time analysis of the multiarmed bandit problem.
  Machine Learning, 47(2-3):235–256.
- 'DQL 9 +D\HV 7 3 DQG .DNDGH 6 0
  Stochastic linear optimization under bandit feedback.
  In Proceedings of the 21st Annual Conference on Learning (COLT).