ΟΙΚΟΝΟΜΙΚΟ ΠΑΝΕΠΙΣΤΗΜΙΟ ΑΘΗΝΩΝ
ATHENS UNIVERSITY OF ECONOMICS AND BUSINESS

Συστήματα Ανάλυσης & Διαχείρισης Μεγάλων Δεδομένων

Εισαγωγή στα Μεγάλα Δεδομένα

Yannis Kotidis

kotidis@aueb.gr

Professor, Department of Informatics

Athens University of Economics and Business

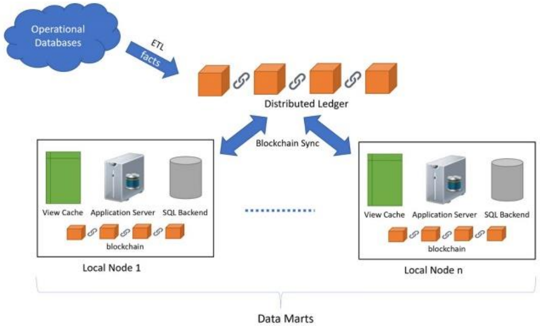
About me

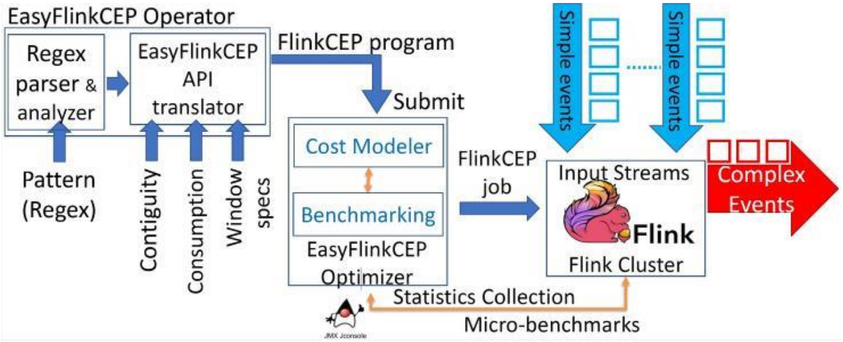
- Professor, Dept of Informatics, Athens University of Economics and Business
  - URL: http://pages.cs.aueb.gr/~kotidis/
  - Email: kotidis@aueb.gr
  - Office: *Α516, Πτέρυγα Αντωνιάδου, Κεντρικό Κτήριο ΟΠΑ*

- Interests: Big Data Systems/Algorithms, Streams, Complex Event Processing, Graphs, Data Warehousing/Analytics, Data Mining

Recent Projects/Student Theses (http://pages.cs.aueb.gr/~kotidis/index.html)

- DeLorean: Compression, Indexing and Analysis Techniques for Time-Series Management
- EasyFlinkCEP: Complex Event Processing using user-defined patterns
- Smart-Views: Decentralized OLAP View Management using Blockchains
- RECOST: Real time management of Complex Streams
- Graph exploration, partitioning, augmentation





Στόχοι – μαθησιακά αποτελέσματα

- Το μάθημα αποσκοπεί στην μελέτη **τεχνικών** και **συστημάτων** τα οποία χρησιμοποιούνται για την αποδοτική **οργάνωση**, **ανάλυση** και **διαχείριση δεδομένων** σε **κεντρικά** και **κατανεμημένα περιβάλλοντα μεγάλης κλίμακας**.
- Μετά την επιτυχή ολοκλήρωση του μαθήματος, οι φοιτητές θα είναι σε θέση να
  1) Γνωρίζουν και να χρησιμοποιούν τεχνικές και συστήματα διαχείρησης και ανάλυσης μεγάλων δεδομένων.
  2) Κατανοούν τα πλεονεκτήματα και μειονεκτήματα των διαφορετικών συστημάτων.
  3) Επιλέγουν και εφαρμόζουν τεχνικές και αλγορίθμους ανάλυσης για αναδυόμενες εφαρμογές μεγάλων δεδομένων.

Υλικό Μαθήματος: E-class

- Ανακοινώσεις/εργασίες/βαθμολογίες
- Διαφάνειες Διαλέξεων
  - φάκελος «έγγραφα»
- Προαιρετικές διαφάνειες, **παραδείγματα κώδικα**
  - φάκελος «έγγραφα/ΒοηθητικόΥλικό»
- Εργασίες Μαθήματος

Βοηθητικά συγγράμματα (προαιρετικά)

- Προπτυχιακές γνώσεις από την περιοχή των Βάσεων Δεδομένων
  - Database Systems The Complete Book (H. Garcia-Molina, J. Ullman, J. Widom)
  - Θεμελιώδεις αρχές συστημάτων Βάσεων Δεδομένων, Τόμος Α (R. Elmasri, S. B. Navathe)
- Ανάλυση Μεγάλων Δεδομένων
  - Mining of Massive Datasets, Jure Leskovec, Anand Rajaraman, Jeff Ullman, http://www.mmds.org/

Ενότητες Μαθήματος (1,2,3)

- **Εισαγωγή** (σημερινή διάλεξη)
  - Χαρακτηριστικά μεγάλων δεδομένων, εφαρμογές, προβλήματα και ενδεικτικές τεχνικές
- **Θεμελιώδεις γνώσεις ανάλυσης και διαχείρισης δεδομένων**
  - Πως συγκρίνω δεδομένα ανάλογα με το μορφότυπο τους?
  - Χρήση του κατακερματισμού για την οργάνωση και διαμοίραση δεδομένων σε κατανεμημένα περιβάλλοντα
- **Αποθήκες δεδομένων / Επιχειρηματική Ευφυΐα**
  - Σχεδίαση, παραδείγματα OLAP, κύβος δεδομένων, όψεις

Ενότητες Μαθήματος (4,5)

- **Συστήματα και τεχνικές διαχείρισης μεγάλων δεδομένων**
  - HDFS/Hadoop/Map-Reduce
  - Hive, Spark (Storm/Flink/Kafka)
  - Graph analytics: Neo4j, GraphFrames, Pregel
- **Εισαγωγή στην ανάλυση & εξόρυξη δεδομένων**
  - Association Rules
  - Link Analysis
  - NN-search (if enough time)
  - Graph Convolutional Networks/Streams – TBD)

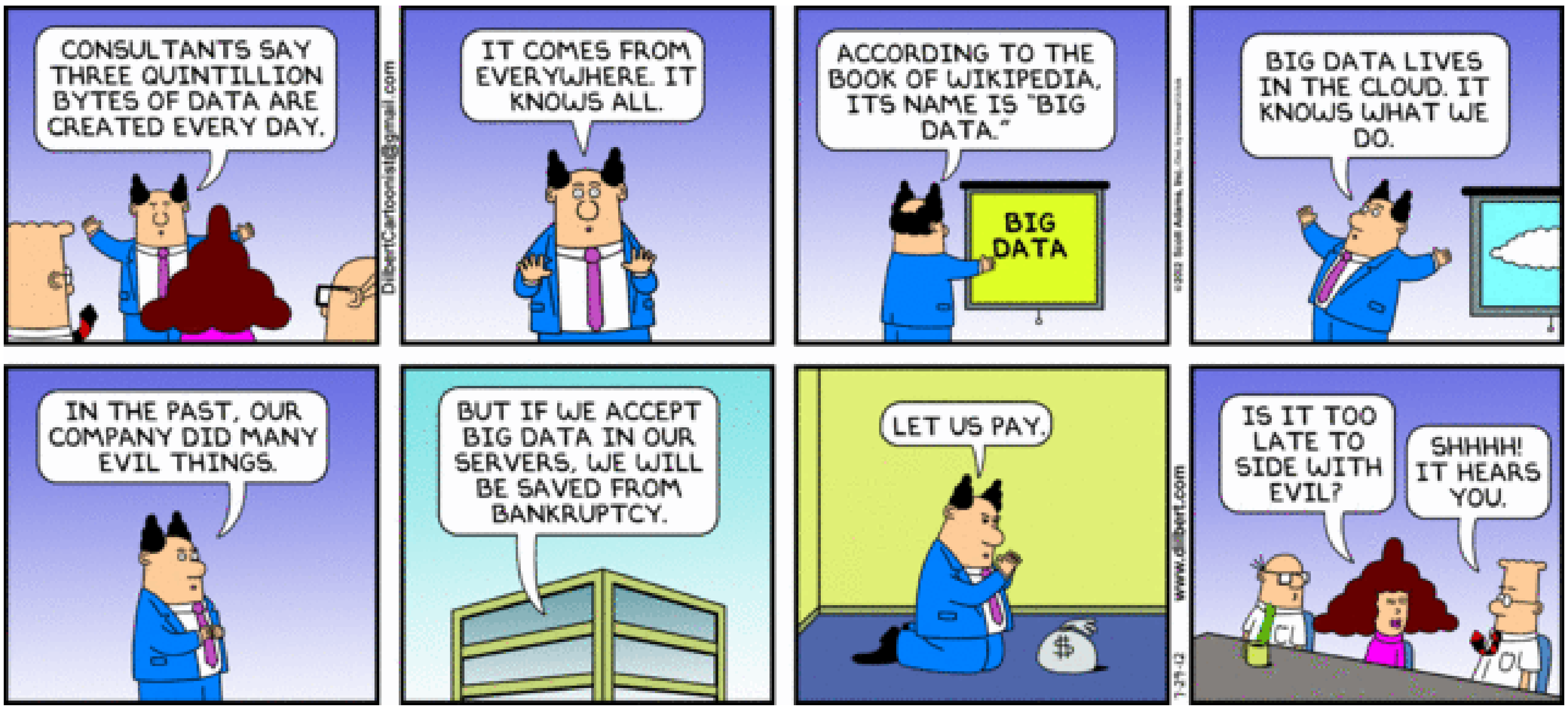
Πρόοδος & Εργασίες

- 1 x 45min πρόοδος με την ολοκλήρωση των εισαγωγικών διαλέξεων (ενότητες 1 & 2)
  - Ενδεικτικά στην αρχή της τρίτης ή τέταρτης διάλεξης
- Δύο <u>υποχρεωτικές (ομαδικές?)</u> εργασίες με τη χρήση πραγματικών συστημάτων
  - Θα προηγηθεί κάθε φορά φροντιστήριο σχετικά με τη χρήση των εργαλείων που θα απαιτηθούν
  - Η πρώτη εργασία θα είναι στην περιοχή των αποθηκών δεδομένων/επιχειρηματικής ευφυΐας
  - Η δεύτερη στην περιοχή των συστημάτων διαχείρισης μεγάλων δεδομένων

Βαθμολογία Μαθήματος

- Πρόοδος : 20%
- Εργασίες : 50%
  - Ομαδική Εργασία 1 : 25%
  - Ομαδική Εργασία 2 : 25%
- Τελική εξέταση : 30%
- Ο μέσος όρος του βαθμού των εργασιών πρέπει να είναι ≥5
- Σταθμισμένος μέσος όρος γραπτών ≥5

Big Data is everywhere and knows it all!

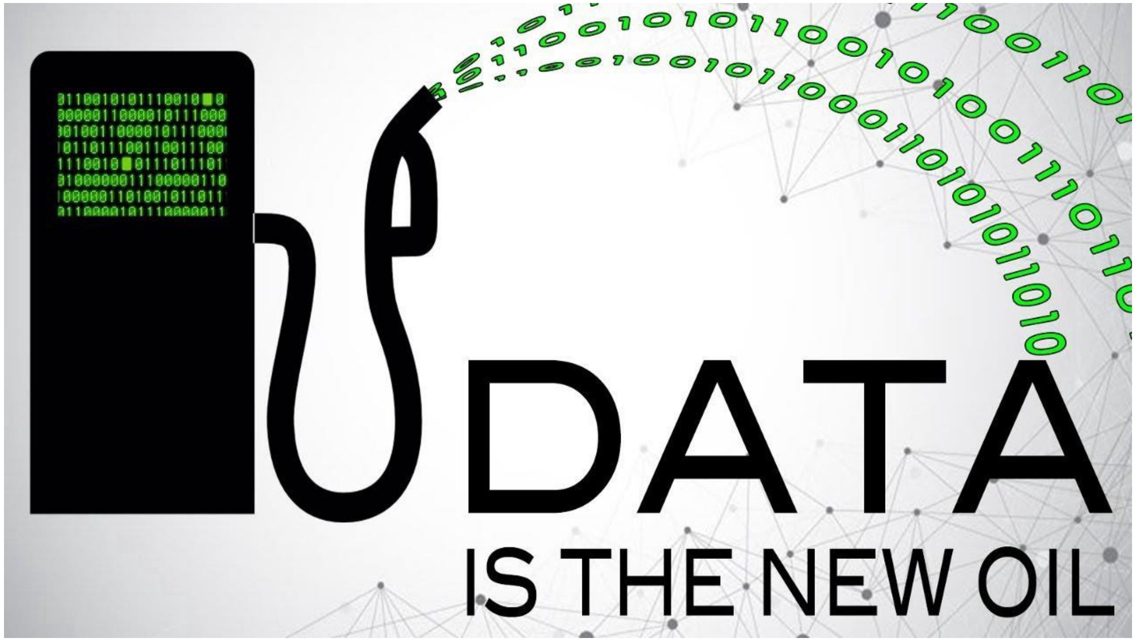


Data is the new oil in the 21st century

- Industrial revolution: abundant fossil fuels, and technological advances launched an era of accelerated change that continues to transform human society.
- Information revolution: data drives the information economy in much the same way that oil has fuelled the industrial economy

Data is the new oil in the 21st century

- Data (such like oil) needs to be
  - Found,
  - Extracted,
  - Cleansed,
  - Refined,
  - Analyzed,
  - Distributed



https://medium.com/@adeolaadesina/data-is-the-new-oil-2947ed8804f6

Data is no oil!

- Oil is finite - data is infinite and reusable
- Via its use oil degrades into a form that is of no use anymore while data is transformed into knowledge

- Common ground: Data is an asset and by using that data, it opens huge opportunities for the business

Data is an asset, not a burden!

Huge advances in our ability to collect data

- Web interactions (e.g. yahoo has 2PB of web data)
- Social Media (tweets, Facebook, etc.)
- Scientific experiments (e.g. NASA EOSDIS archives over1PB/year)
- Business Applications (e.g. Bank/Credit Card transactions)

Gather whatever data you can whenever possible

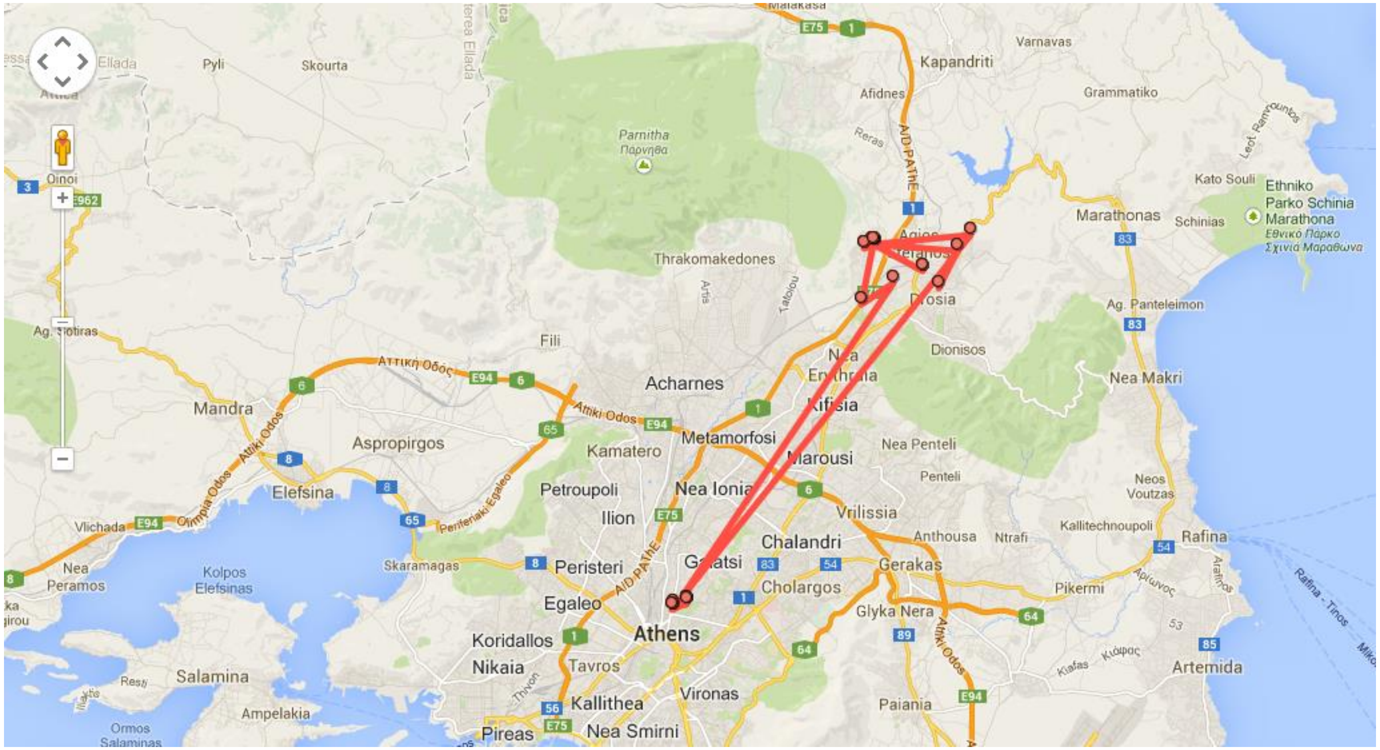
- Data will have value in the future
- …even for purposes not envisioned!

Digital Data Explosion

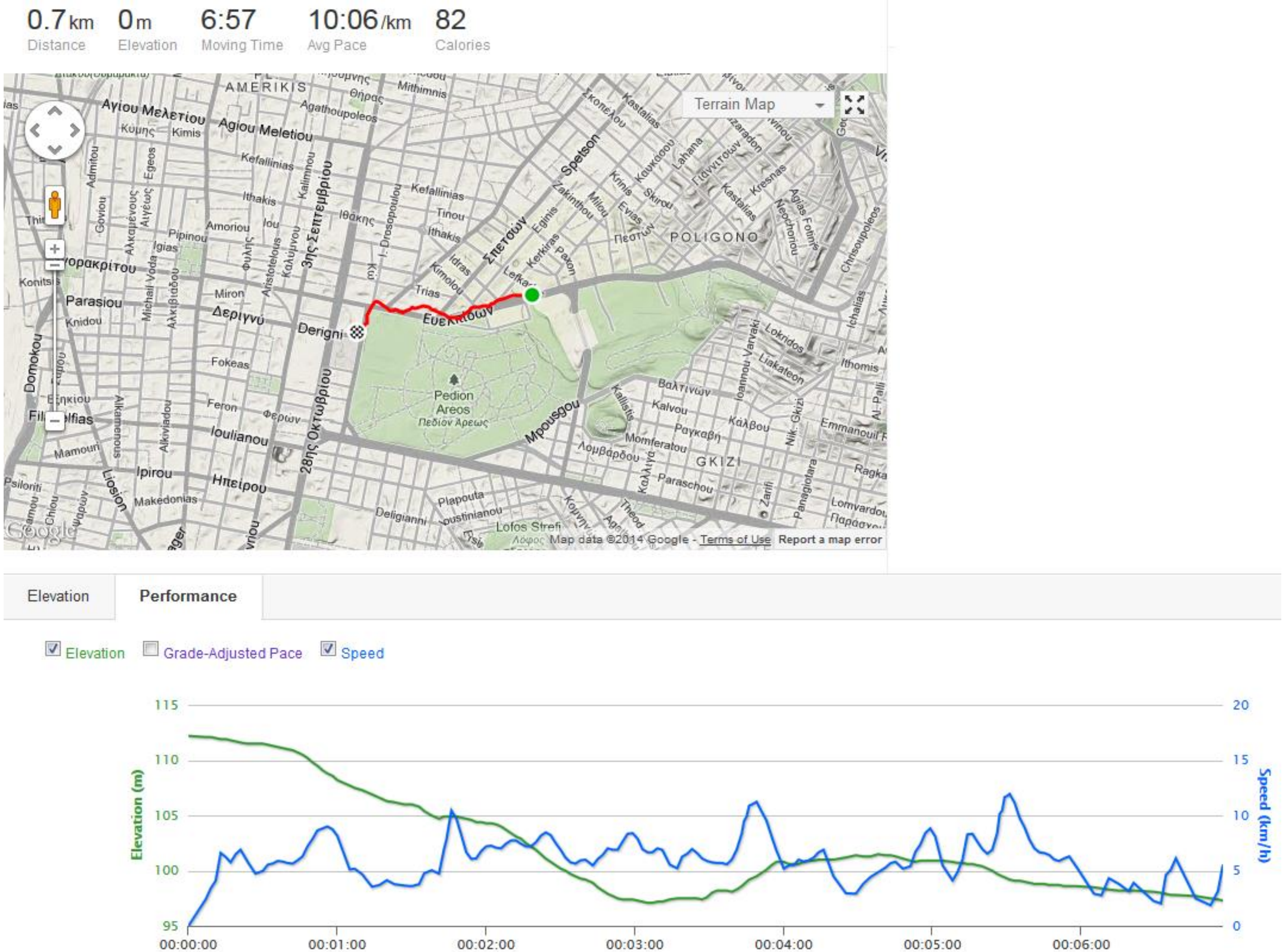
- Everything we see, read, hear, write, and measure can now be in a digital form!!
- Every few days we generate more data than we did from the dawn of civilization until 2000
  - Multimedia, scientific, sensor, etc. data is becoming prevalent

How to use this data to drive new growth?

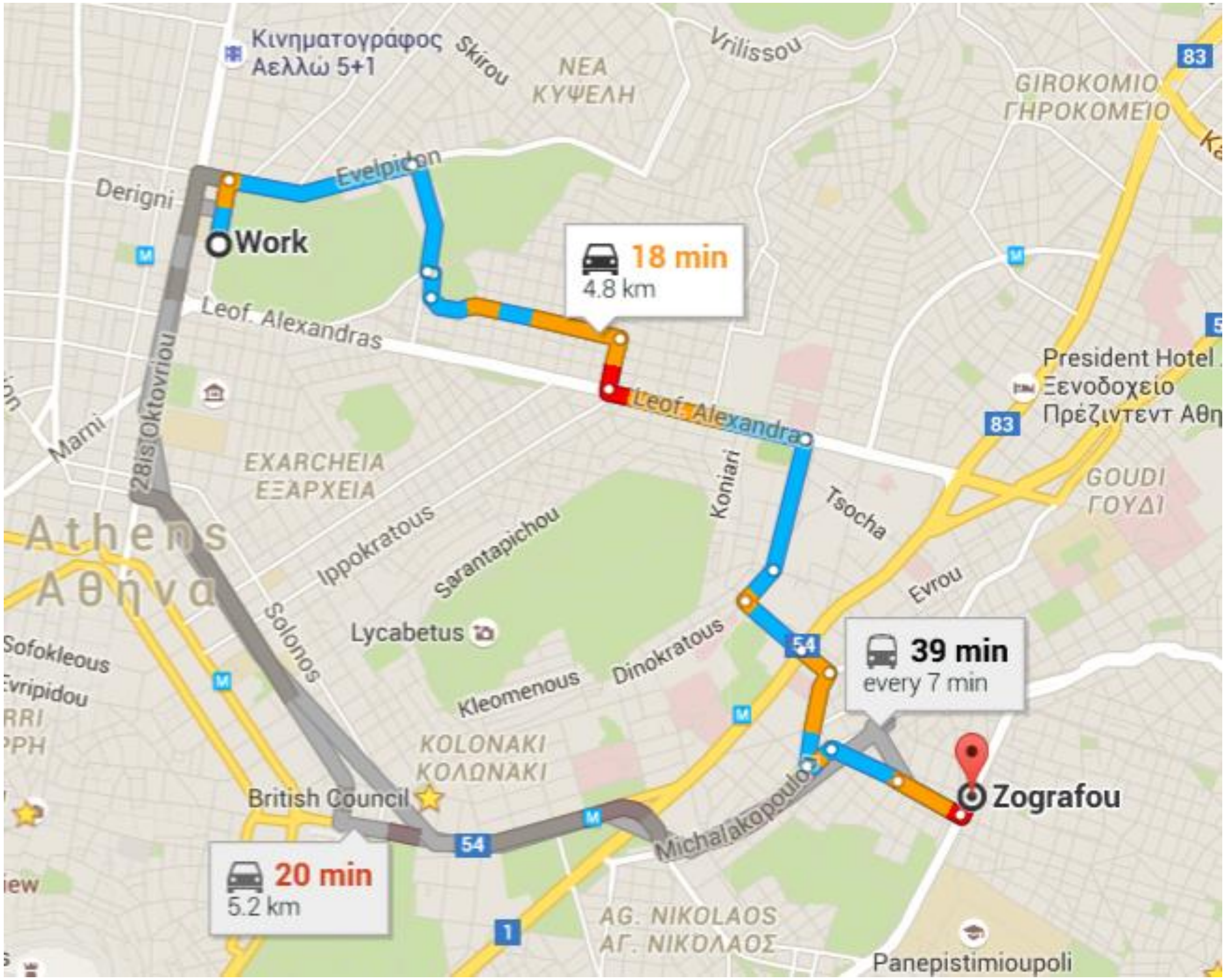
Location history based on cellular connections



Phone GPS tracking

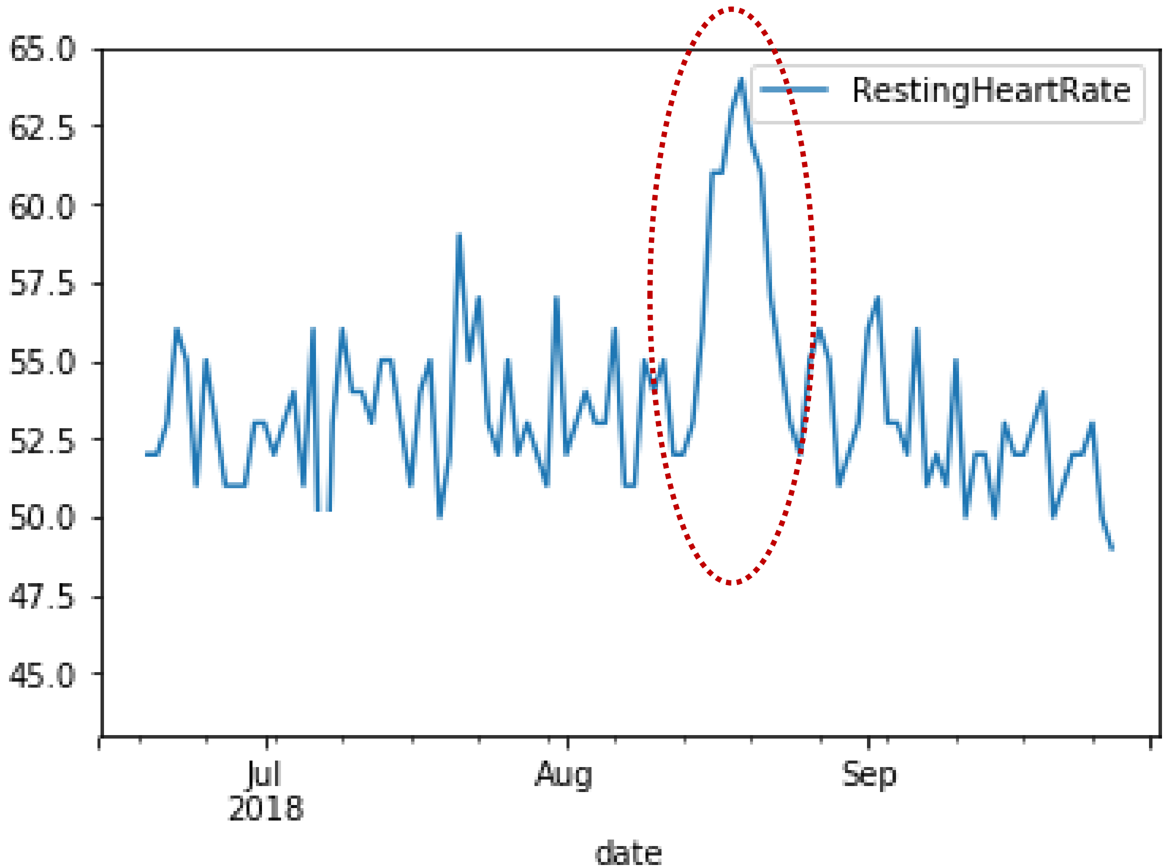


Provide useful services: Live traffic data



Another Application: Fitness Analytics

How do you explain this peak?

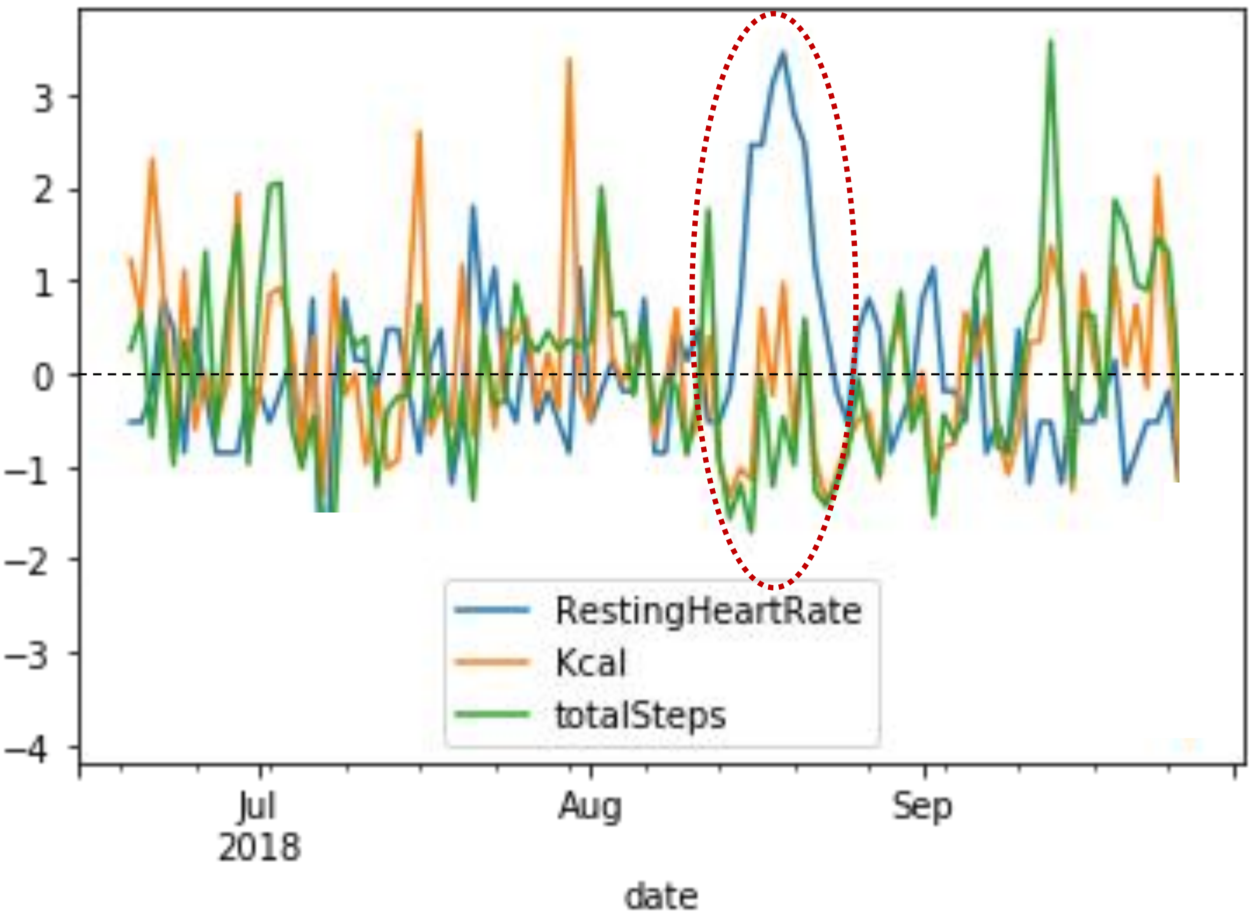


- **Descriptive analytics**: answer queries looking back in time [this example]
- **Predictive analytics**: forecasting [what is my marathon predicted time?]
- **Prescriptive analytics**: planning in order to achieve predicted outcomes [e.g. workout schedule]

More data → more insights

Kcal(down) & totalSteps(down)→RestHR(up)

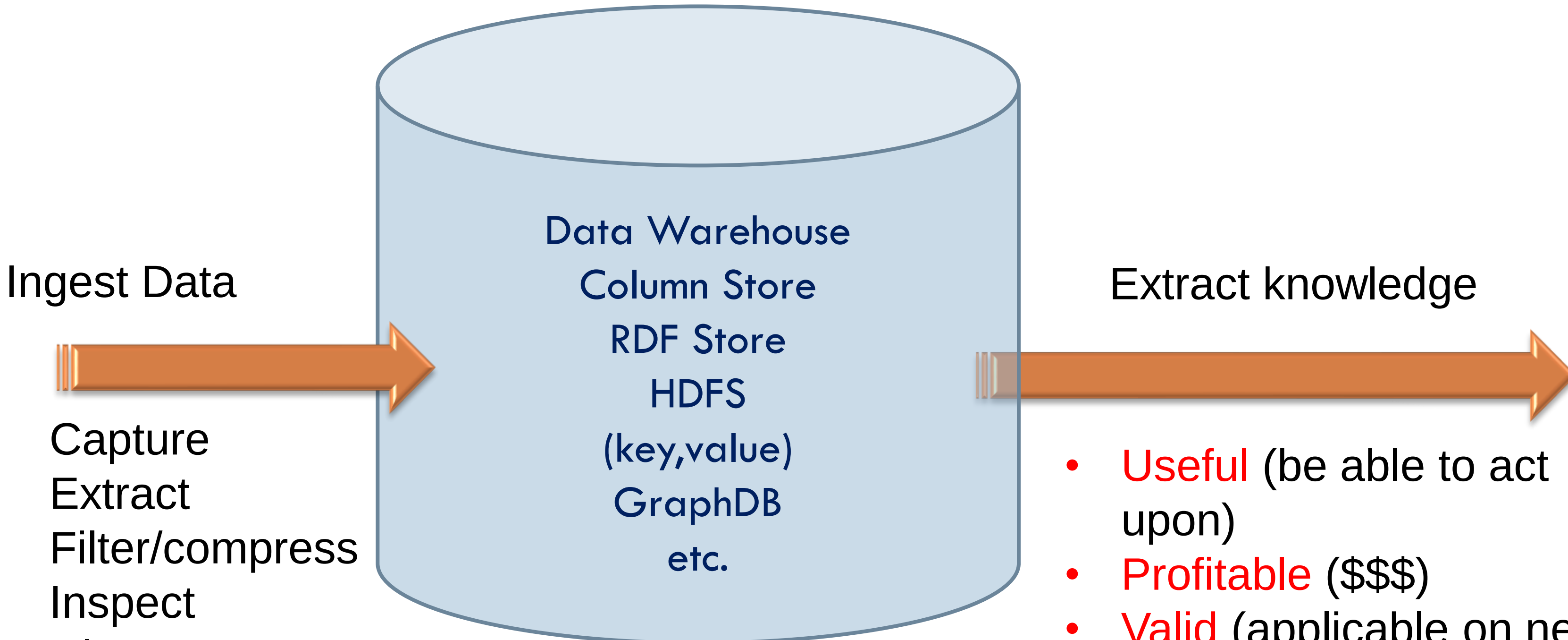
Exercise(down) → Fitness (down)



Data Mining

- The process of analyzing data to identify new information in the form of features, patterns or relationships
- Has become a well-established discipline related to Artificial Intelligence, Machine Learning and Statistical Analysis
  - Led by advances in computer hardware and database technology
    - Data warehousing, Business Intelligence, Cloud Computing, Big Data frameworks

The big (&very abstract) picture



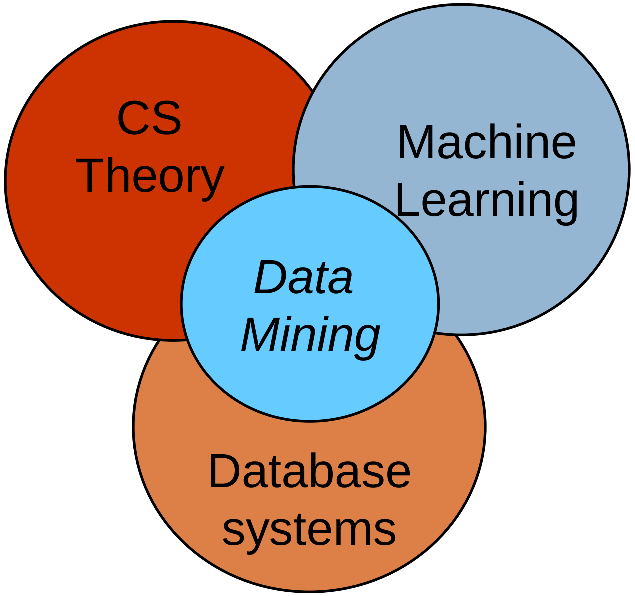
Capture
Extract
Filter/compress
Inspect
Cleanse
Transform
Integrate
Load/Index
Aggregate
…

Heterogeneity
Scale
Timeliness
Privacy

- Useful (be able to act upon)
- Profitable ($$$)
- Valid (applicable on new data with some certainty)
- Unexpected (non-obvious to the expert user)

Data Mining: Cultures

- **Different cultures:**
  - To a DB person, data mining is an extreme form of **analytic processing** – queries that examine large amounts of data
    - Result is the query answer, focus on the process/algorithm
  - To a ML person, data-mining is the **inference of models**
    - Result is the parameters of the model



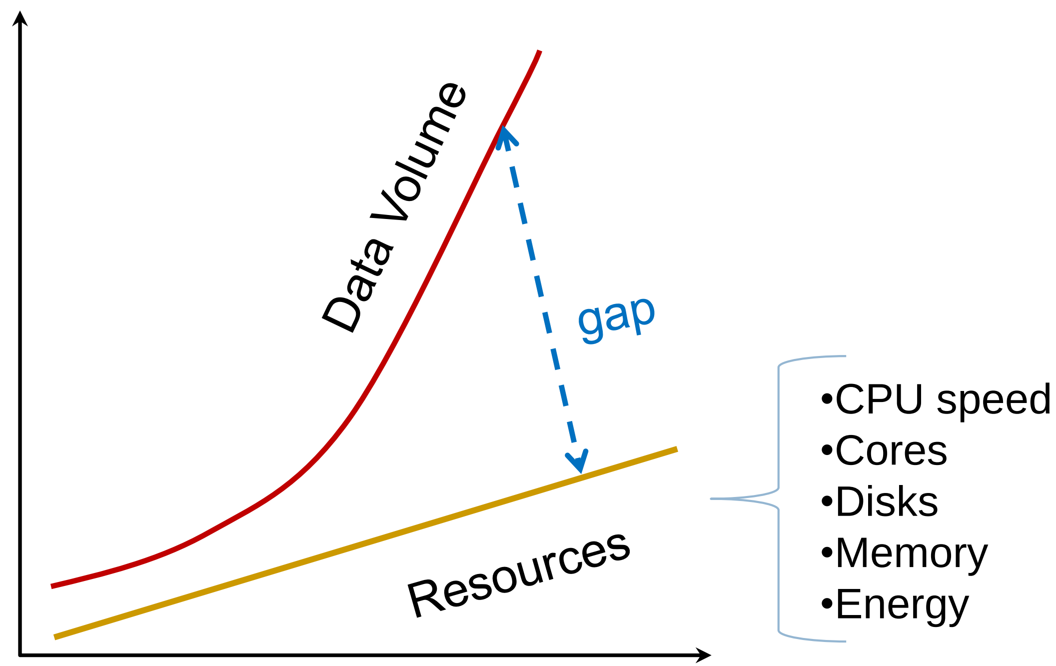
Slide from J. Leskovec, A. Rajaraman, J. Ullman: Mining of Massive Datasets, http://www.mmds.org

Limiting factors

- Hardware
  - Technological/economical limitations
- Software
  - Complexity of deploying, monitoring and maintaining computing resources
    - Huge advances in this area in the past decades ✓
  - Algorithmic complexity of certain tasks
    - Theory and practice need to converge

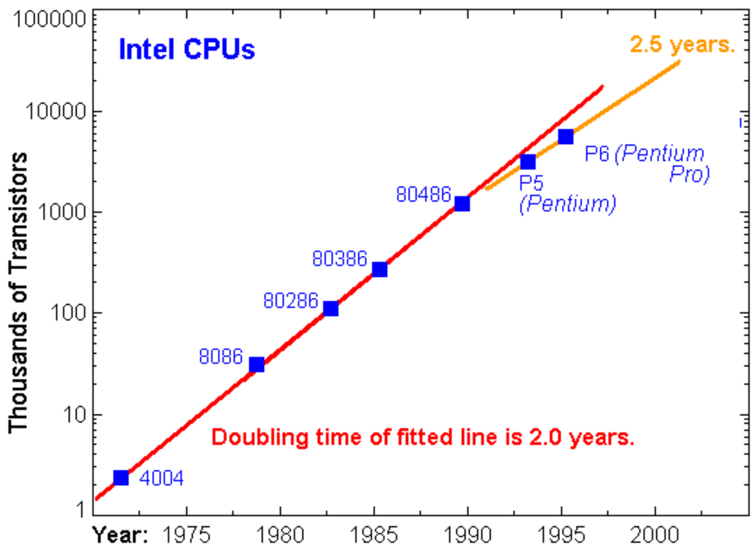
Mind the (technological) gap!

- Data is scaling faster than compute resources, and CPU speeds are static.
  - Moore's law is not coming to our rescue anymore…



Gordon Moore's Law
co-founder of Intel, 1965

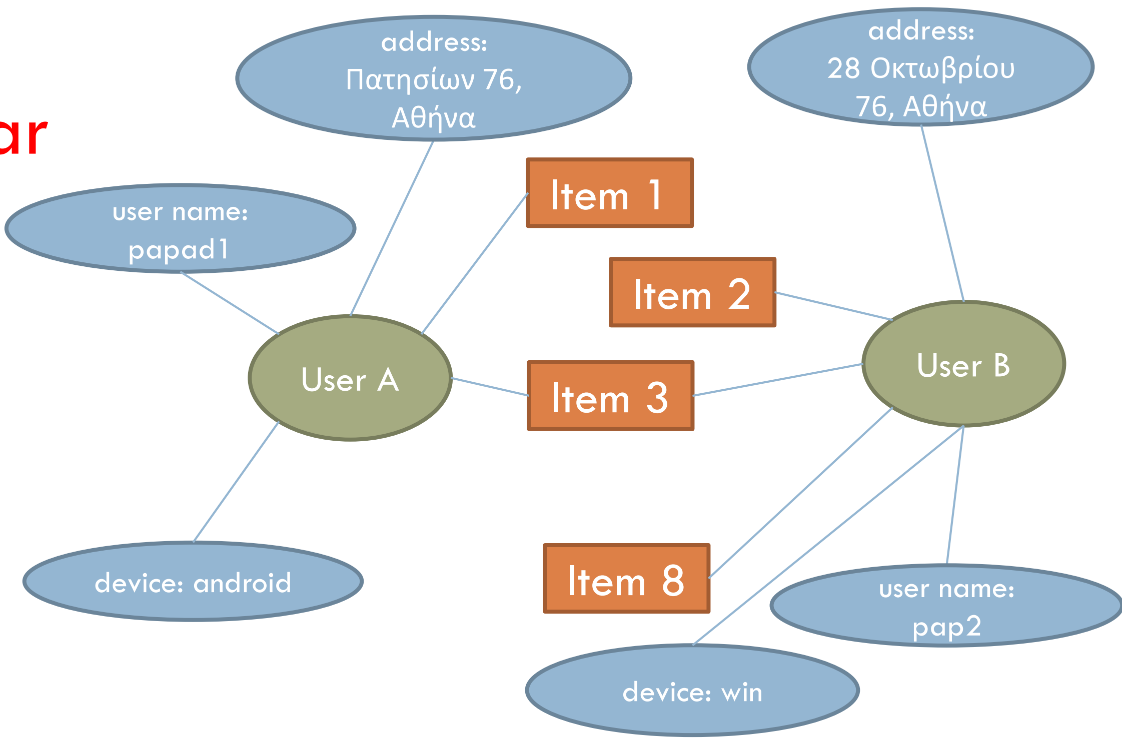
- **Prediction:** the number of transistors per square inch on integrated circuits had doubled every year since the integrated circuit was invented. Moore predicted that this trend would continue for the foreseeable future.



  - x2 transistors per square inch / 18 months
  - HDDs: < 0.5 euro/GB

Complexity of a simple (yet very important) computation

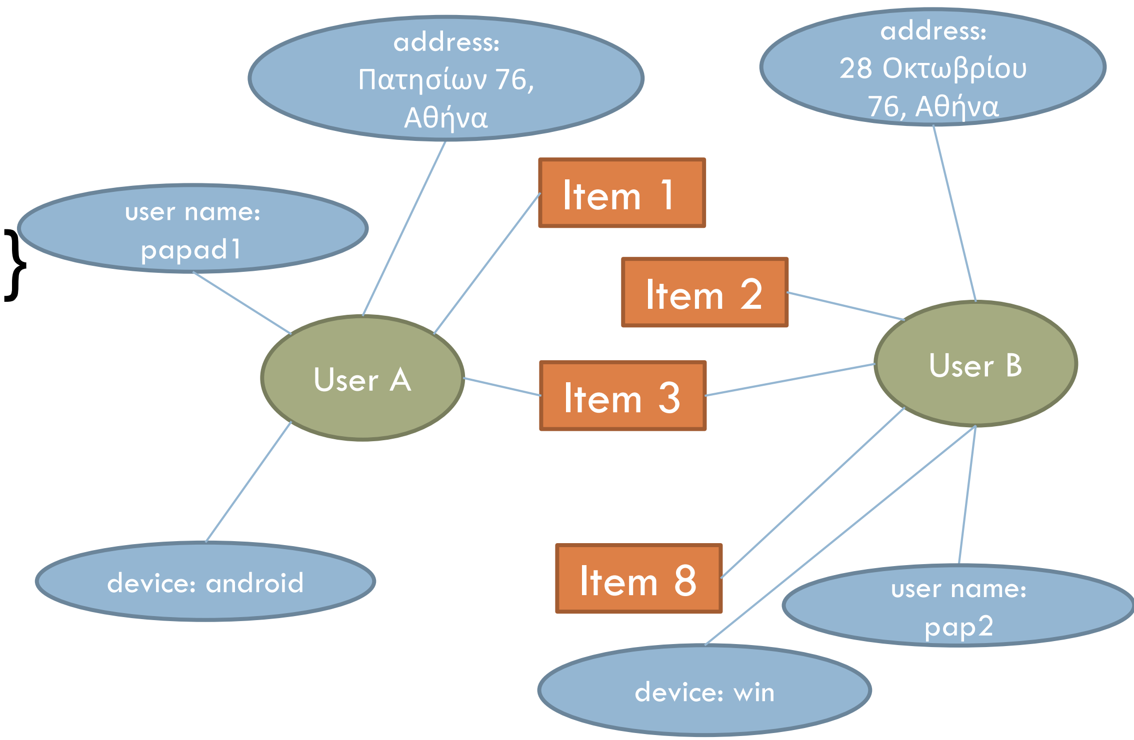
- Given a collection of customer data, compute most similar pairs
- Applications
  - Identity Resolution
  - Fraud detection
  - Customer Segmentation
  - Collaborative filtering



userA: papad1,android,{item1,item3}, “Πατησίων 76, Αθήνα”
userB: pap2,win,{item2,item3,item8}, “28 Οκτωβρίου 76, Αθήνα”
…

How to compare customers based on these data?

- “papad1” vs “pap2”
- android vs win
- {item1,item3} vs {item2,item3,item8}
- “Πατησίων 76, Αθήνα” vs “28 Οκτωβρίου 76, Αθήνα”



userA: papad1,android,{item1,item3}, “Πατησίων 76, Αθήνα”
userB: pap2,win,{item2,item3,item8}, “28 Οκτωβρίου 76, Αθήνα”
…

How to compare customers based on these data?

- “papad1” vs “pap22”
- android vs win

address 1

address 2

We will address these problems in the next lecture!

For now assume we have a function sim(user1,user2) that estimates the similarity between two users based on their data attribute values

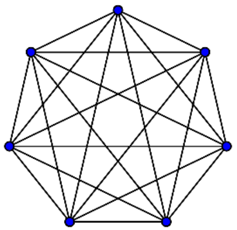
Οκτωβρίου 76, Αθήνα”

deviceid2

userA: papad1,android,{item1,item3}, “Πατησίων 76, Αθήνα”
userB: pap2,win,{item2,item3,itemN}, “28 Οκτωβρίου 76, Αθήνα”
…

Let us focus on the **running time**

- Run brute-force all-pairs similarity computation in your favorite programming language
- For n customers we need $\frac{n(n-1)}{2}$ comparisons



  - CS theory: task complexity is O(n^2)
  - Assume task completes in 5 minutes (yeah!)
- In a year from now, dataset gets 100 times larger
- How long will in take for the same task to compute?

Ans: ~100^2*5min = $\frac{50000}{60*24}$ days = 34,7 days > 1 month!

Scale-up versus Scale-out

- They refer to different strategies for expanding your computing resources to handle the growth of work
- Scale-up (vertical scaling): adding more/better resources to an existing system to reach a desired state of performance
  - More powerful CPU/GPU
  - More RAM
  - Larger/faster Disks
  - More network interfaces

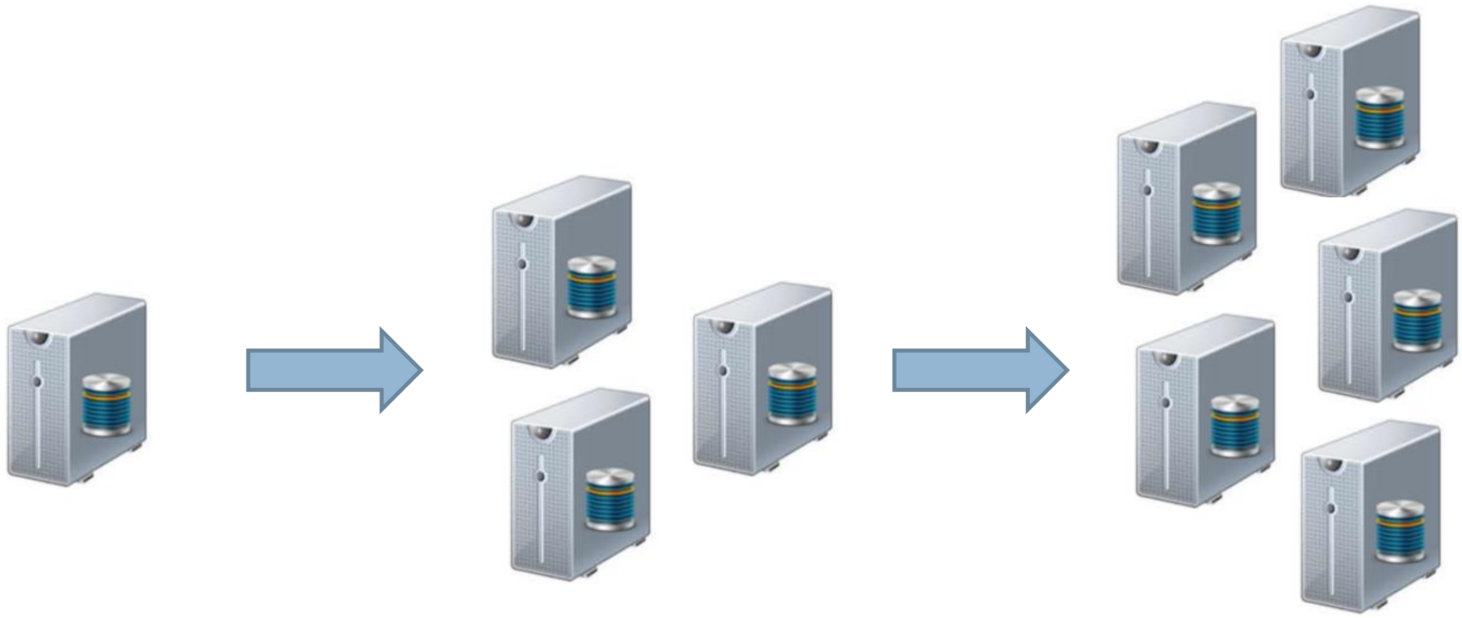
- In cloud computing environments this translates to moving up to larger, more powerful instances

AWS Compute Optimized instances

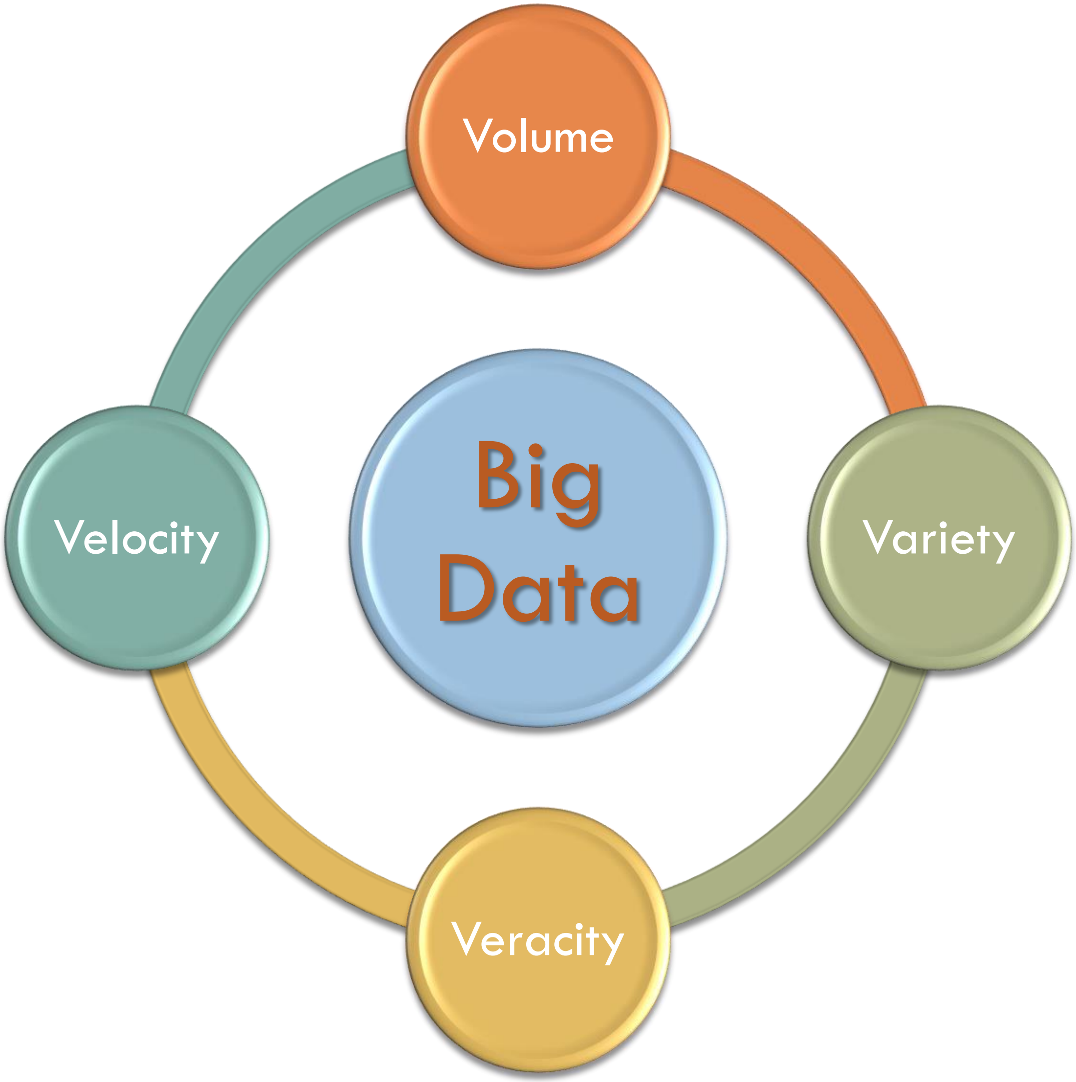
Model	vCPU	Memory (GiB)	Instance Storage (GiB)	Network Bandwidth (Gbps)
c5.large	2	4	EBS-Only	Up to 10
c5.xlarge	4	8	EBS-Only	Up to 10
c5.2xlarge	8	16	EBS-Only	Up to 10
c5.4xlarge	16	32	EBS-Only	Up to 10
c5.9xlarge	36	72	EBS-Only	10
c5.12xlarge	48	96	EBS-Only	12
c5.18xlarge	72	144	EBS-Only	25
c5.24xlarge	96	192	EBS-Only	25
c5.metal	96	192	EBS-Only	25
c5d.large	2	4	1 x 50 NVMe SSD	Up to 10
c5d.xlarge	4	8	1 x 100 NVMe SSD	Up to 10
c5d.2xlarge	8	16	1 x 200 NVMe SSD	Up to 10
c5d.4xlarge	16	32	1 x 400 NVMe SSD	Up to 10
c5d.9xlarge	36	72	1 x 900 NVMe SSD	10
c5d.12xlarge	48	96	2 x 900 NVMe SSD	12
c5d.18xlarge	72	144	2 x 900 NVMe SSD	25
c5d.24xlarge	96	192	4 x 900 NVMe SSD	25
c5d.metal	96	192	4 x 900 NVMe SSD	25

Horizontal scaling

- Scale-out: increase capacity by adding more instances
  - May reduce costs by employing less sophisticated resources to accommodate variable workloads



Big Data – The 4 Vs



Big Data: Volume

- Organizations process terabytes or even petabytes of raw data.
  - Turn 12 terabytes of Tweets created each day into improved product sentiment analysis.
  - Typical bottleneck: move data across the memory hierarchy
    - One HDD reads 12TB @ 145 MB/sec in ~24 hours
    - One NVMe SSD reads 12TB @ 2GB/sec in ~1,7 hours
    - Common tasks require multiple passes over the dataset
    - Need to also consider CPU processing time…

Big Data: Velocity

- Ability to react quickly to streaming data
  - Real-Time Enterprise: reduce the gap between when data is recorded in an organization and when it is available for information processing and decision-making.
  - For time-sensitive processes such as catching fraud, big data must be used as it streams into your enterprise in order to maximize its value.
  - Scan 5 million trade events created each day to identify potential fraud.

Big Data: Variety

- Big data is any type of data - structured and unstructured data (or anything in between) such as text, sensor data, time series, audio, video, click streams, log files, graph structures and more.
  - Does the relational model meet your data needs?
    - Key-value pairs?, column-based, documents-oriented? graphs?
- New insights are found when analyzing these data types together.
  - But they often live in different (data) eco-systems…

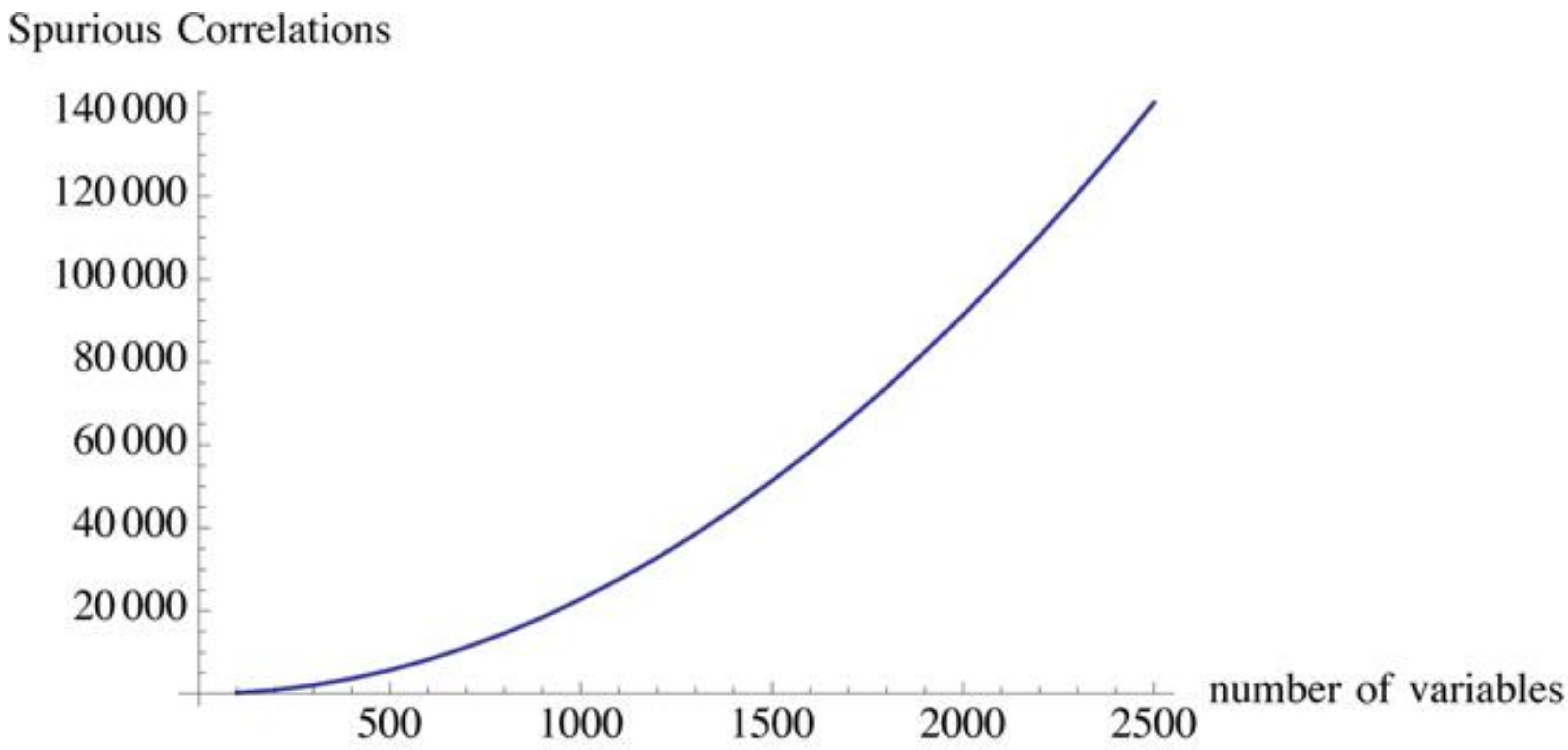
Big Data: Veracity

- How to deal with uncertain or imprecise data
  - In traditional applications there was always the assumption that the data is certain, clean, and precise
- Need to act based on information collected from disparate sources or the social web
  - How much faith can we put in social media data like Tweets, Facebook posts?
  - Can you explain your ML models?
  - How can we act upon information/processes if we don't completely trust or understand them?
  - Can you modify your algorithms to provide strong statistical guarantees over imprecise data?

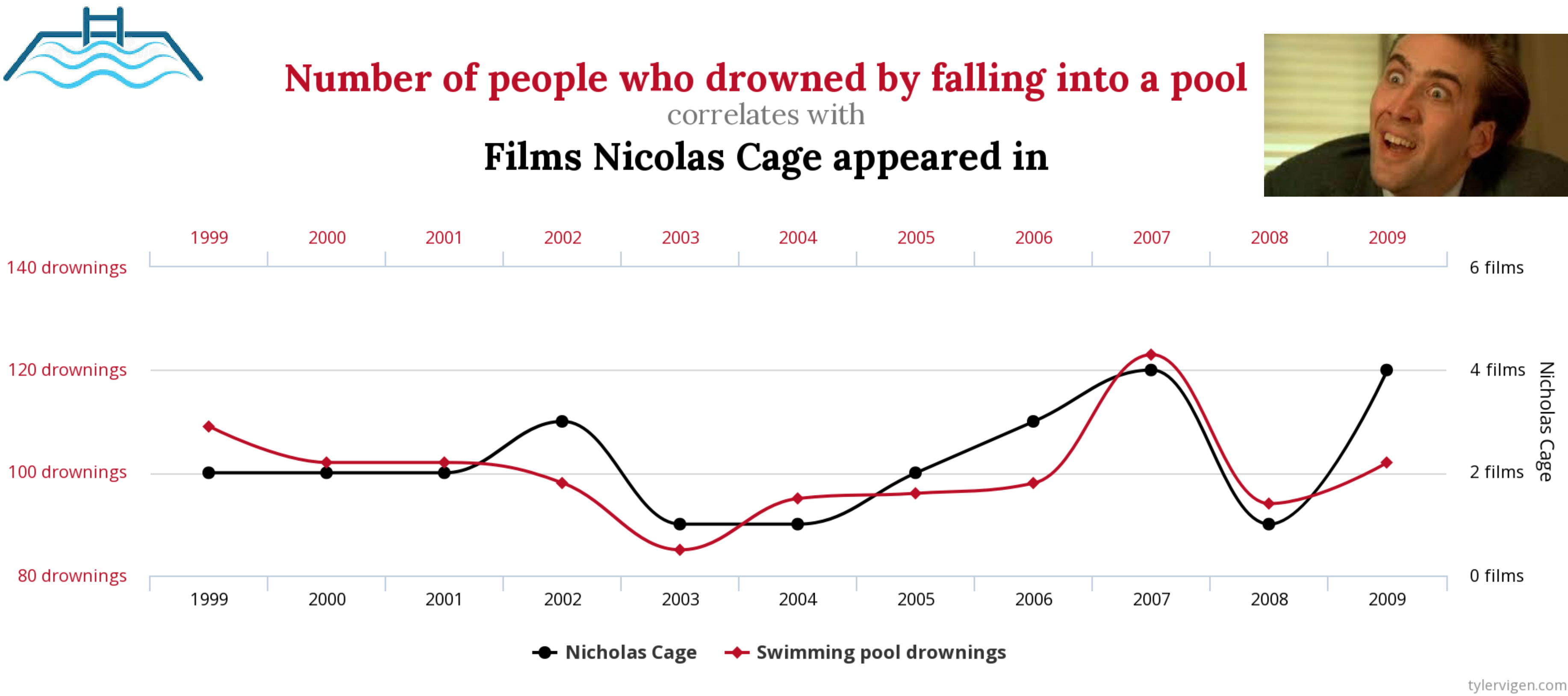
Implications of 4Vs in data analysis

- Big data → big noise → big errors?
- Need faster/scalable algorithms
  - Partitioning/Parallelization helps sometimes but best you can hope for is linear speed up
    - Some algorithms are hard to parallelize
  - Theoretical bounds reached
    - Trade accuracy for efficiency
  - Provision for data that is always in flux

Beware the Big Errors of ‘Big Data’ (Nassim N. Taleb)

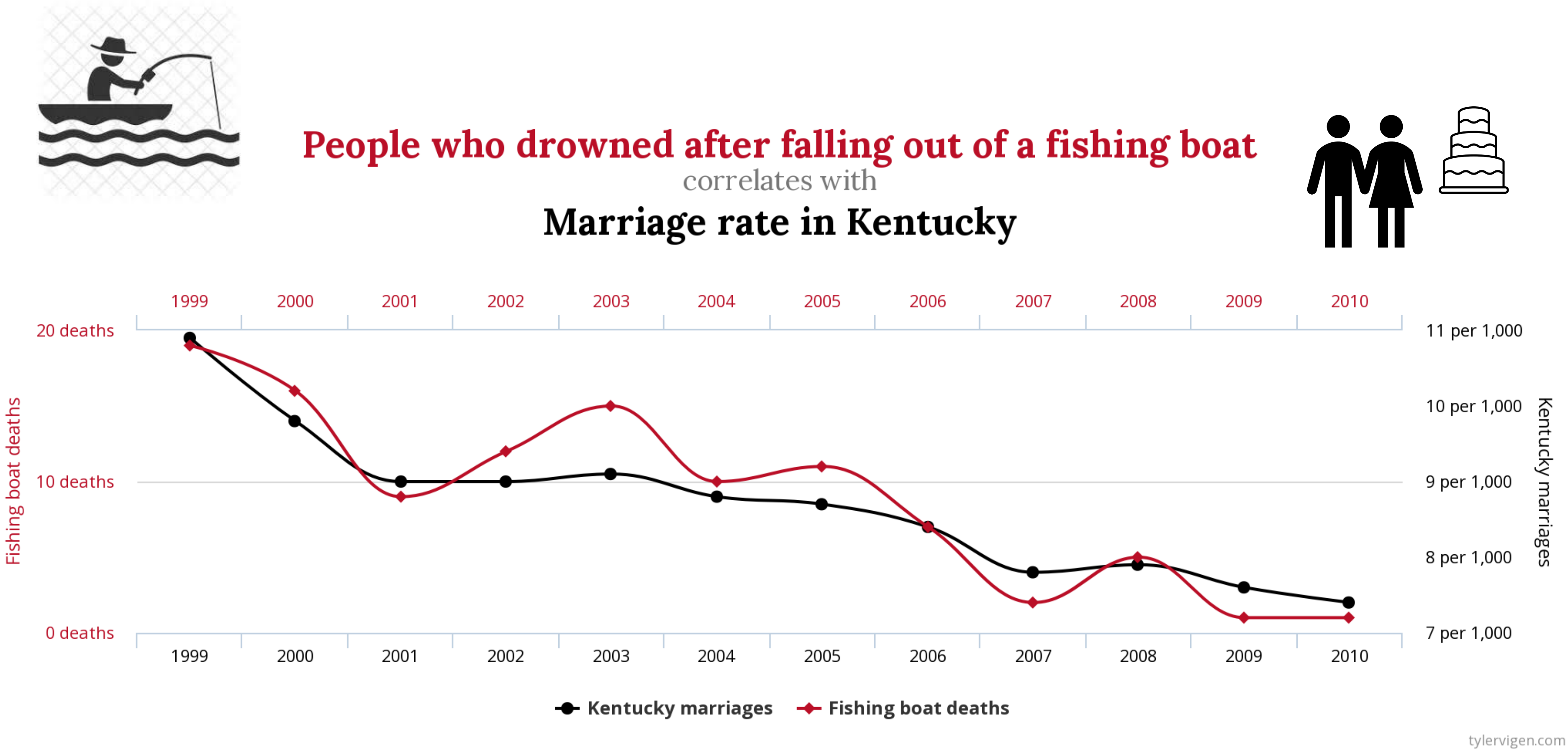


Spurious Correlations (http://tylervigen.com/)



Correlation: 66.7%

Spurious Correlations (http://tylervigen.com/)



Correlation: 95.2%

Rhine Paradox* – (1)

- Joseph Rhine was a parapsychologist in the 1950's who hypothesized that some people had Extra-Sensory Perception (ESP).
- He devised an experiment where subjects were asked to guess 10 hidden cards – red or blue.
- He discovered that almost 1 in 1000 had ESP – they were able to get all 10 right!

*example from http://infolab.stanford.edu/~ullman/mmds.html

Rhine Paradox – (2)

- He told these people they had ESP and called them in for another test of the same type.
- Alas, he discovered that almost all of them had lost their ESP.
- What did he conclude?
  - Answer on next slide.

Rhine Paradox – (3)

- He concluded that you shouldn't tell people they have ESP; it causes them to lose it.

Meaningfulness of Answers

- A big data-mining risk is that you will “discover” patterns that are meaningless.
- When looking for a property make sure that the property does not allow so many possibilities that random data will surely produce facts “of interest”

Example Case*: detect "evil-doers"

- There are1 billion people out there who might be evil-doers
- Out of those, about 100 are indeed evil-doers
  - This is the number of "events" (people) you expect to find in your investigation
- Make a hypothesis: a pair of people should be under investigation if they visit on two different days the same hotel
  - Maybe different hotel on each day

*example from http://www.mmds.org/

Simplifying Assumptions

- Look for people who, on two different days, were both at the same hotels.
  - 1 billion people who might be evil-doers
  - A person goes to a hotel one day in 100
  - Loot at booking records of 100K hotels
  - Examine hotel records for 1000 days to find evil-doers

Assume Random Behavior

- Probability any two people both decide to visit a hotel on any given day is $0.01*0.01 = 0.0001$
  - There are 10^5 hotels to choose from
    - Assume hotels are visited with same probability (not realistic)
  - Thus, probability that they visit the same hotel is $p=10^{-4} * 10^{-5}=10^{-9}$
- Probability that they visit the same hotel on two different days is $p^2=10^{-18}$ (hotels may differ on the two days)

What we have found

- Probability of observing an event on random data is very small: 0.000000000000000001
- Thus, if we see one such pair of people it should be investigated, right?

The effects of big data in calculations

- Event = two people were at the same hotel on two different days
- There are n=1billion people resulting in

$$\binom{n}{2} \approx \frac{n^2}{2} = 5*10^{17}$$ pairs of people

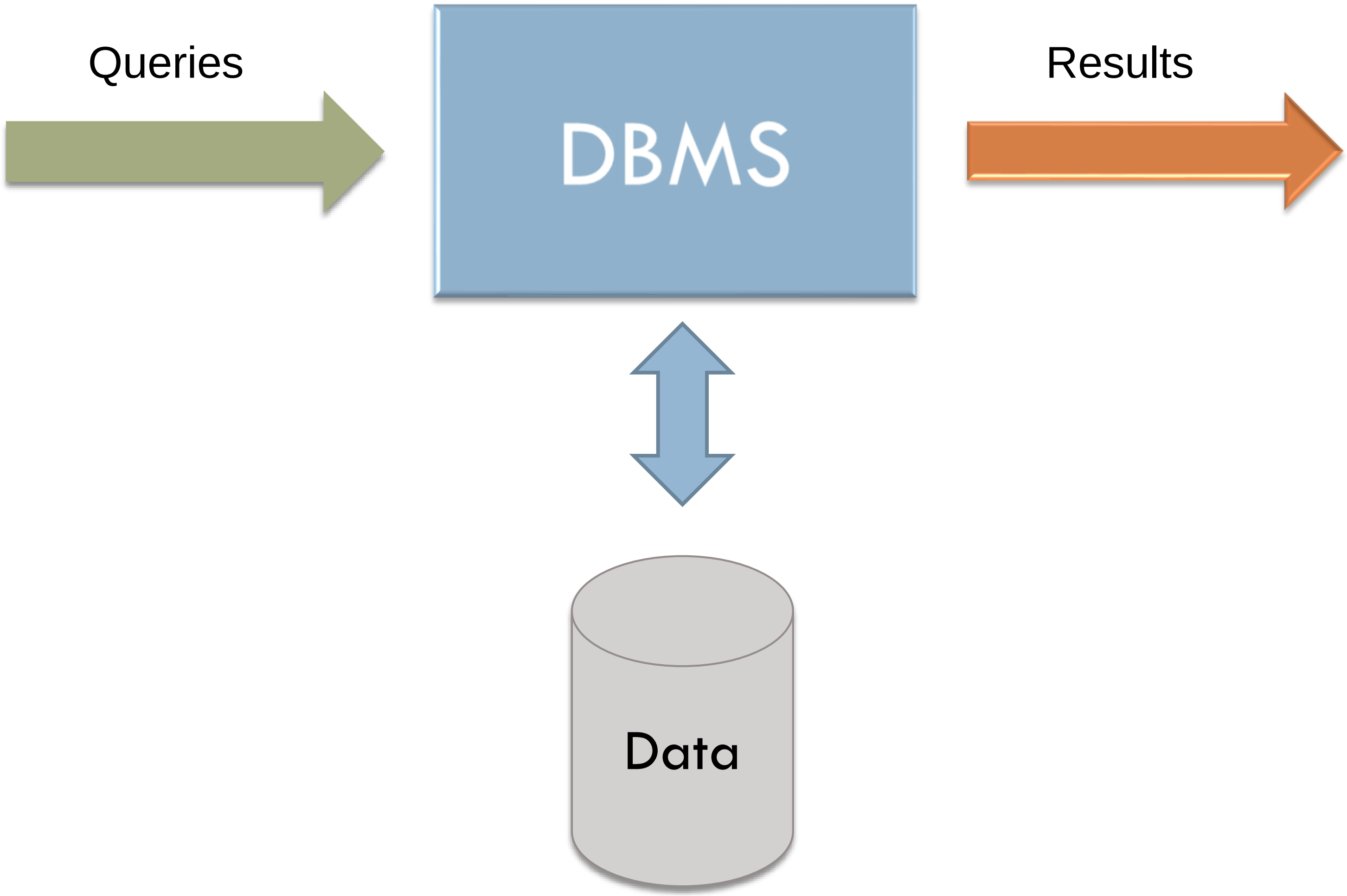
- Similarly, there are $\binom{1000}{2} \approx \frac{1000^2}{2} = 5*10^5$ pairs of days to look for

Expected number of events

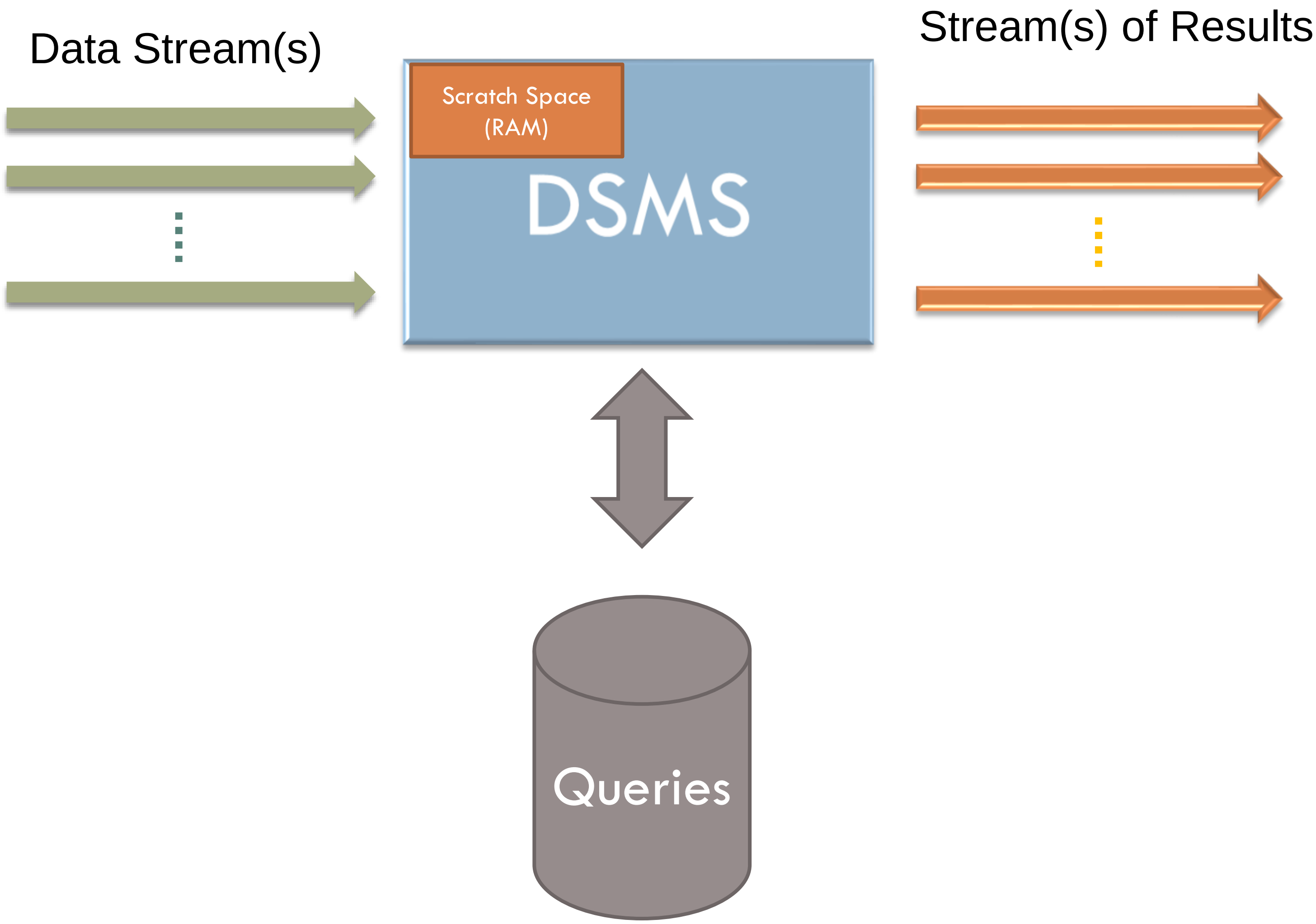
- $\underbrace{(5*10^{17})}_{\text{Pairs of people}} * \underbrace{(5*10^{5})}_{\text{Pairs of days}} * \underbrace{10^{-18}}_{\text{Probability of an event}} = 250000$ events

- Each event is a pair of people (who have visited the same hotels on two occasions)
- Thus, there are 250K pairs of people to investigate
  - But there are only100 real evil-doers
  - Is it feasible? Does it justify the intrusion on people's lives?

Traditional Data Processing

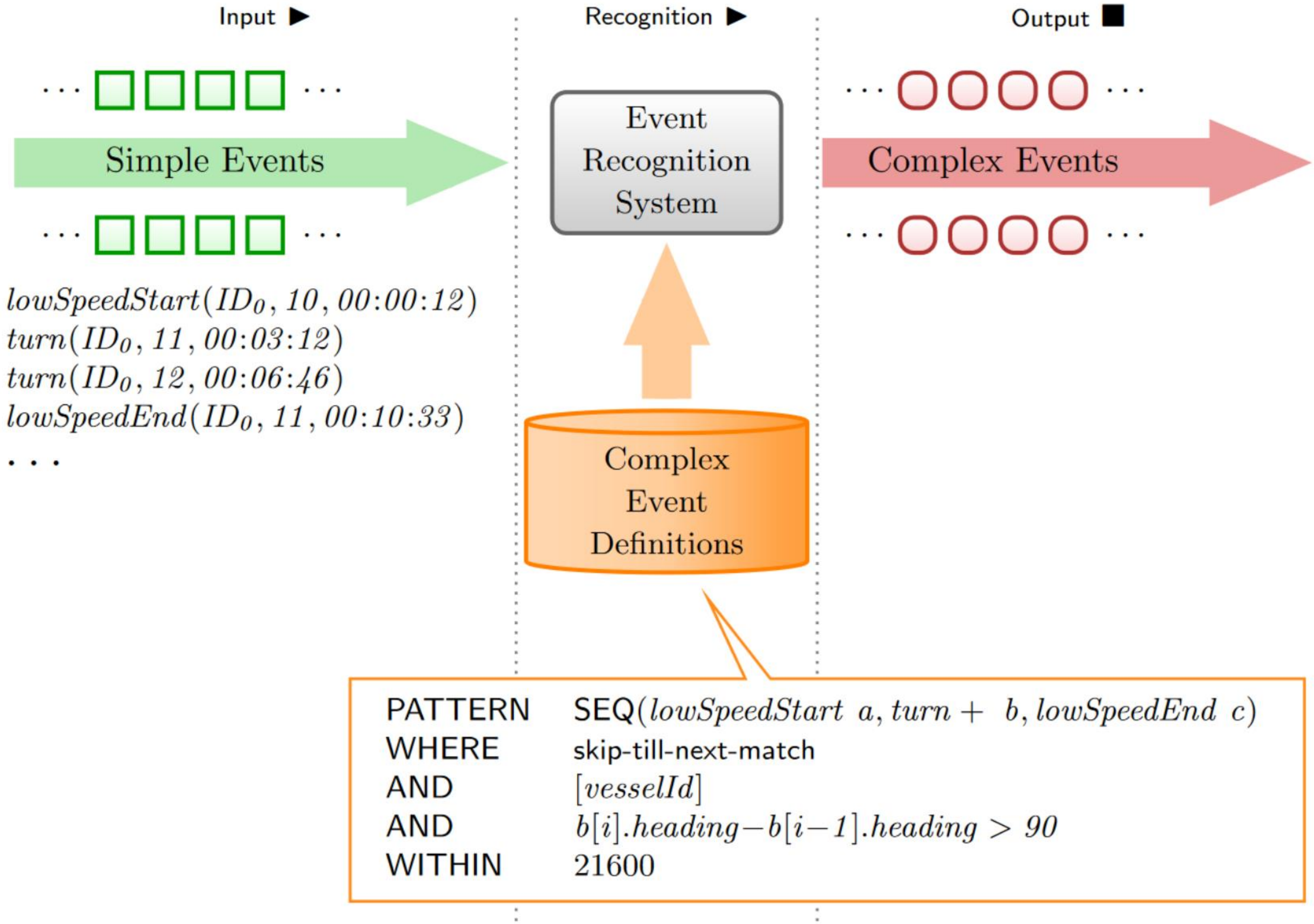


Stream Processing



Related topic: Complex Event Processing

(example from: http://cer.iit.demokritos.gr/publications/papers/2020/VLDB-D-19-00003_CRVersion.pdf)



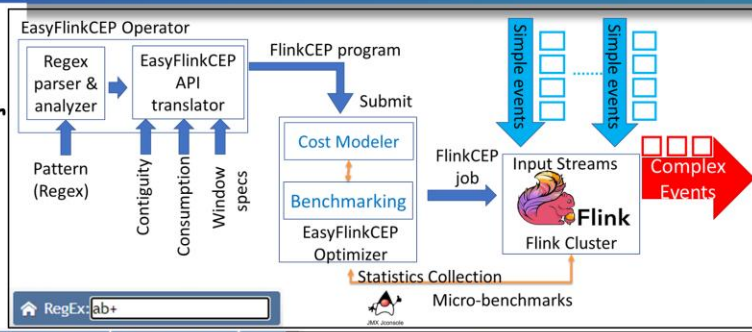
Nikos Giatrakos, Eleni Kougioumtzi, Antonios Kontaxakis, Antonios Deligiannakis, Yannis Kotidis

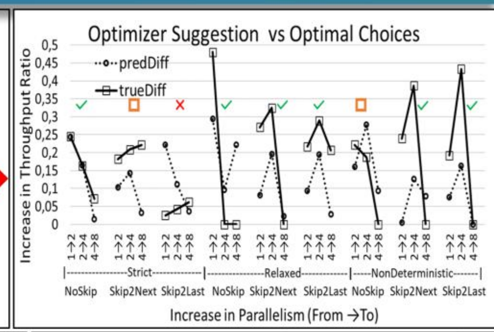
ATHENA

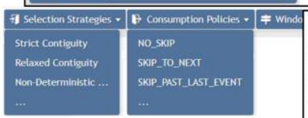
ATHENS UNIVERSITY OF ECONOMICS AND BUSINESS

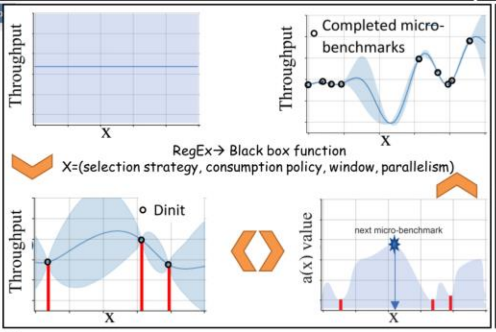
EasyFlinkCEP: Big Event Data Analytics for Everyone

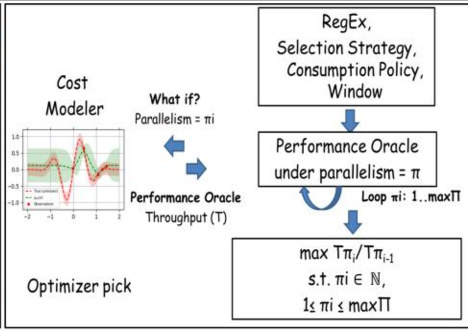
- Complex Event Processing (CEP) in FlinkCEP:
  - † Distributed processing over computer clusters
  - † Language of high expressive power
  - × Low level language (Scala/Java)
  - × Cluster admin decisions needed
- EasyFlinkCEP Prototype
  - EasyFlinkCEP Operator
    - No coding, uses Regular Expressions
    - graphical definition of CEP parameters
  - EasyFlinkCEP Optimizer
    - automates FlinkCEP job configurations (parallelism)





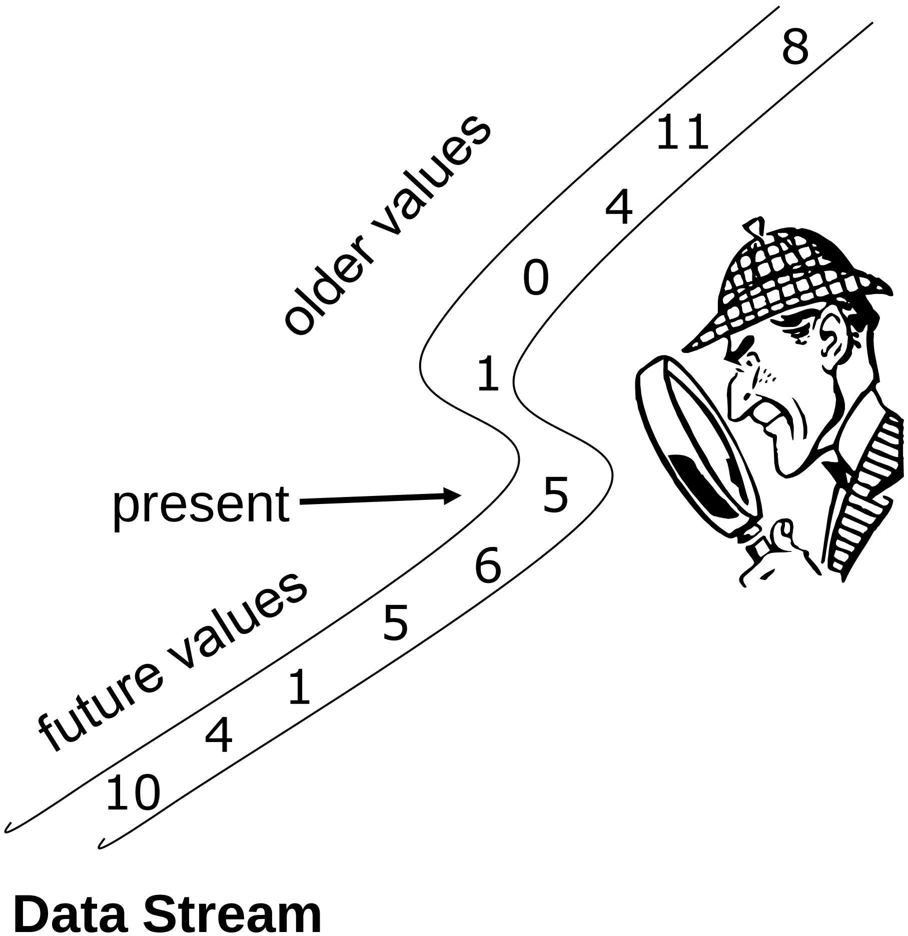






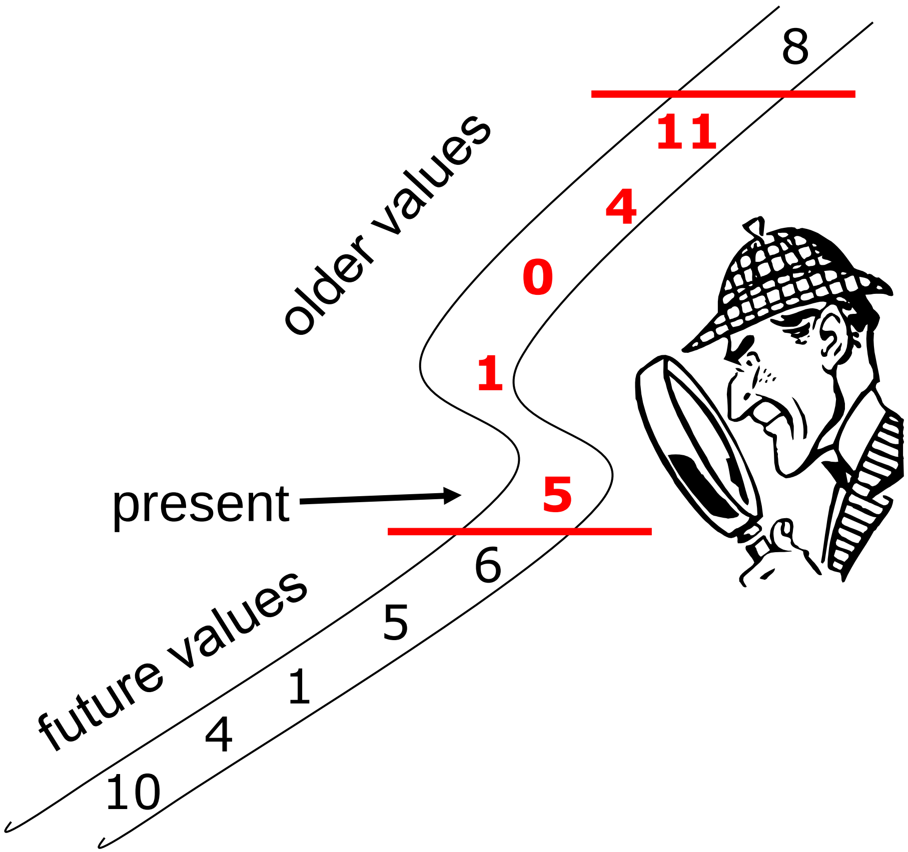
Achievements: (1) Non-programmer event analysts rapidly develop and deploy new CEP pipelines. (2) Exploits the processing capacity of modern hardware without requiring practitioners to make cluster administration decisions.

Stream processing: exact computations over infinite data



- For a stream of *n* values, some problems require O(*n*) memory in order to compute a definite answer, others don't
- Consider the following computations
  - Maximum/minimum value in a stream
  - Average value?
  - Median value?
  - Most frequent value?

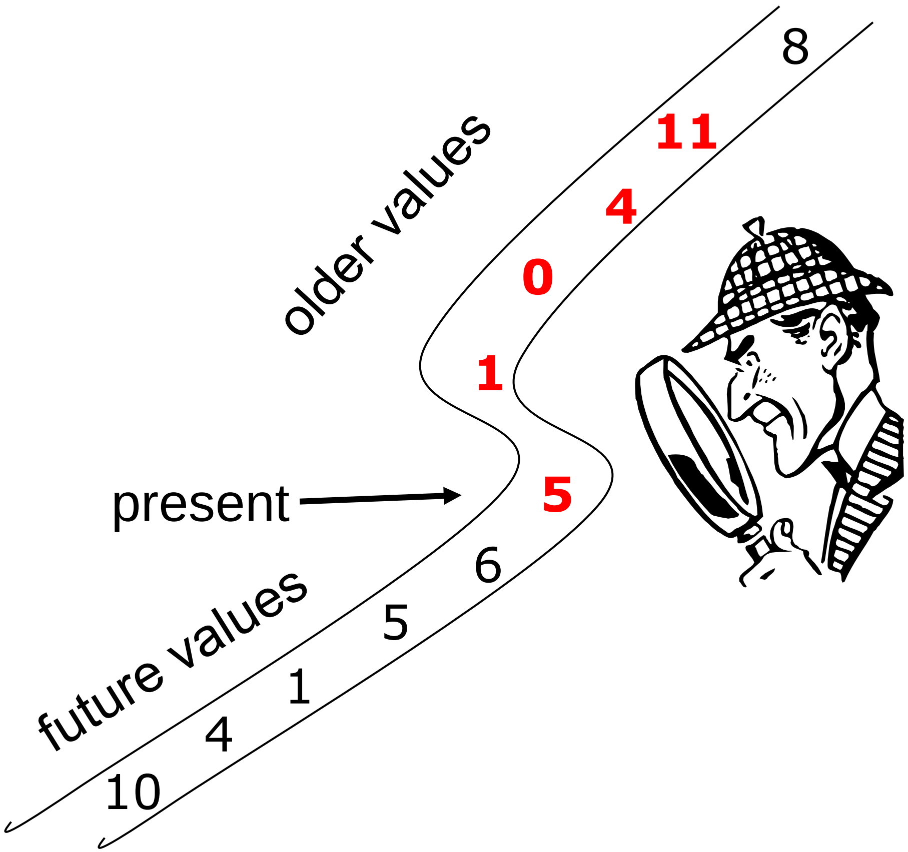
Windows: used to segment a continuous data stream into batches of tuples



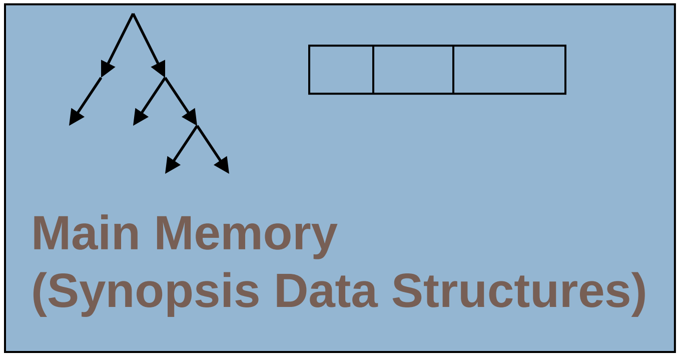
Data Stream

- Restrict the computation on the most recent tuples (window)
  - Tuple-based window: 5 most recent tuples (example on the left)
  - Time-based window: all data in the past 15 minutes
- The previous issue still holds (for n = window size)

Approximate query processing

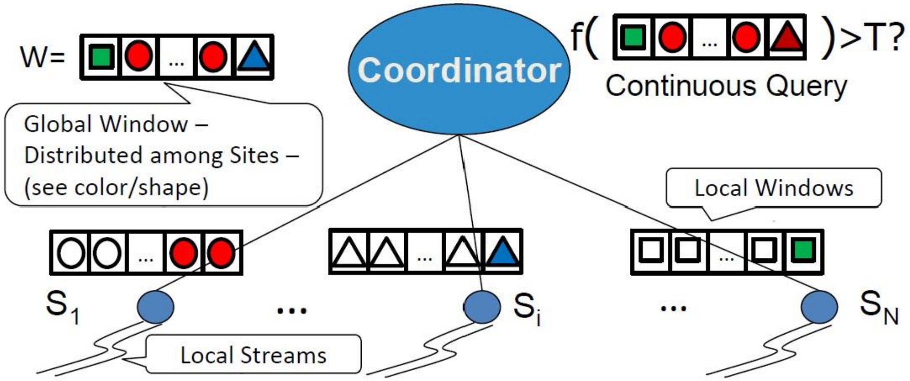


Data Stream

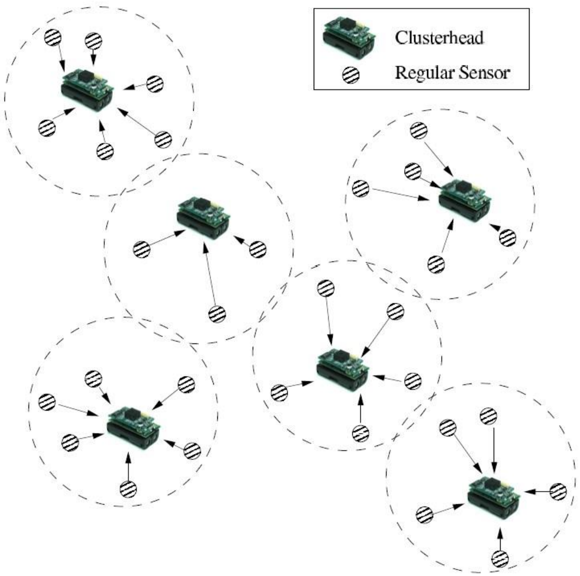


- Maintain synopses over the data and use them at query time to produce approximate answers
  - Example: data sketches, discussed next

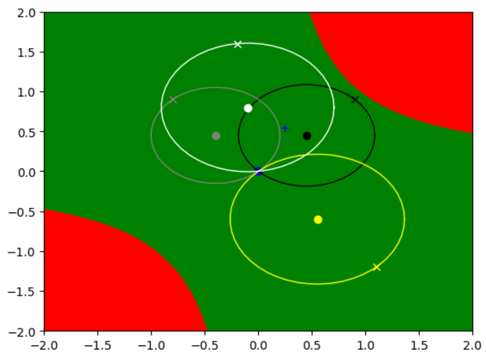
Distributed Stream Processing



Distributed Monitoring Example (Nikos Giatrakos)



In-network outlier detection (Kotidis et. al)



Geometric Monitoring

Stream processing example (1): Most frequent items

- Compute most-frequent #hashtags each day
  - 500 million tweets each day
  - Multiple hashtags / tweet

#a, #b, #a, #a, #d, #b, #c, #a, #a, #b, #a, #a, #a, #a, #a

1 day, hundreds of millions stream records

Stream processing example (2): moment estimation (Window=last 15 hashtags)

a, b, c, b, d, a, c, d, a, b, d, c, a, a, b

stream 1

$m_a = 5$

$m_b = 4$

$m_c = 3$

$m_d = 3$

S=2nd moment = 25+16+9+9=59

a, b, a, a, d, a, c, a, a, a, a, a, a, a, a

stream 2

$m_a = 12$

$m_b = 1$

$m_c = 1$

$m_d = 1$

S=2nd moment = 144+1+1+1=147

S is a measure of how uneven the distribution is

Another Streaming Application

- Compare twitter usage across different countries in real-time
  - Connect to twitter API
  - Filter based on location (e.g. Greece)
  - Parse tweets, find hashtags
  - Compute frequencies
  - Compare frequency distributions

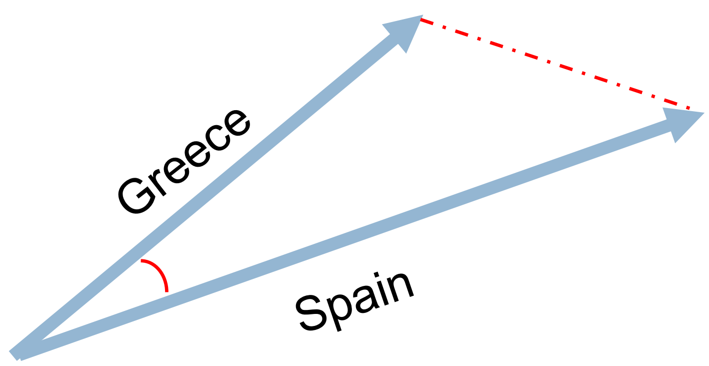
Bag of hashtags for Greece

(#android,5)
(#MeToo,1)
(#iphone,1)
(#NBAfinals,2)

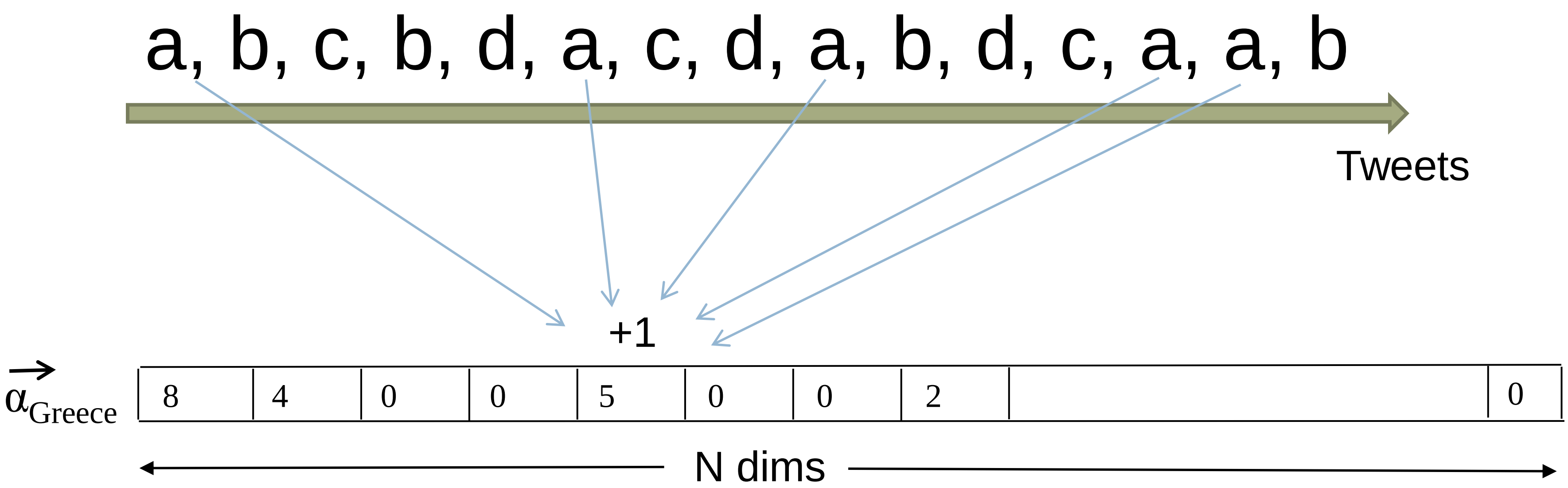
Compute frequencies

A simple idea (just to keep going)

- For each country, embed all frequencies into a single vector
- Compare counties by comparing their respective vectors
  - We will discuss details of alternative metrics in the next lecture



Frequency vector for Greece



- Each hashtag (string) in mapped to a coordinate in a N dimensional space
- The coordinate value is a counter that depicts the frequency of this particular hashtag

What does it mean?

My Data (hashtags = strings from Greek tweets):

a, b, c, b, d, a, c, d, a, b, c, a, a, d, e, c

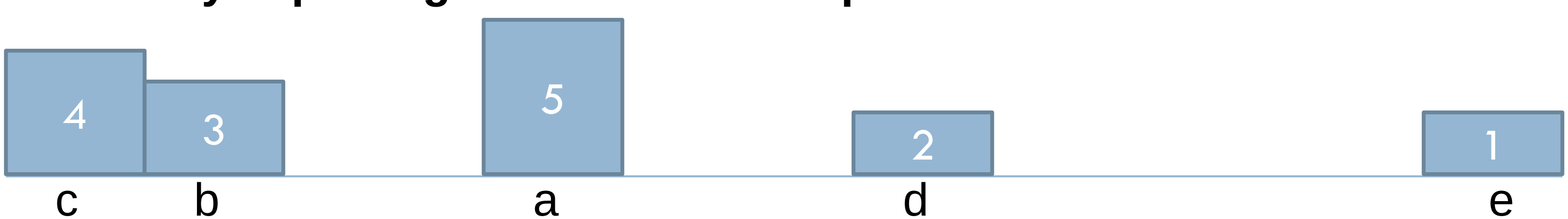
Time

How I chose to represent this information in my program:

$\vec{\alpha}_{\text{Greece}}$

4	3	0	0	5	0	0	2		1
c	b			a			d		e

What I am actually capturing with the above representation:



Note

- This representation is “correct” if comparing frequency distributions using vectors is my means of analyzing this data
  - Dimensionality curse?
- Don’t jump into a “convenient” representation
- Consider the pros and cons of each approach
  - Goals, accuracy, performance tradeoffs, feasibility

Hashing: map keys to an integer domain

……….#paobc……………..#paobc

Tweets

h("#paobc")=7

Slot 0 Slot 1 Slot 7

$\vec{\alpha}_{Greece}$

8	4	0	0	5	0	0	2		0

N dims

N=2^m for h() returning m-bit integer values

- In this example key values are the different hashtags (that we do not know in advance)
- We need a function h(s) that maps a string s to an integer (next lecture)

Now that I have these vectors, I can compare them!

- Vector for Greece

#aek, #paobc, #oly

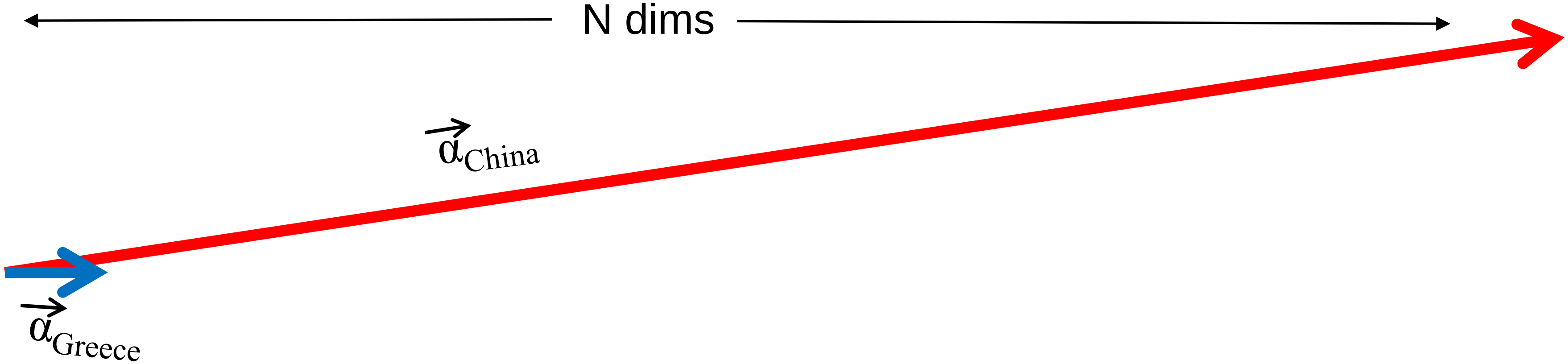
$\vec{\alpha}_{Greece}$										
	8	0	0	0	5	0	0	2		0

← N dims →

- Vector for China (not likely but for the shake of this example…)

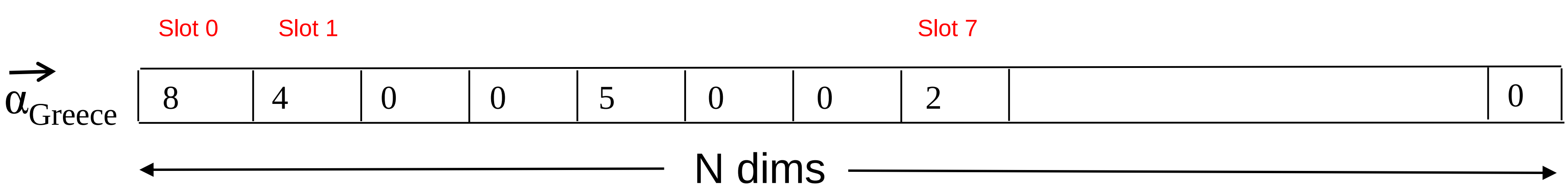
$\vec{\alpha}_{China}$										
	795	0	0	0	508	0	0	204		0

← N dims →



Ooops!

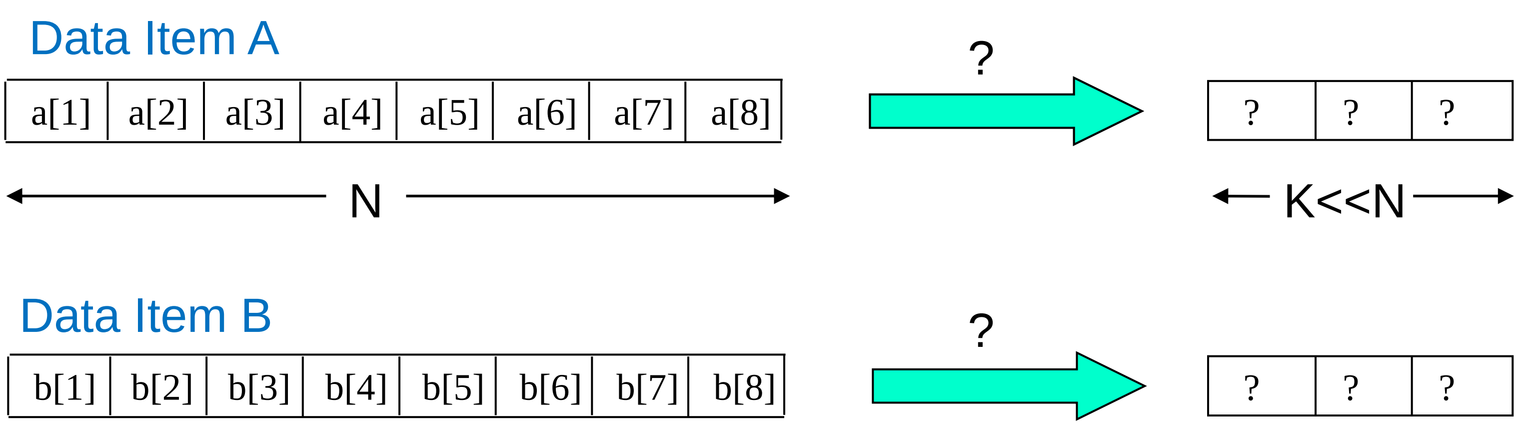
- In order to avoid collisions, I chose a large number for N (e.g. $N=2^{32} = 4294967296$)
  - Thus, hash values are 4-byte integers
- Each slot holds a 4-byte integer counter (freq)
- Thus, each vector occupies 16GB of RAM if stored "uncompressed"



$N=2^m$ for h() returning m-bit integer values

Data sketches

- Mathematical representations of data that allow useful information to be extracted effectively
  - Preserve distance computations (approximately)
  - Have small time/space complexity
  - Allow for real-time changes in data



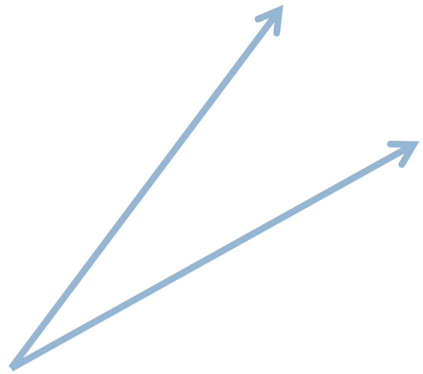
Dot (inner) product between two vectors

- $\vec{x} \cdot \vec{y} = \Sigma(x_k * y_k)$
- Example:

$$\vec{x} = (1,3,0,5)$$
$$\vec{y} = (1,0,1,6)$$

- Then:

$$\vec{x} \cdot \vec{y} = 1*1+3*0+0*1+5*6=31$$
$$= |\vec{x}| * |\vec{y}| * \cos(\theta(\vec{x}, \vec{y}))$$



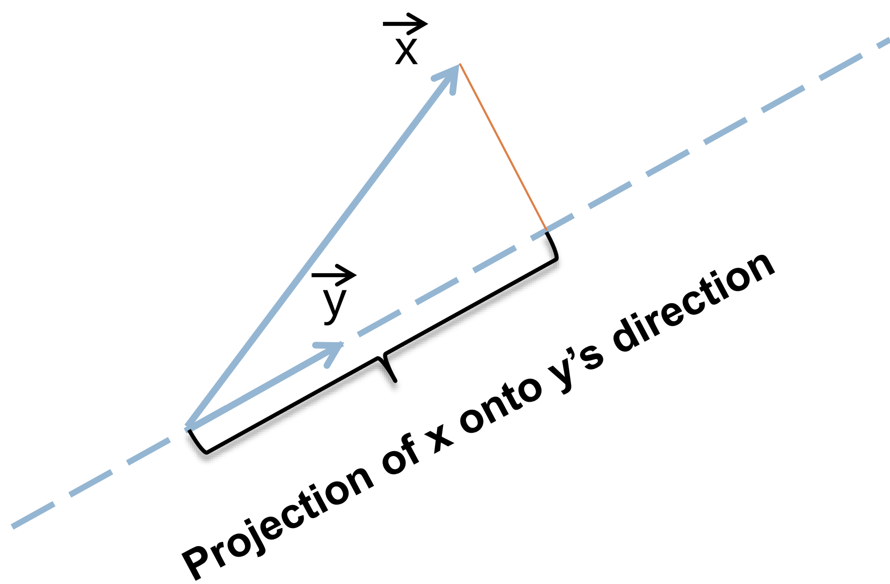
Dot product with unit vector

- $\vec{x} \cdot \vec{y} = \Sigma(x_k * y_k)$
- Example for unit vector $\vec{y}$:

$$\vec{x} = (1,3,0,5)$$
$$\vec{y} = (1/2,1/2,1/2,1/2)$$

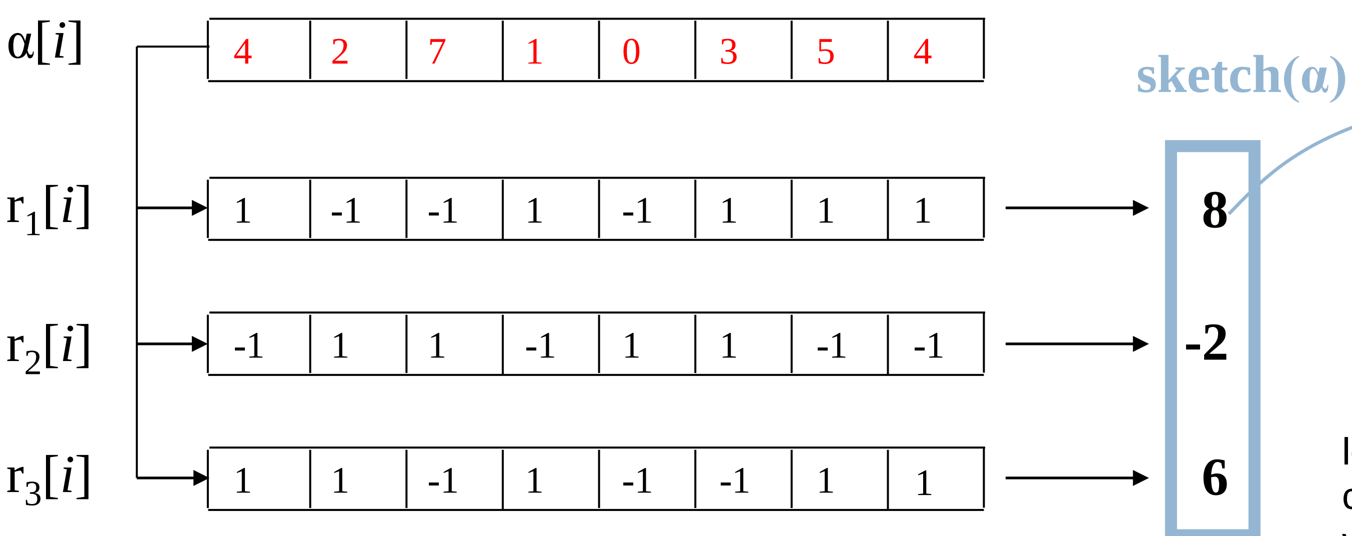
- Notice that $|\vec{y}|=1$
- Then:

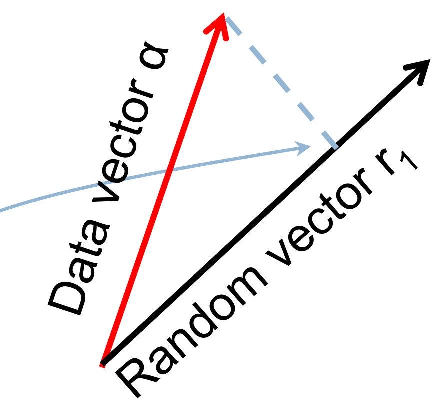
$$\vec{x} \cdot \vec{y} = 1/2+3/2+5/2=9/2$$
$$= |\vec{x}| * 1 * \cos(\theta(\vec{x}, \vec{y}))$$



Linear Projections (AMS Sketches)

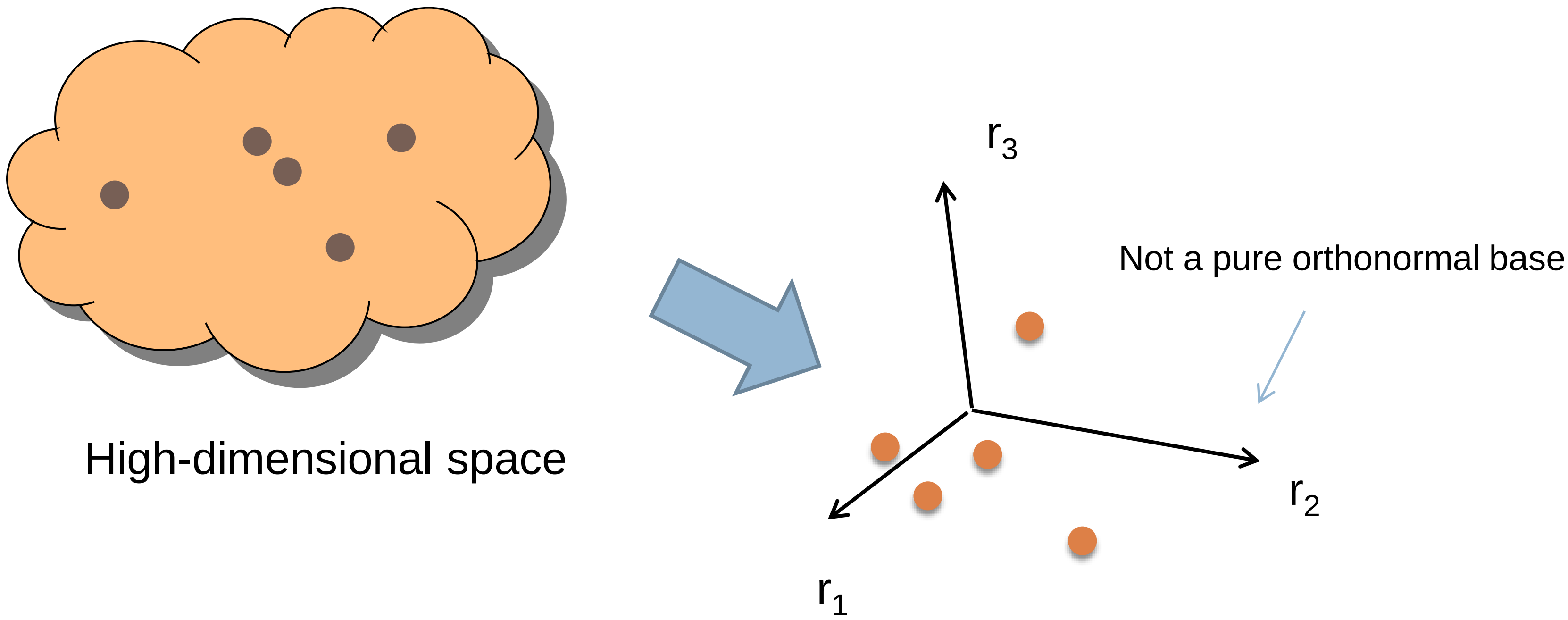
- [Alon96]: inner (dot) product of data vector with $O(\log(N/\delta)/\varepsilon^2)$ pseudo-random vectors {-1,+1} (linear projections)
  - ε: approximation error
  - δ: failure probability





lemma: we can estimate the cosine similarity among two vectors from their sketches

Random Projections

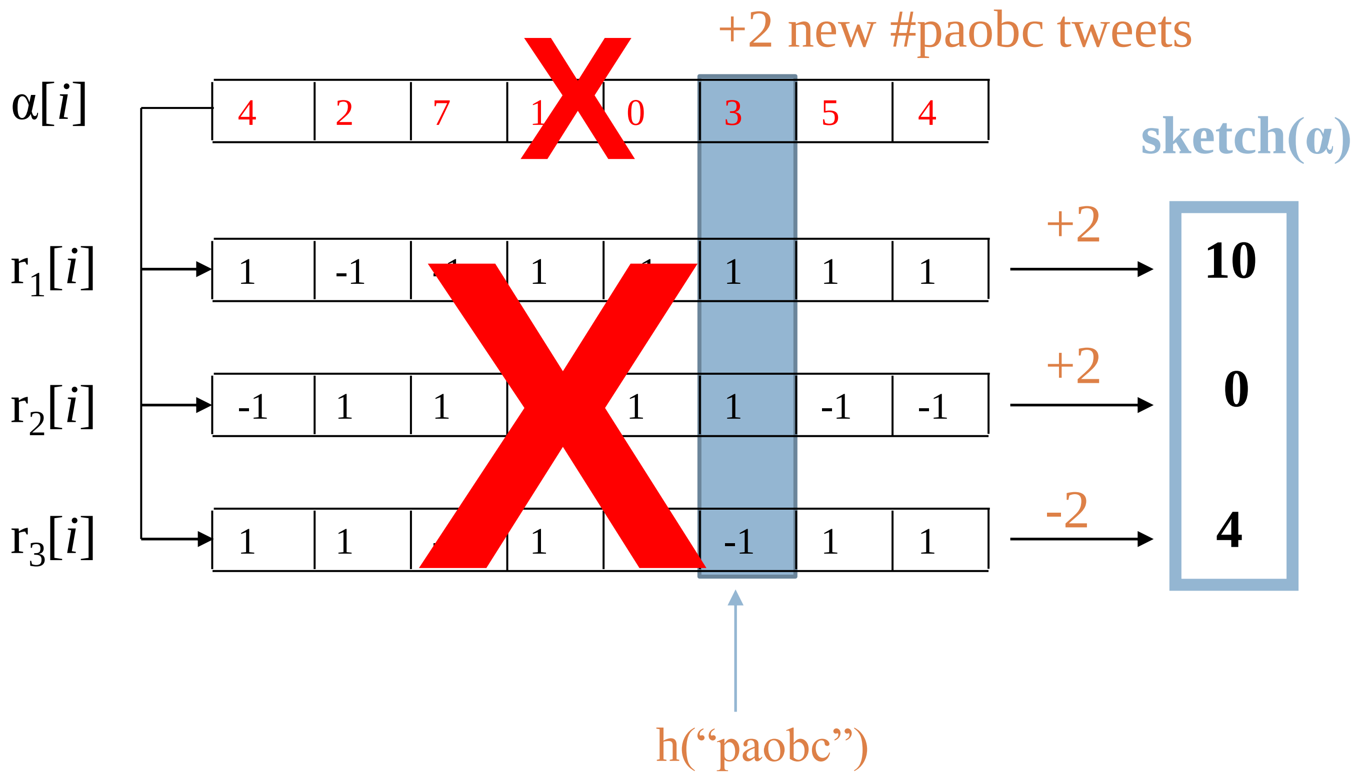


What can we do with them

- Estimate norms, distances, dot products with (ε,δ)-guarantees
  - ε: approximation error
  - δ: failure probability
- Using much less space/time than using the real vectors
  - Need $O(e^{-2}(\log 1/\delta))$ time and space (addressed volume, velocity)
    - Note: there are more accurate sketching techniques available in the literature

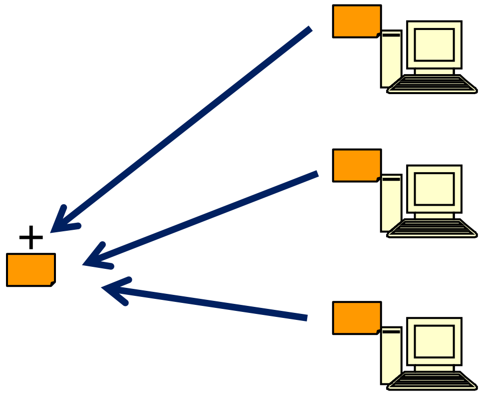
Updatability (addresses velocity)

- Linearity permits incremental updates
  - Thus, suitable for streaming data!



Sketches: Recap

- Simple Linear Projections (efficient computation)
- Permit *incremental* updates
- Sketches are *compassable*



What we have achieved

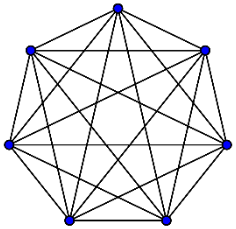
- Reduced (significantly) memory footprint of the data analysis algorithm
  - Data now fits in memory → processing is orders of magnitude faster
- Have introduced (controlled) impression

What is (still) missing?

- ?

Recall complexity of pair-wise computations

- For an all-pair computation we need to perform n*(n-1)/2 comparisons



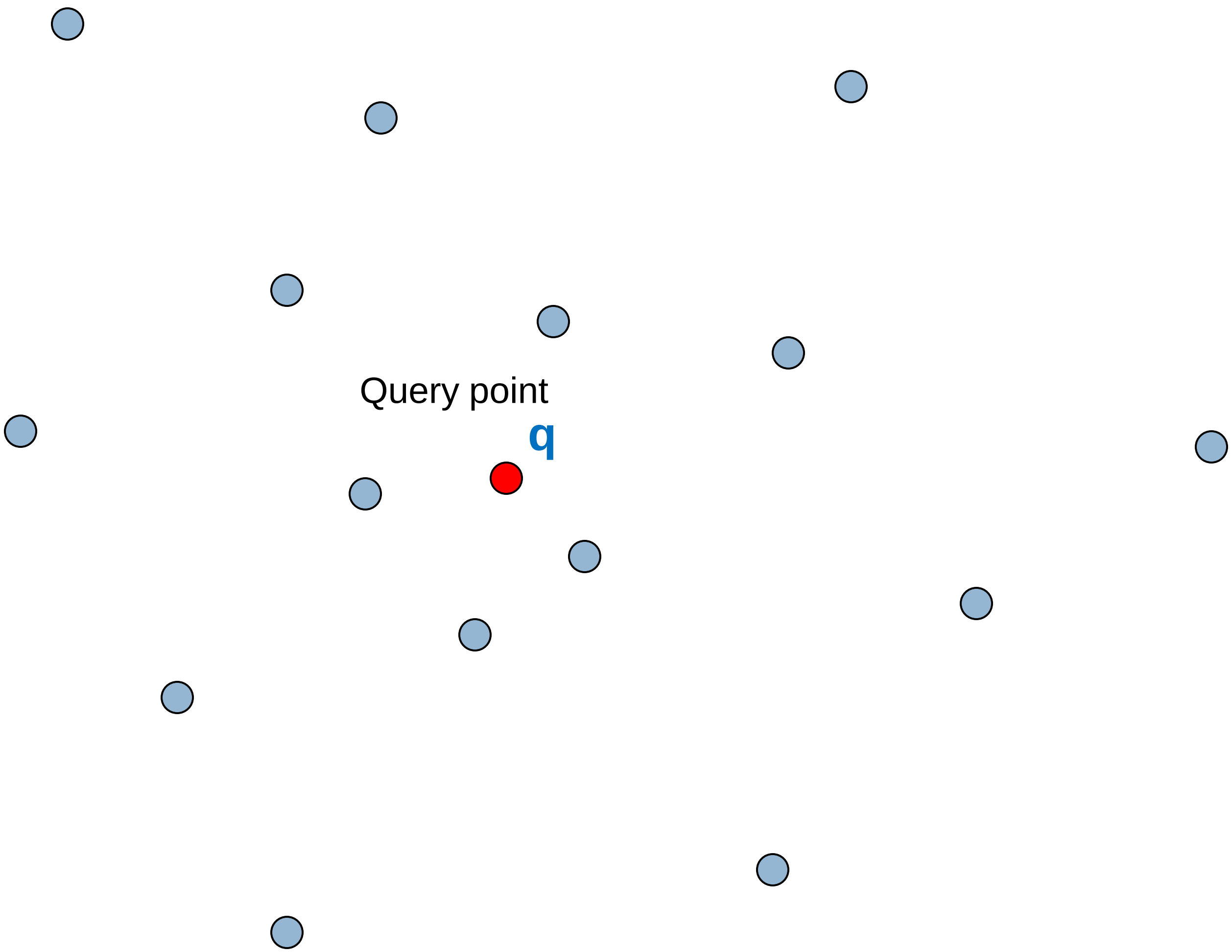
- For a Nearest-Neighbor query NN-k(q) we need to compute n-1 distances (using q as a source)

- How do we scale these computations?
  - With the use of indexes!

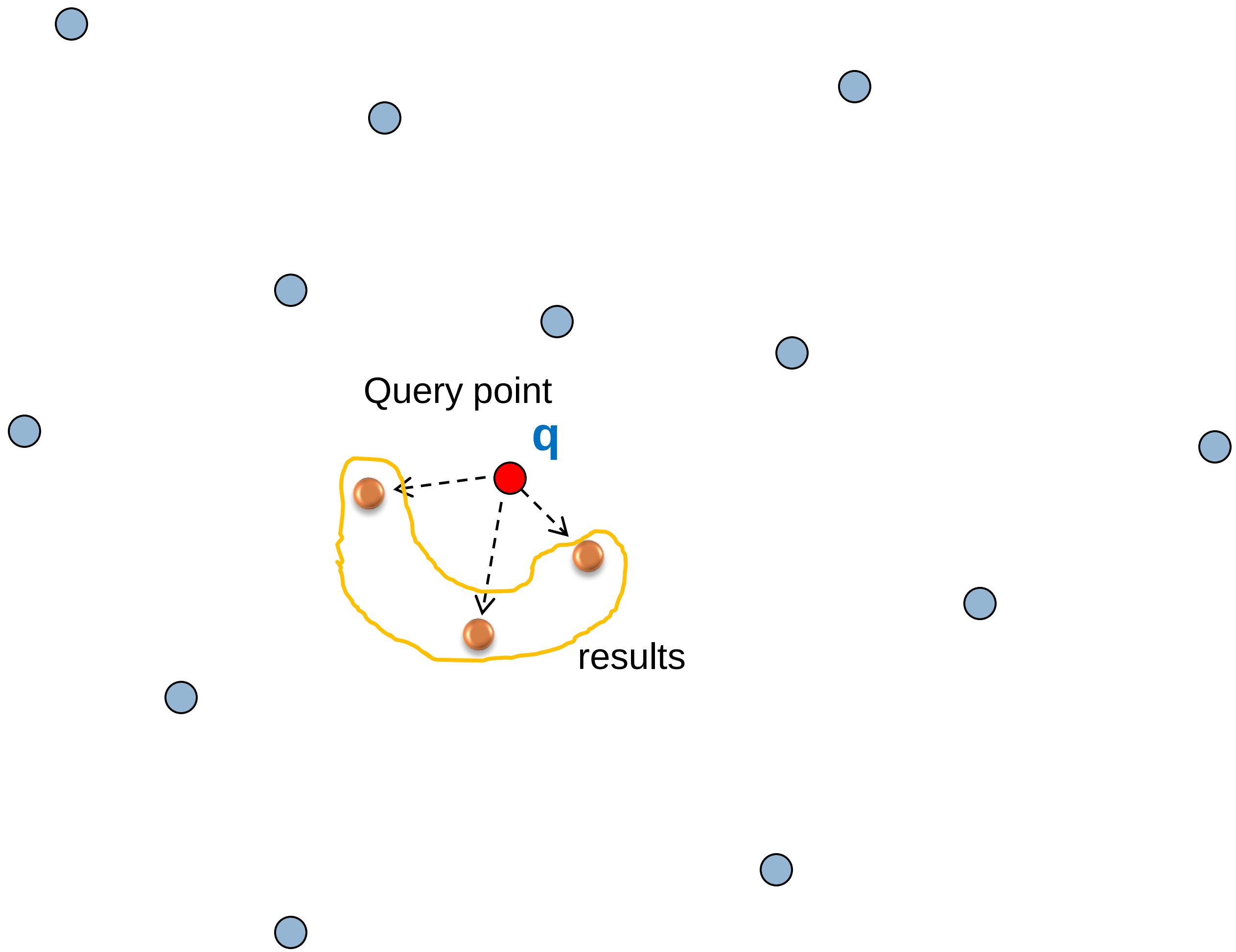
Nearest Neighbor Queries Example

- Spatial (2-dim) domain: find me 3 restaurants nearest to my location (=query point q)
  - NN-k(q) (k=3) query

Nearest Neighbor Query



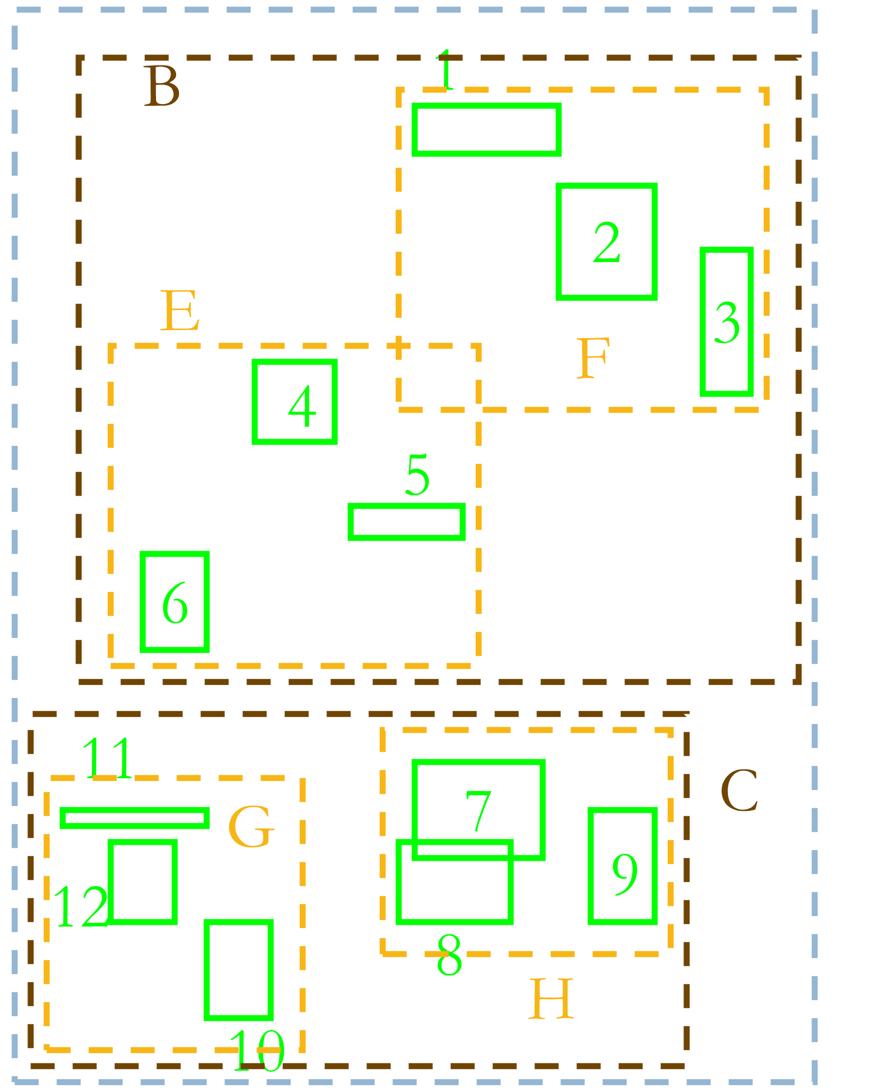
Nearest Neighbor Query



Dimensionality Curse

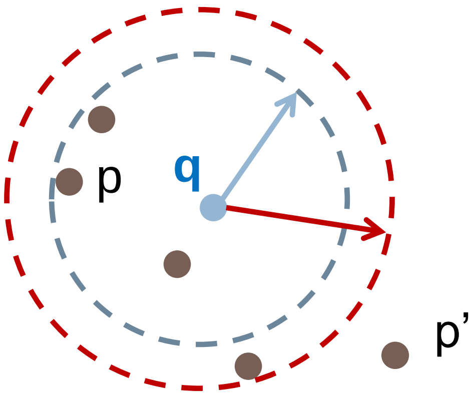
- Curse of dimensionality renders common indexes ineffectual
  - Often full scan of DB is preferable but slow
- Consider also: velocity & volume of big data

R-Tree



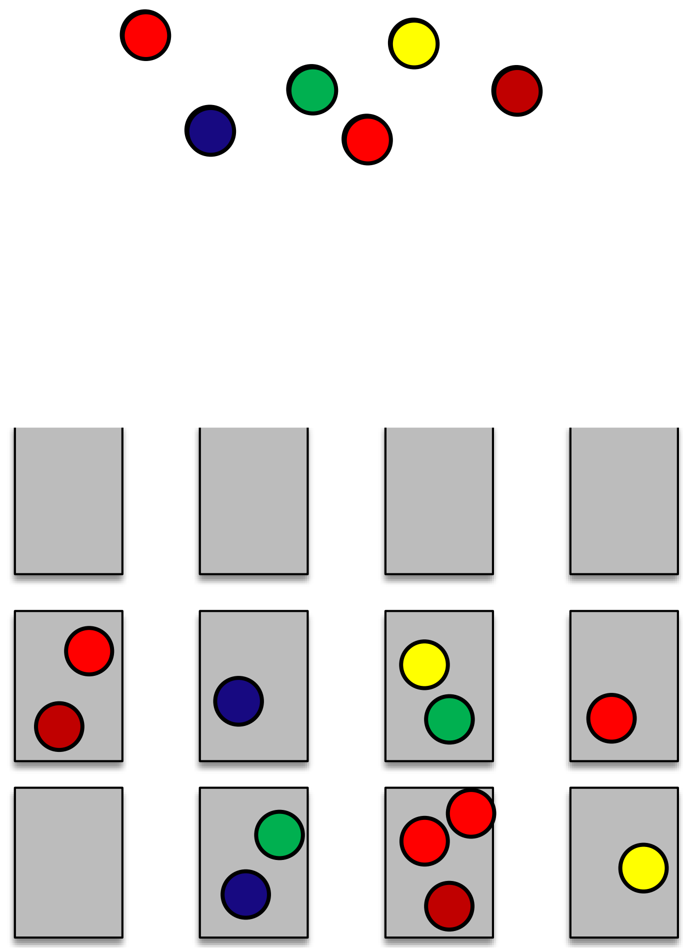
“Approximation” to the rescue (again)

- c-Approximate k-NN problem: build data structure which
  - If there is a point p: dist(p,q)≤R, p is returned with high probability
    - i.e. high probability of not missing a true NN = few false negatives
  - If dist(p’,q)>cR, the probability of returning p’ is small
    - Most results are true NN = few false positives
      - False positives may be pruned in a second step



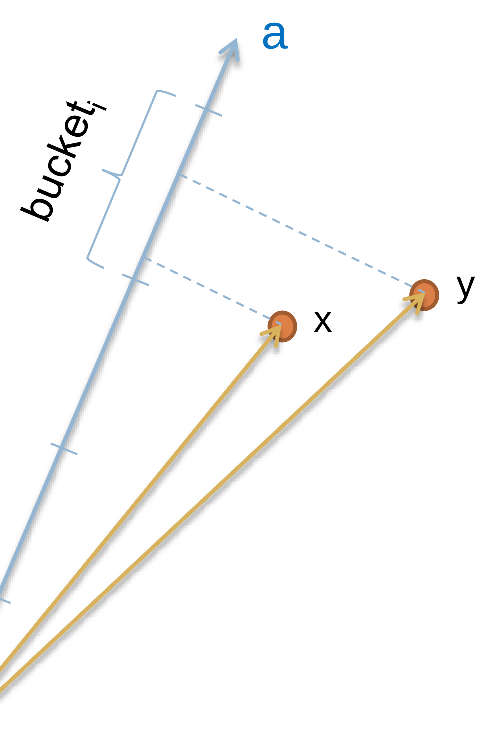
Locality Sensitive Hashing (LSH)

- Assign items to **buckets** using a hash function **h(x)**
  - E.g. h(●)=1
  - Details of function h() depend on the preferred similarity metric:
    - Similar objects are hashed to the same bucket with high probability
    - Dissimilar objects are hashed to the same bucket with very small probability
- Repeat several times



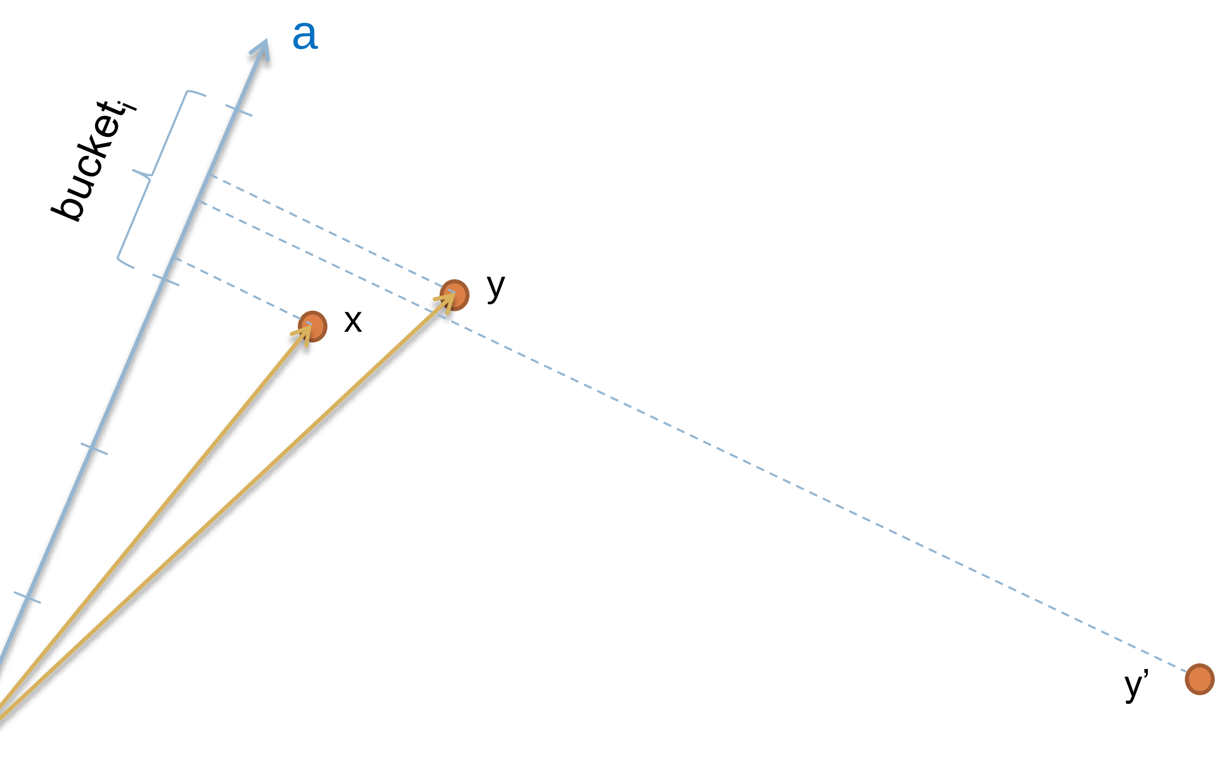
Buckets (1-4)

Intuition of a hash function that preserves the Euclidian Distance



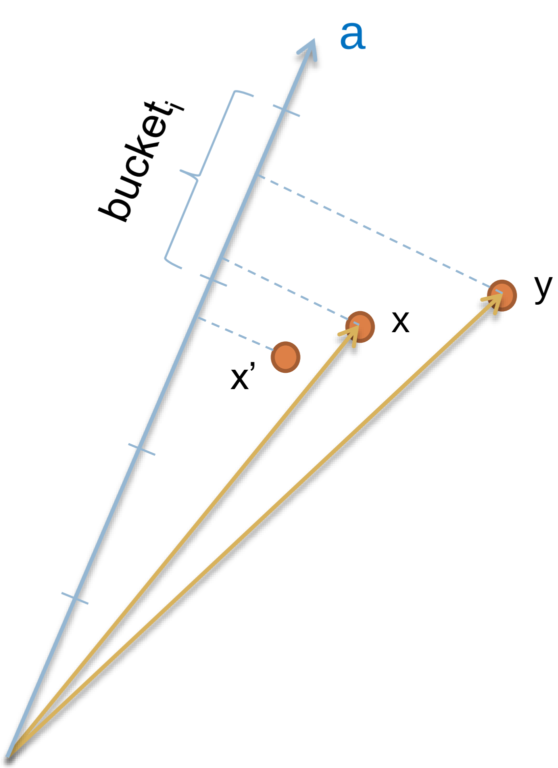
Recall : length of projection of vector x onto a is the inner product a.x

False positives



In this example y' is a false positive (will be pruned when computing true distance)

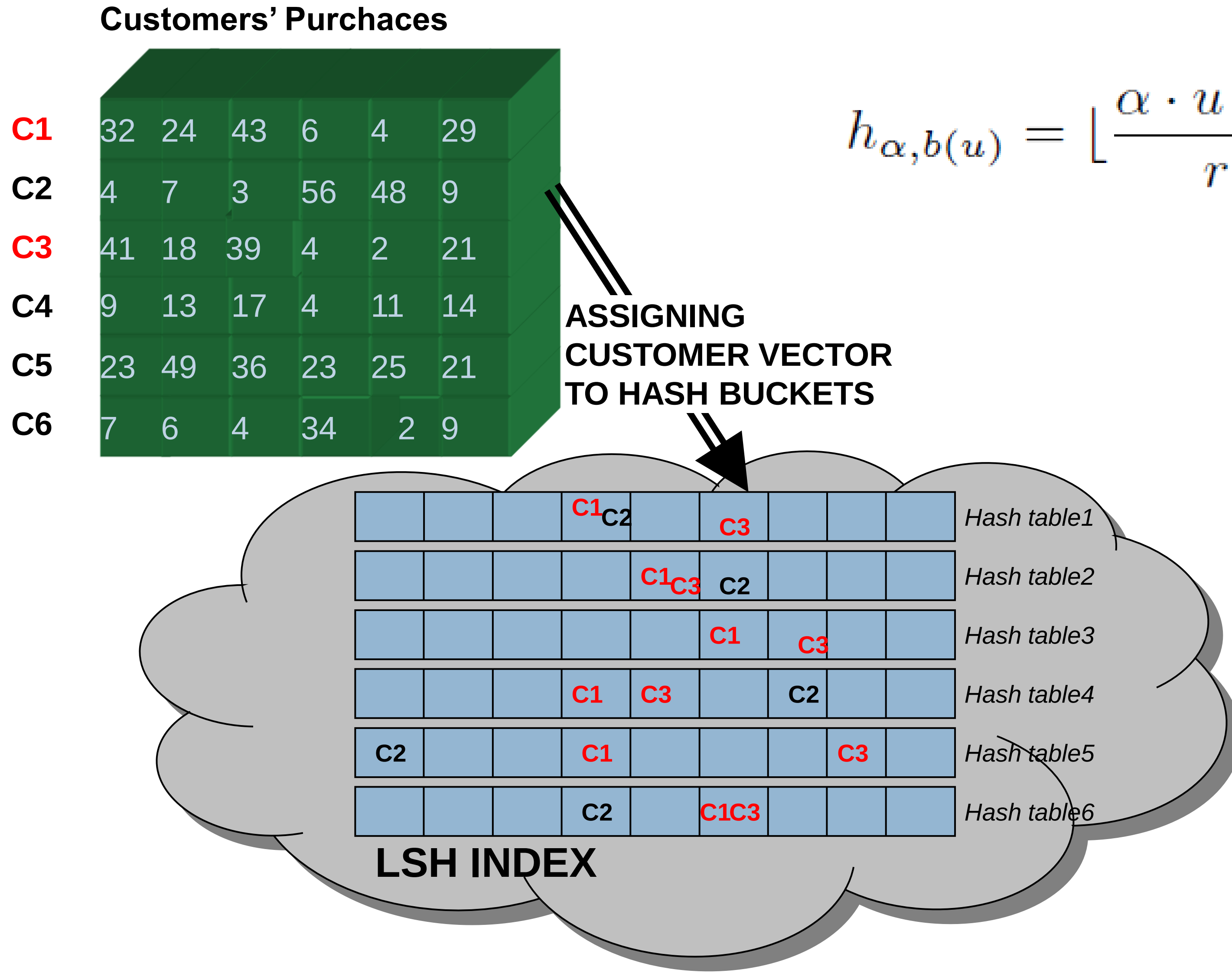
False negatives



In this example x' is a false negative (unless we use additional hash functions)

LSH example for Basket Data

$$h_{\alpha,b(u)} = \lfloor \frac{\alpha \cdot u + b}{r} \rfloor$$



More on LSH

- Families of hash function exist for several popular distance (similarity) metrics
  - Euclidian, Manhattan, Jaccard
- Hashing on multiple hash tables is parallelizable

  …and map-reduce-able!

Personal View

- Past work on Data Streams from Databases and Algorithms community may help overcome some of the obstacles in dealing with Big Data
- We can revisit Data Analysis/Mining algorithms (Clustering, Eigenvector Analysis, Outlier detection) so as to benefit from methods and techniques developed in those areas

Summary

- Big data raises several issues in Data Analysis
  - Scale, noise, dynamics, heterogeneity, inter-dependencies
- Data analysis itself can also be used to help improve the quality and trustworthiness of big data, understand its semantics, and provide intelligent querying functions
- Coordination & integration between different technological platforms is required
  - Data Warehouses/NoSQL platforms/DSMS/DM&ML libraries

Word Cloud from today's lecture

Bibliography on Sketches & LSH (beyond scope of this class)

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- Noga Alon, Yossi Matias, Mario Szegedy: The Space Complexity of Approximating the Frequency Moments. STOC 1996: 20-29.
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- Alexandr Andoni, Piotr Indyk: Near-optimal hashing algorithms for approximate nearest neighbor in high dimensions. Commun. ACM 51(1): 117-122 (2008).

THANK YOU!