Airavat: Security and Privacy for MapReduce

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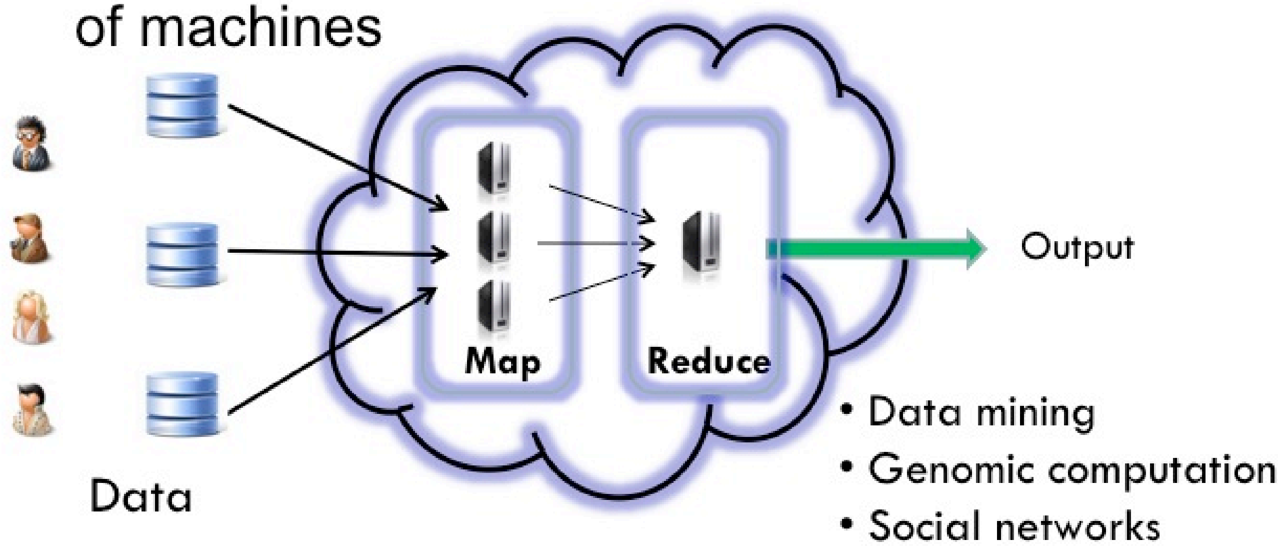
[Most slides from author`s presentation http://z.cs.utexas.edu/users/osa/airavat/]

Computing in the year 201X

- Illusion of infinite resources
- Pay only for resources used
- Quickly scale up or scale down …

Programming model in year 201X

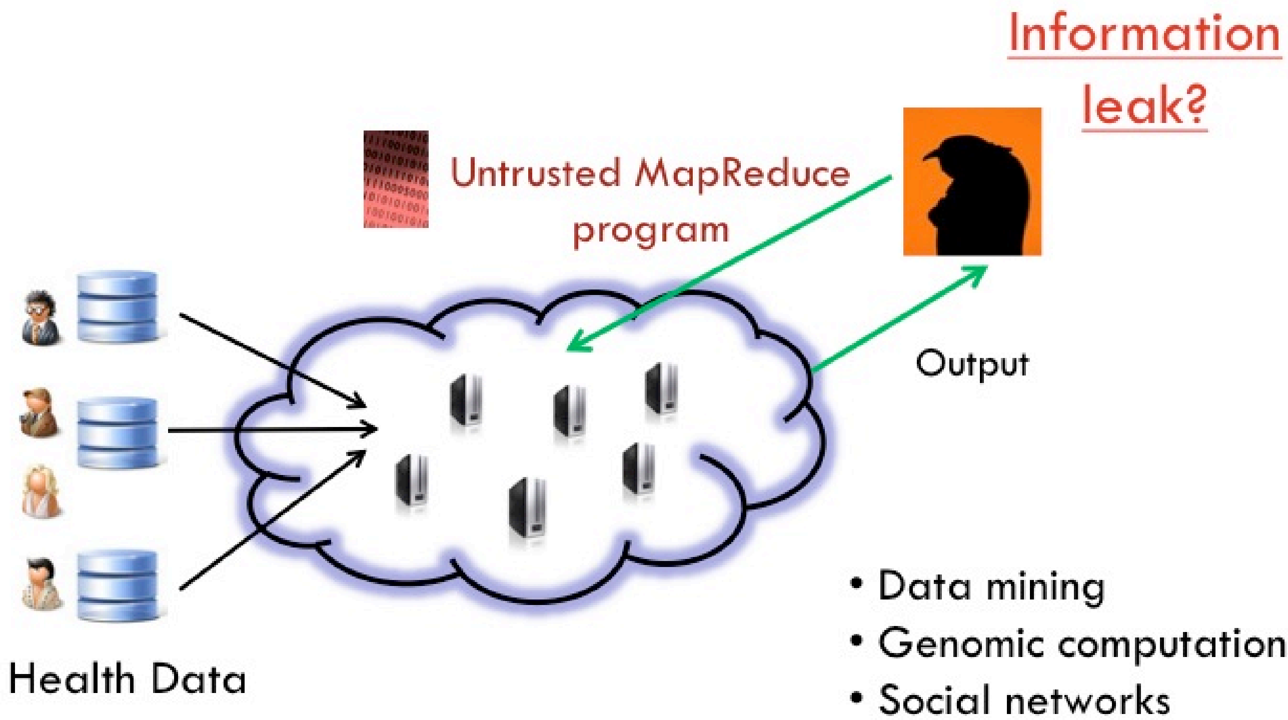
- Frameworks available to ease cloud programming
- MapReduce: Parallel processing on clusters of machines



Programming model in year 201X

- Thousands of users upload their data
  - Healthcare, shopping transactions, census, click stream
- Multiple third parties mine the data for better service
- Example: Healthcare data
- Incentive to contribute: Cheaper insurance policies, new drug research, inventory control in drugstores…
- Fear: What if someone targets my personal data?
  - Insurance company can find my illness and increase premium

Privacy in the year 201X ?



Use de-identification?

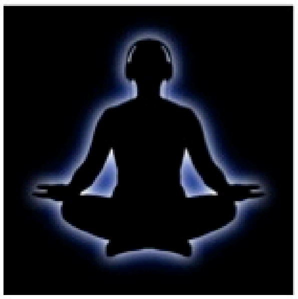
- Achieves ‘privacy’ by syntactic transformations
  - Scrubbing , k-anonymity …
- Insecure against attackers with external information
  - Privacy fiascoes: AOL search logs, Netflix dataset

Run untrusted code on the original data?

How do we ensure privacy of the users?

Audit the untrusted code?

- Audit all MapReduce programs for correctness?



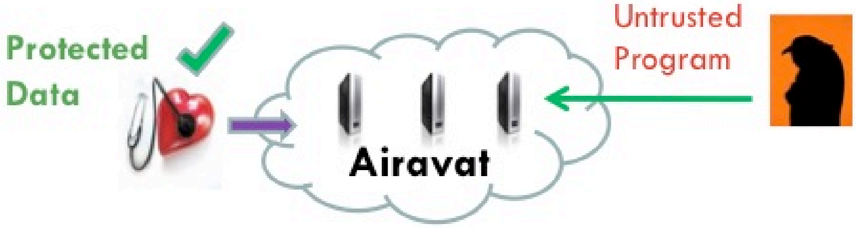
Hard to do! Enlightenment?

Also, where is the source code?

Aim: Confine the code instead of auditing

This talk: Airavat

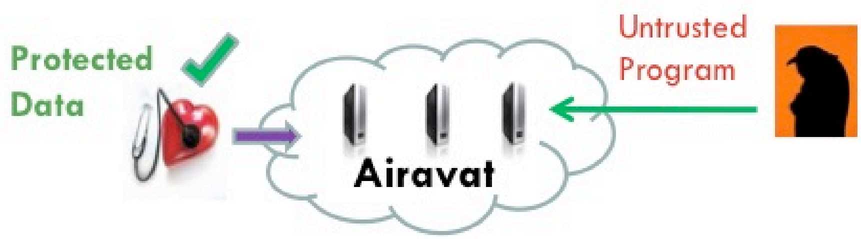
Framework for privacy-preserving MapReduce computations with untrusted code.



Airavat is the elephant of the clouds (Indian mythology).

Airavat guarantee

Bounded information leak* about any individual data after performing a MapReduce computation.



**Differential privacy*

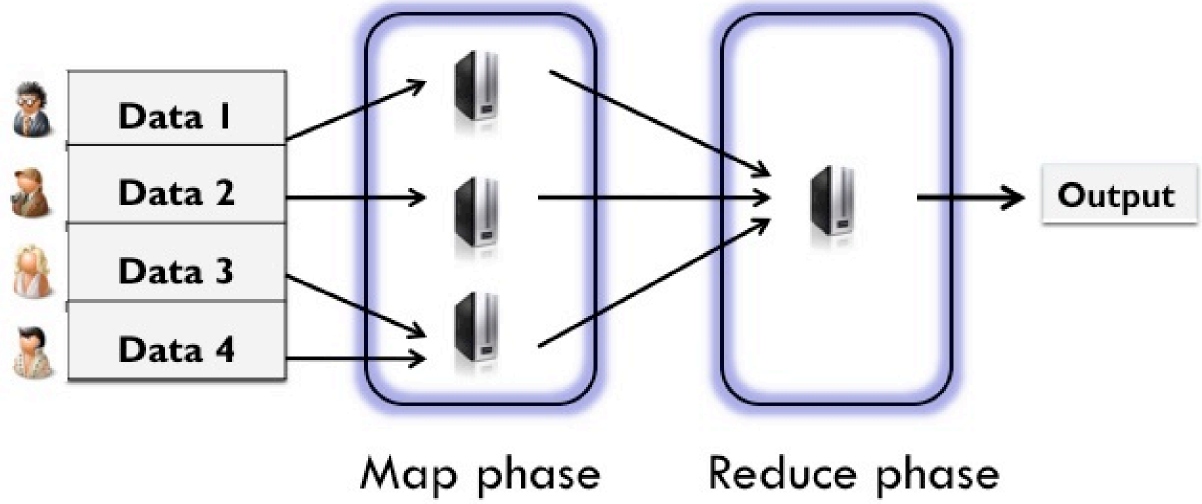
Outline

- Motivation
- Overview
- Enforcing privacy
- Evaluation
- Summary

Background: MapReduce

$\text{map}(k_1, v_1) \rightarrow \text{list}(k_2, v_2)$

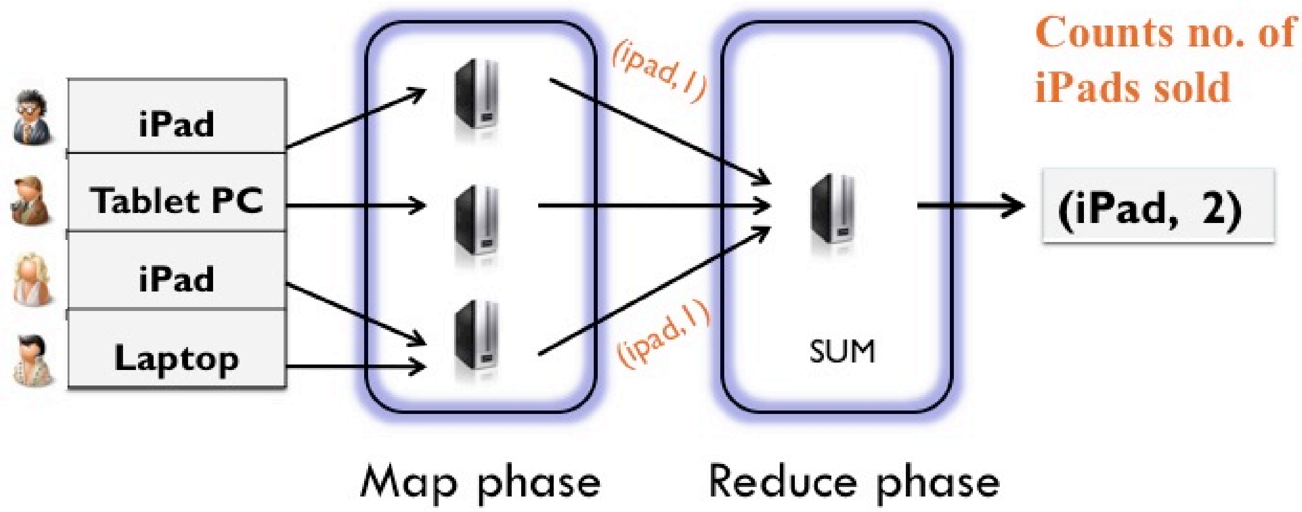
$\text{reduce}(k_2, \text{list}(v_2)) \rightarrow \text{list}(v_2)$



MapReduce example

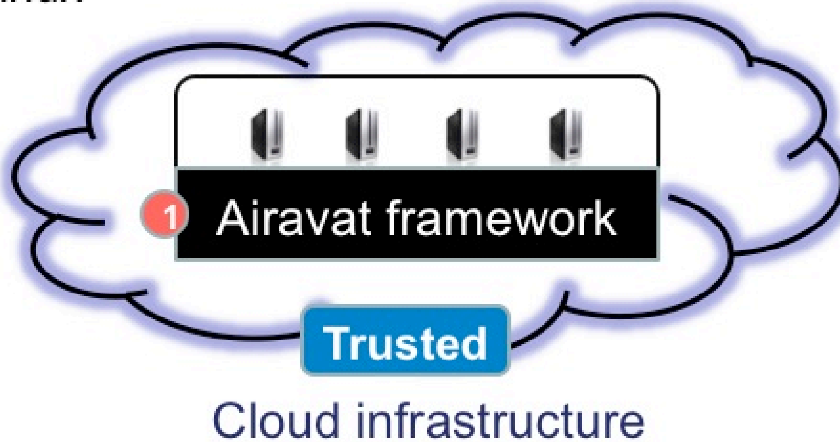
Map(input)→{ if (input has iPad) print (iPad, 1) }

Reduce(key, list(v))→{ print (key + ","+ SUM(v)) }



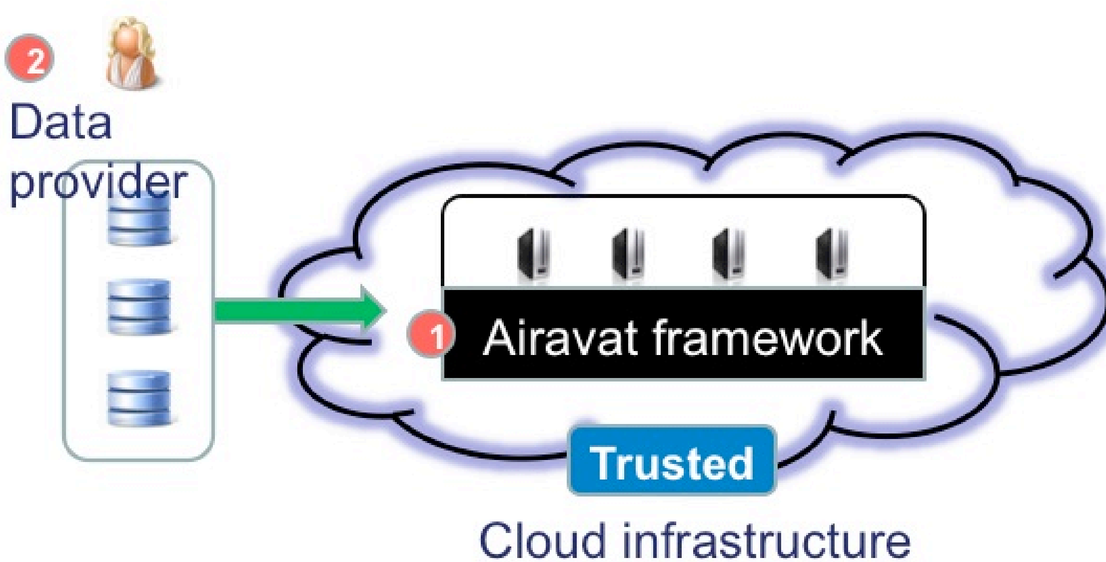
Airavat model

- Airavat framework runs on the cloud infrastructure
  - Cloud infrastructure: Hardware + VM
  - Airavat: Modified MapReduce + DFS + JVM + SELinux



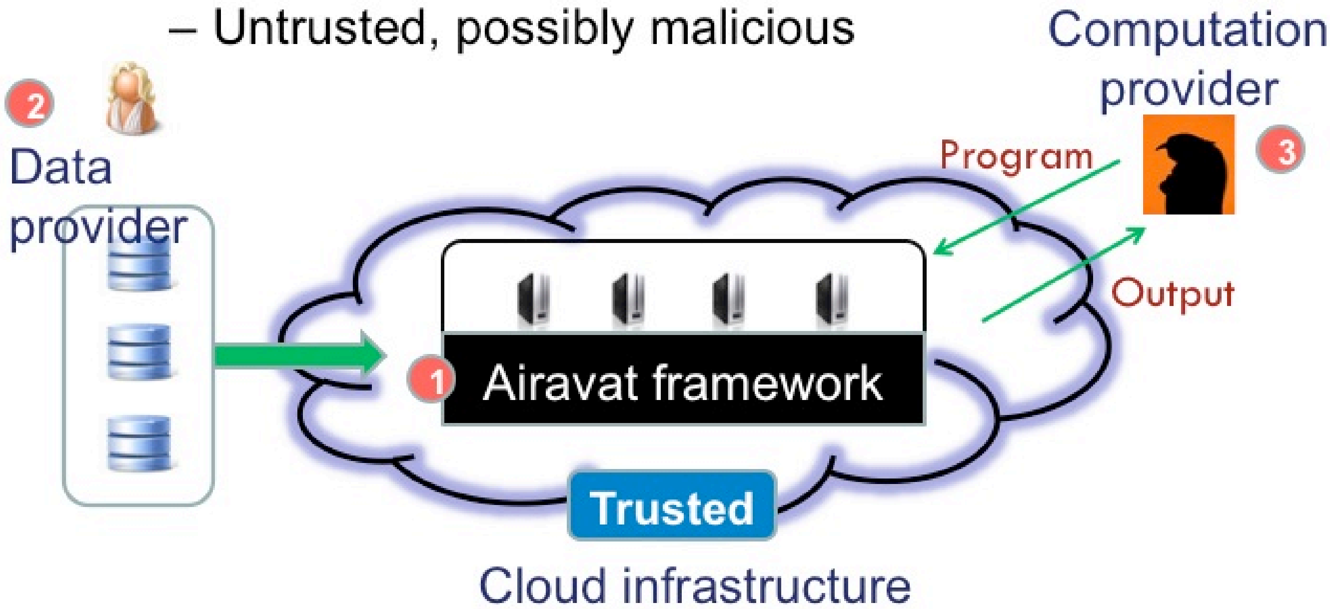
Airavat model

- Data provider uploads her data on Airavat
  - Sets up certain privacy parameters



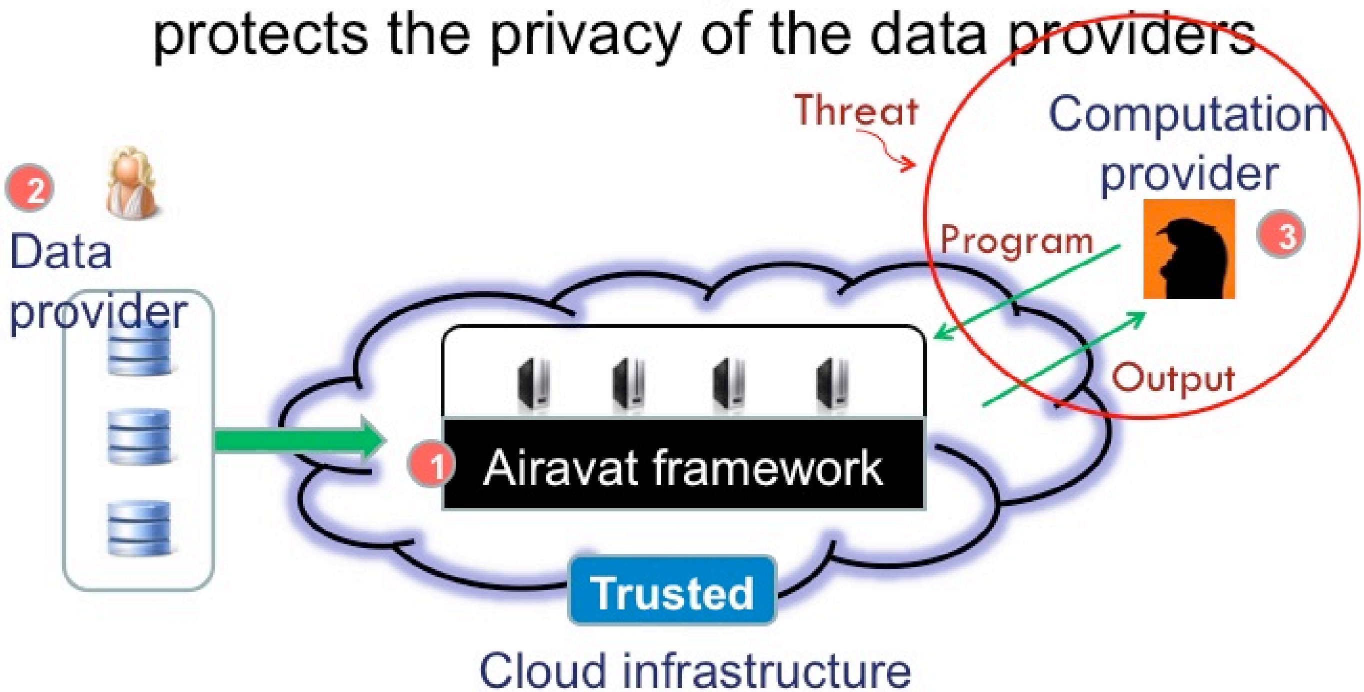
Airavat model

- Computation provider writes data mining algorithm
  - Untrusted, possibly malicious



Threat model

- Airavat runs the computation, and still protects the privacy of the data providers



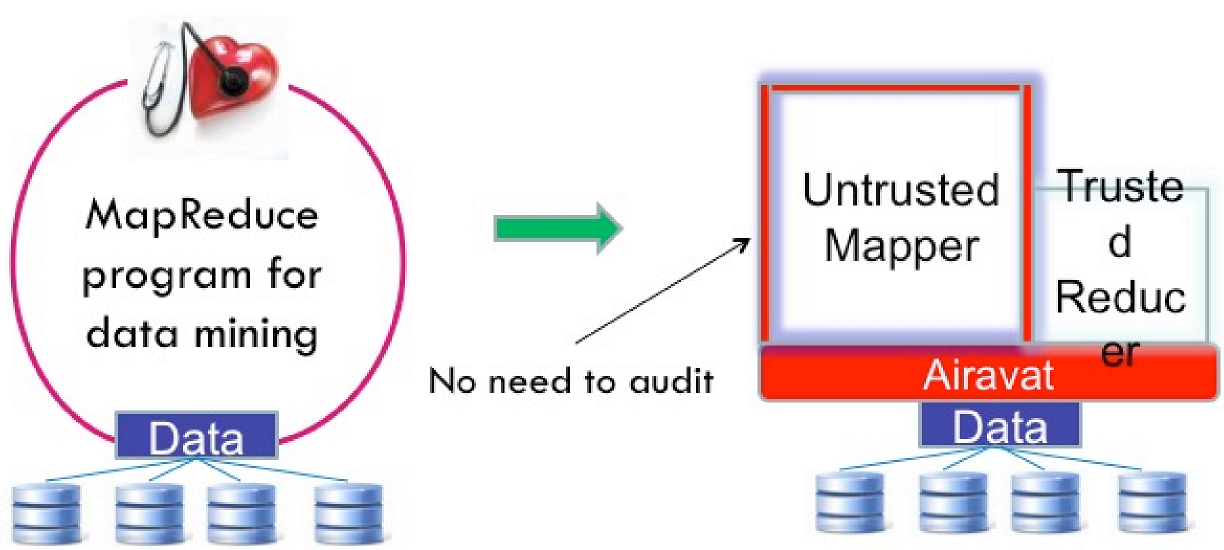
Roadmap

- What is the programming model?
- How do we enforce privacy?
- What computations can be supported in Airavat?

Programming model

Split MapReduce into untrusted mapper + trusted reducer

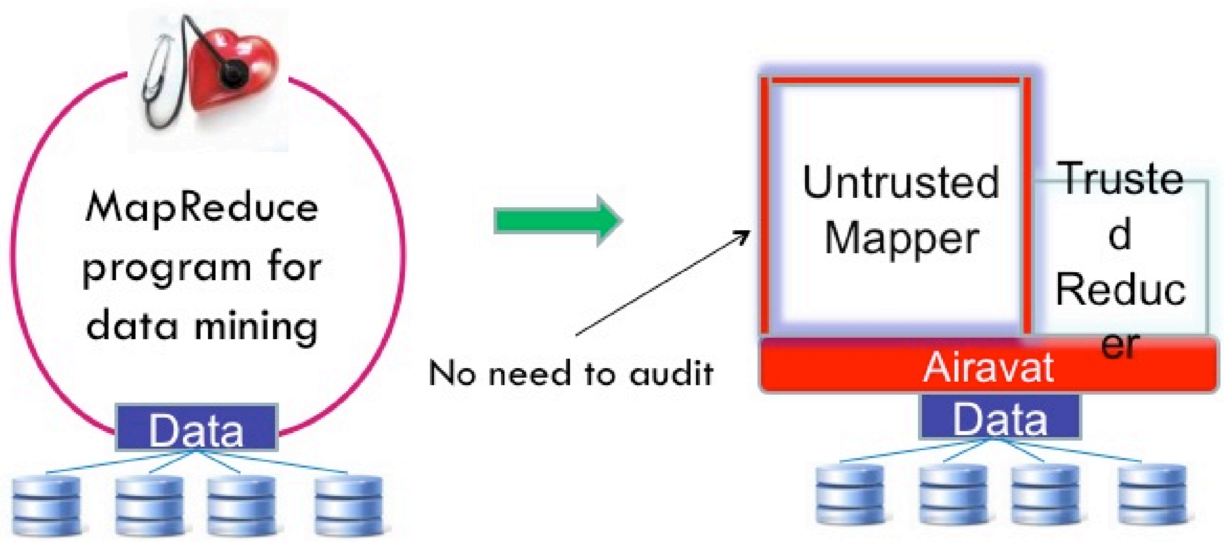
Limited set of stock reducers



Programming model

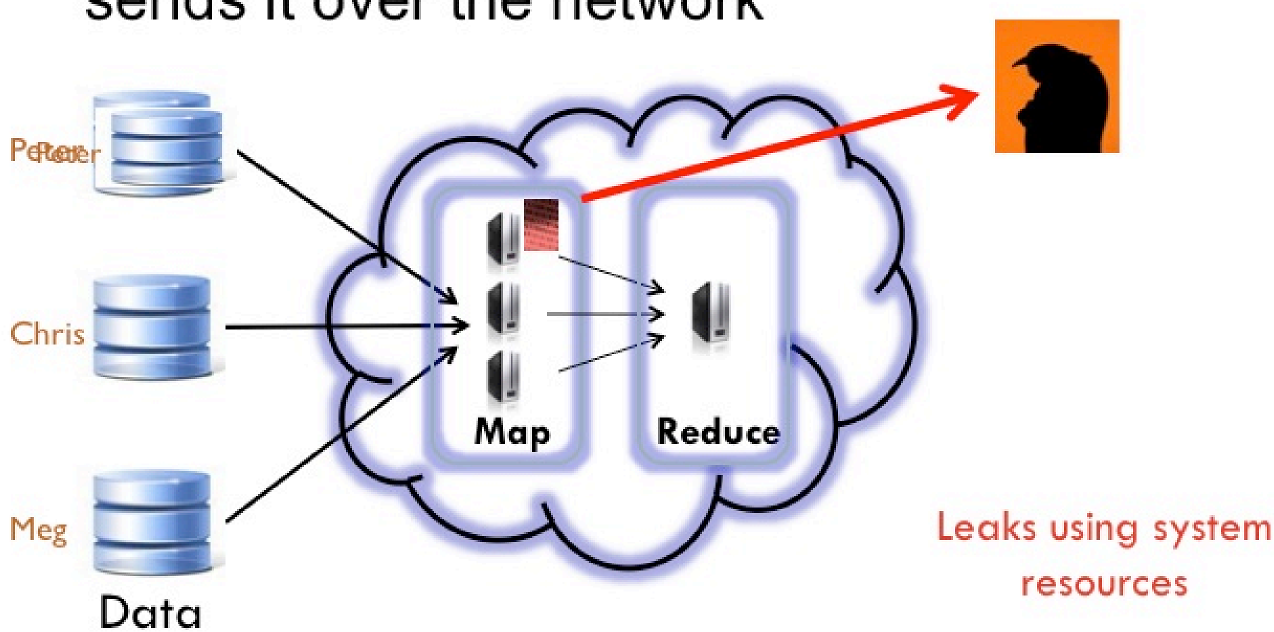
Need to confine the mappers !

Guarantee: Protect the privacy of data providers



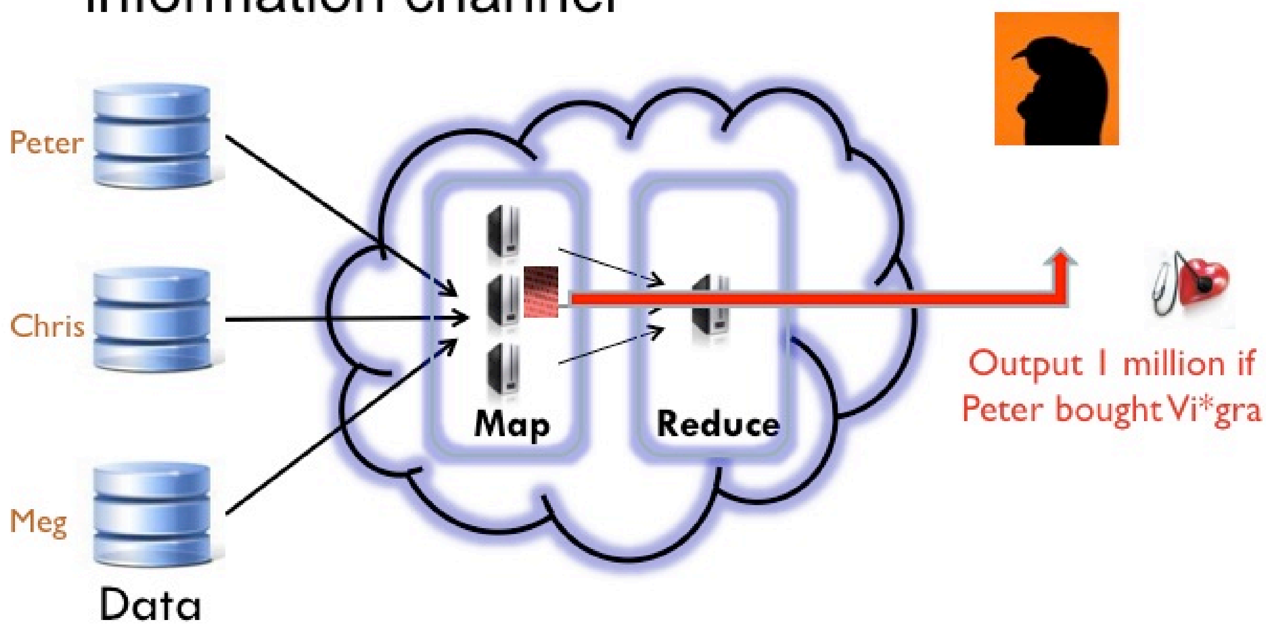
Challenge 1: Untrusted mapper

- Untrusted mapper code copies data, sends it over the network



Challenge 2: Untrusted mapper

- Output of the computation is also an information channel

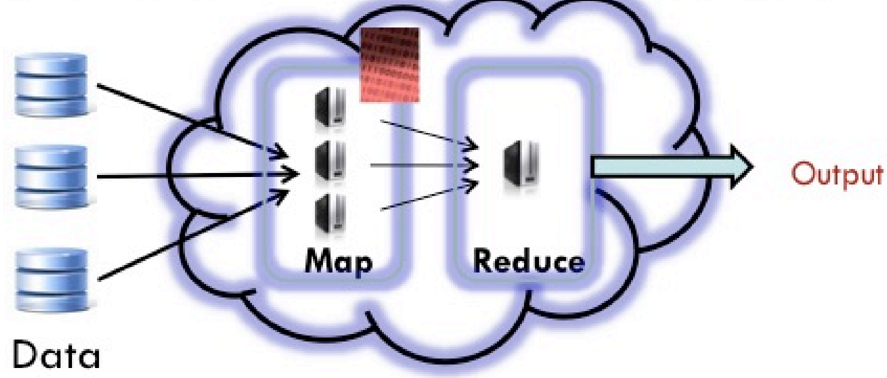


Airavat mechanisms

Mandatory access control ✚ Differential privacy

Prevent leaks through storage channels like network connections, files…

Prevent leaks through the output of the computation



Back to the roadmap

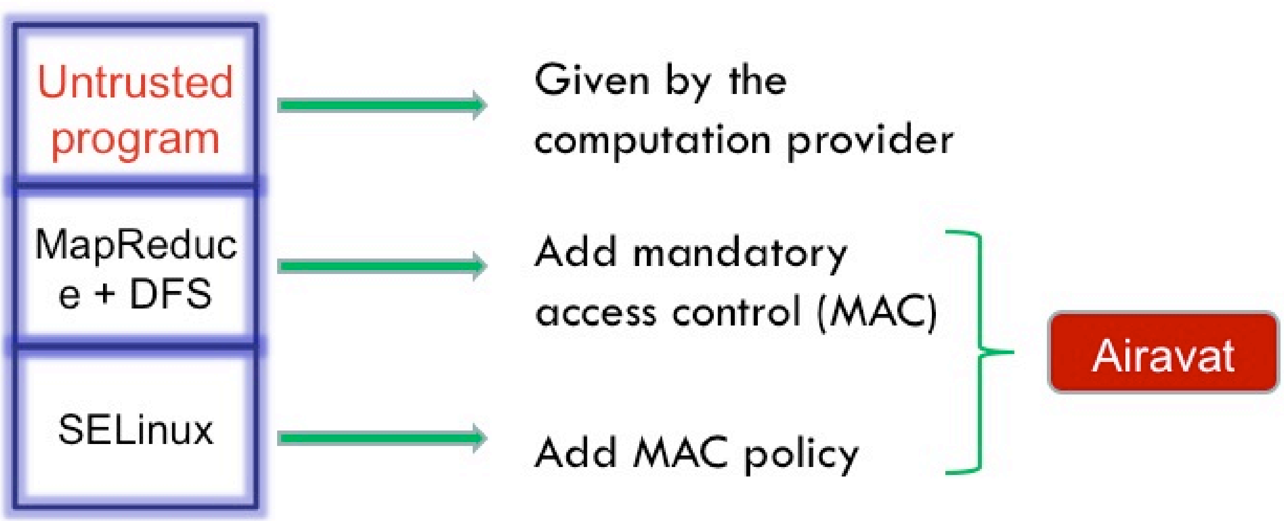
- What is the programming model?

Untrusted mapper + Trusted reducer

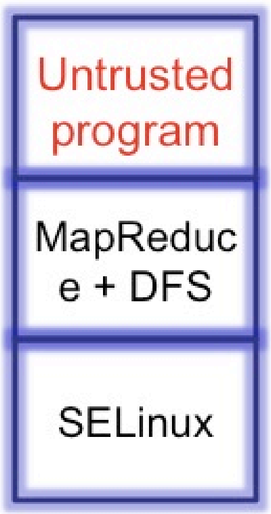
- How do we enforce privacy?
  - Leaks through system resources
  - Leaks through the output

- What computations can be supported in Airavat?

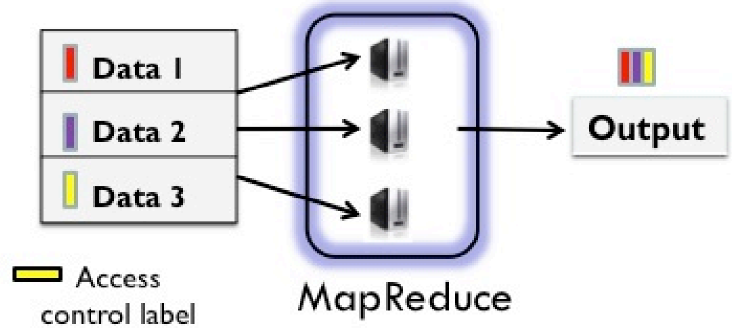
Airavat confines the untrusted code



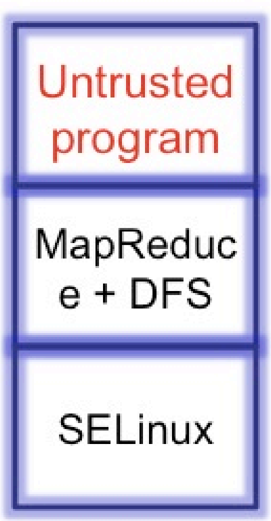
Airavat confines the untrusted code



- We add mandatory access control to the MapReduce framework
- Label input, intermediate values, output
- Malicious code cannot leak labeled data



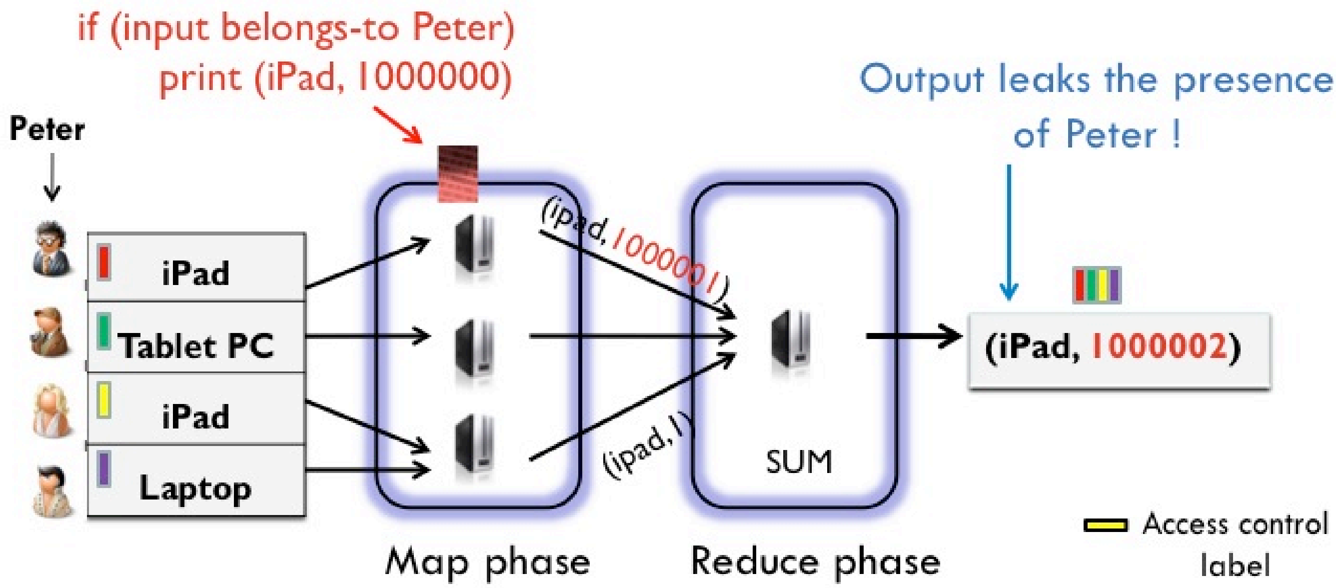
Airavat confines the untrusted code



- SELinux policy to enforce MAC
- Creates trusted and untrusted domains
- Processes and files are labeled to restrict interaction
- Mappers reside in untrusted domain
  - Denied network access, limited file system interaction

But access control is not enough

- Labels can prevent the output from been read
- When can we remove the labels?



But access control is not enough

Need mechanisms to enforce that the output does not violate an individual's privacy.

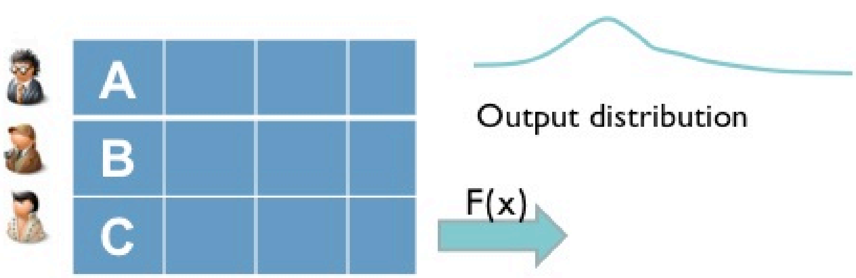
Background: Differential privacy

A mechanism is differentially private if every output is produced with similar probability whether any given input is included or not

Cynthia Dwork. *Differential Privacy*. ICALP 2006

Differential privacy (intuition)

A mechanism is differentially private if every output is produced with similar probability whether any given input is included or not



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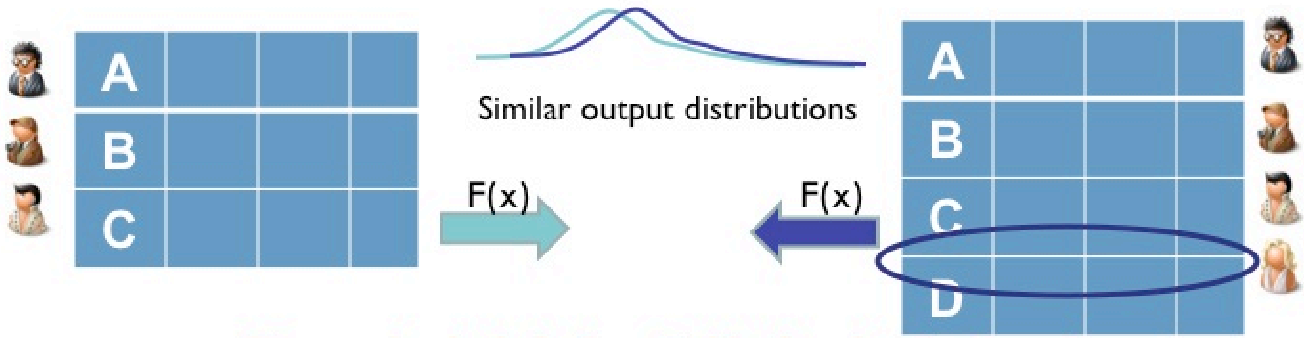
Differential privacy (intuition)

A mechanism is differentially private if every output is produced with similar probability whether any given input is included or not

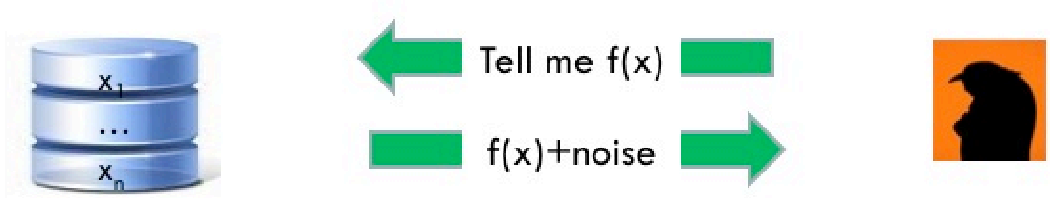


Bounded risk for D if she includes her data!

Cynthia Dwork. *Differential Privacy*. ICALP 2006

Achieving differential privacy

- A simple differentially private mechanism



- How much noise should one add?

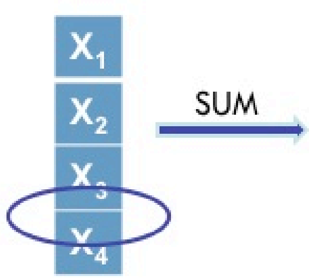
Achieving differential privacy

- Function sensitivity (intuition): Maximum effect of any single input on the output
  - Aim: Need to conceal this effect to preserve privacy

- Example: Computing the average height of the people in this room has low sensitivity
  - Any single person's height does not affect the final average by too much
  - Calculating the maximum height has high sensitivity

Achieving differential privacy

- Function sensitivity (intuition): Maximum effect of any single input on the output
  - Aim: Need to conceal this effect to preserve privacy
- Example: SUM over input elements drawn from [0, M]

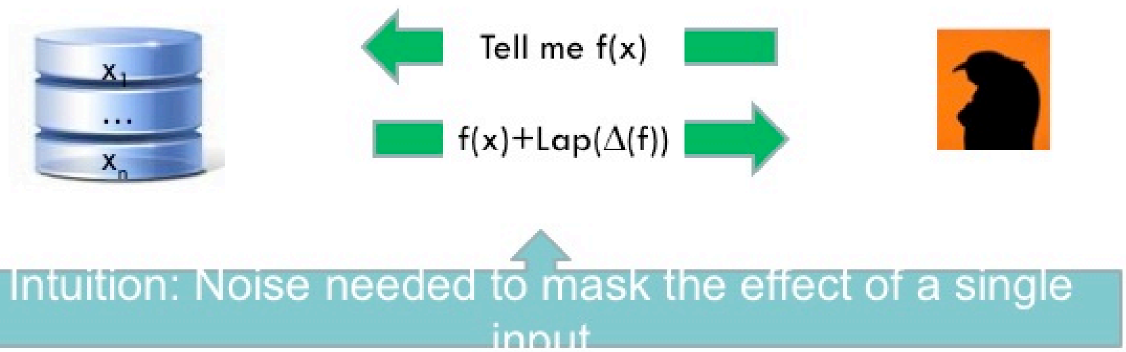


Sensitivity = M

Max. effect of any input element is M

Achieving differential privacy

- A simple differentially private mechanism



Δ(f) = sensitivity

Lap = Laplace distribution

Back to the roadmap

- What is the programming model?

Untrusted mapper + Trusted reducer

- How do we enforce privacy?
  - Leaks through system resources
  - Leaks through the output

MAC

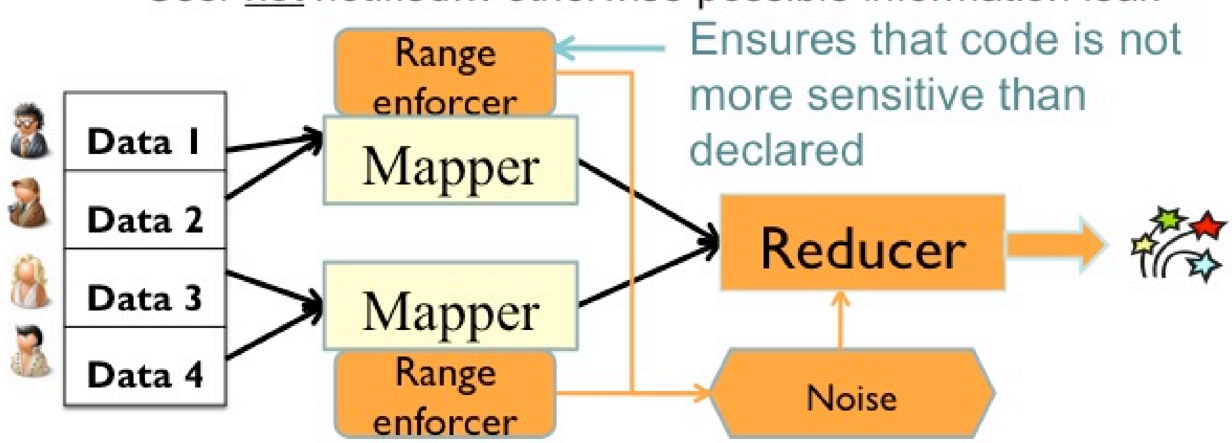
- What computations can be supported in Airavat?

Enforcing differential privacy

- Mapper can be any piece of Java code ("black box") but…
- Range of mapper outputs must be declared in advance
  - Used to estimate "sensitivity" (how much does a single input influence the output?)
  - Determines how much noise is added to outputs to ensure differential privacy
- Example: Consider mapper range [0, M]
  - SUM has the estimated sensitivity of M

Enforcing differential privacy

- Malicious mappers may output values outside the range
- If a mapper produces a value outside the range, it is replaced by a value inside the range
  - User <u>not</u> notified… otherwise possible information leak



Enforcing sensitivity

- All mapper invocations must be independent
- Mapper may not store an input and use it later when processing another input
  - Otherwise, range-based sensitivity estimates may be incorrect
- We modify JVM to enforce mapper independence
  - Each object is assigned an invocation number
  - JVM instrumentation prevents reuse of objects from previous invocation

Roadmap. One last time

- What is the programming model?

Untrusted mapper + Trusted reducer

- How do we enforce privacy?
  - Leaks through system resources
  - Leaks through the output

MAC

Differential Privacy

- What computations can be supported in Airavat?

What can we compute?

- Reducers are responsible for enforcing privacy
  - Add an appropriate amount of random noise to the outputs
- Reducers must be trusted
  - Sample reducers: SUM, COUNT, THRESHOLD
  - Sufficient to perform data mining algorithms, search log processing, recommender system etc.
- With trusted mappers, more general computations are possible
  - Use exact sensitivity instead of range based estimates

Sample computations

- Many queries can be done with untrusted mappers
  - How many iPads were sold today?
  - What is the average score of male students at UT?
  - Output the frequency of security books that sold more than 25 copies today.
- … others require trusted mapper code
  - List all items and their quantity sold

Revisiting Airavat guarantees

- Allows differentially private MapReduce computations
  - Even when the code is untrusted
- Differential privacy => mathematical bound on information leak
- What is a safe bound on information leak ?
  - Depends on the context, dataset
  - Not our problem

Outline

- Motivation
- Overview
- Enforcing privacy
- Evaluation
- Summary

Implementation details

SELinux policy
- Domains for trusted and untrusted programs
- Apply restrictions on each domain

450 LoC

MapReduce
- Modifications to support mandatory access control
- Set of trusted reducers

5000 LoC

JVM
- Modifications to enforce mapper independence

500 LoC

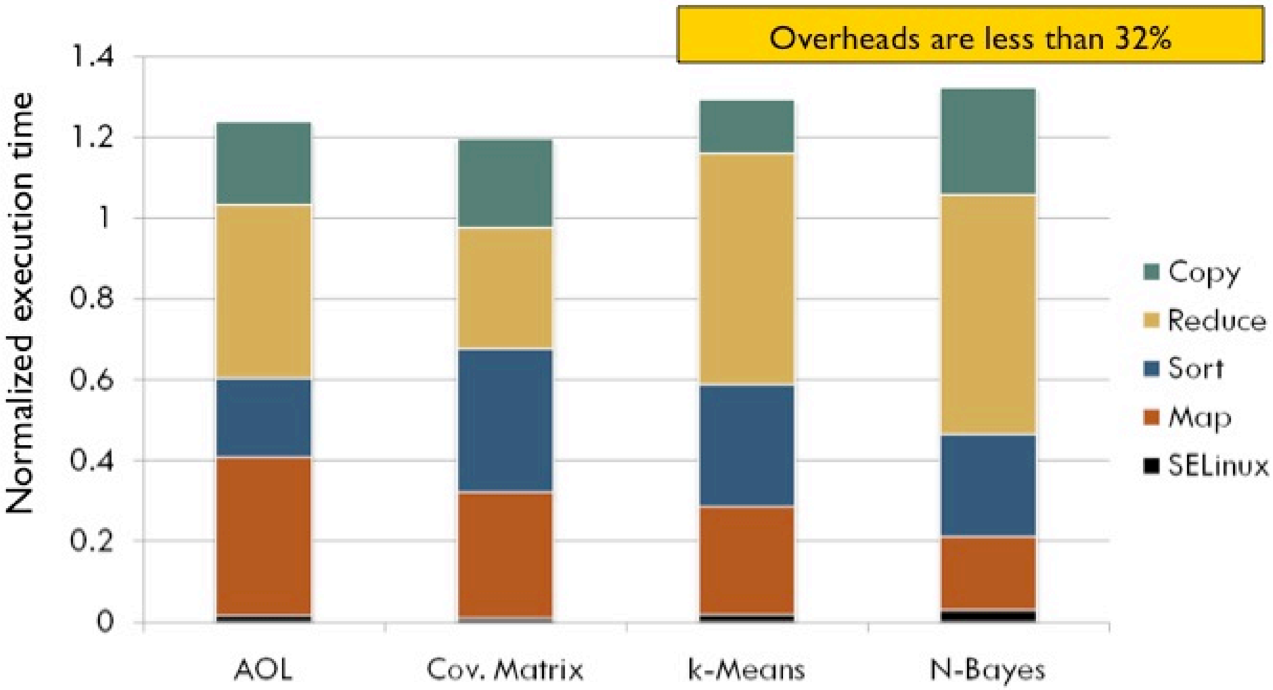
LoC = Lines of Code

Evaluation : Our benchmarks

- Experiments on 100 Amazon EC2 instances
  - 1.2 GHz, 7.5 GB RAM running Fedora 8

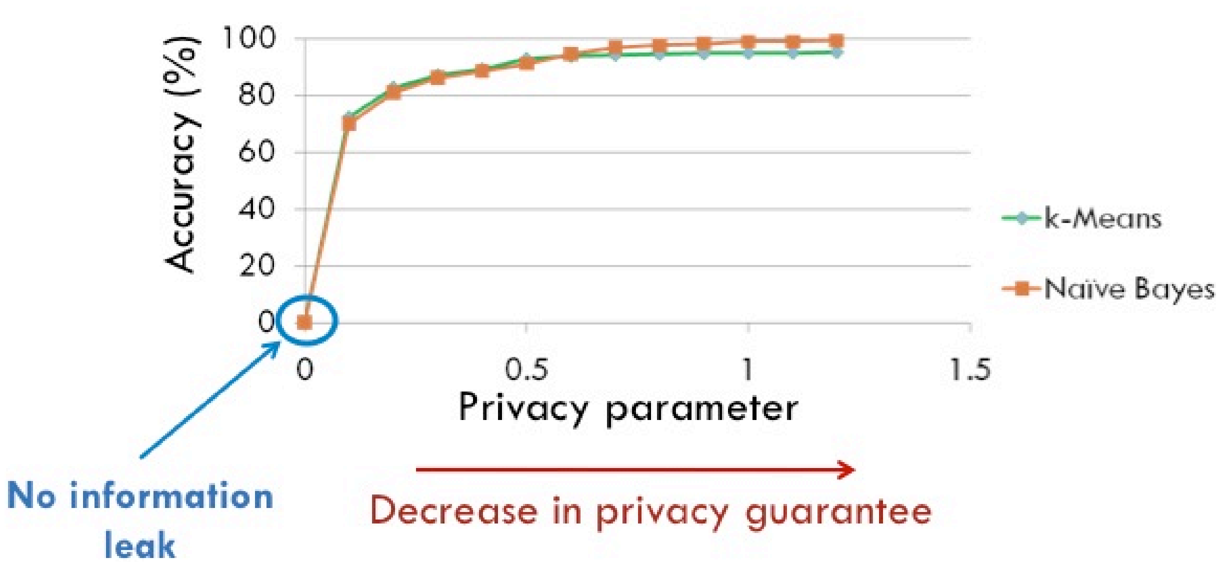
Benchmark	Privacy grouping	Reducer primitive	MapReduce operations	Accuracy metric
AOL queries	Users	THRESHOLD, SUM	Multiple	% queries released
kNN recommender	Individual rating	COUNT, SUM	Multiple	RMSE
K-Means	Individual points	COUNT, SUM	Multiple, till convergence	Intra-cluster variance
Naïve Bayes	Individual articles	SUM	Multiple	Misclassification rate

Performance overhead



Evaluation: accuracy

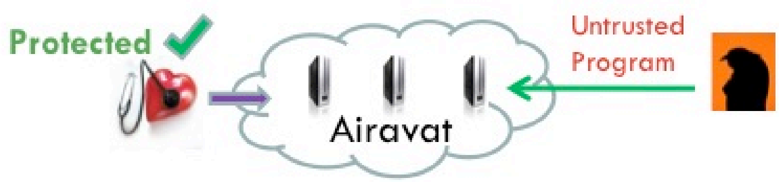
- Accuracy increases with decrease in privacy guarantee
- Reducer : COUNT, SUM



**Refer to the paper for remaining benchmark results*

Airavat in brief

- Airavat is a framework for privacy preserving MapReduce computations
- Confines untrusted code
- First to integrate mandatory access control with differential privacy for end-to-end enforcement



THANK YOU