



**TRƯỜNG ĐẠI HỌC BÁCH KHOA HÀ NỘI**  
HANOI UNIVERSITY OF SCIENCE AND TECHNOLOGY

# Data integration and preprocessing

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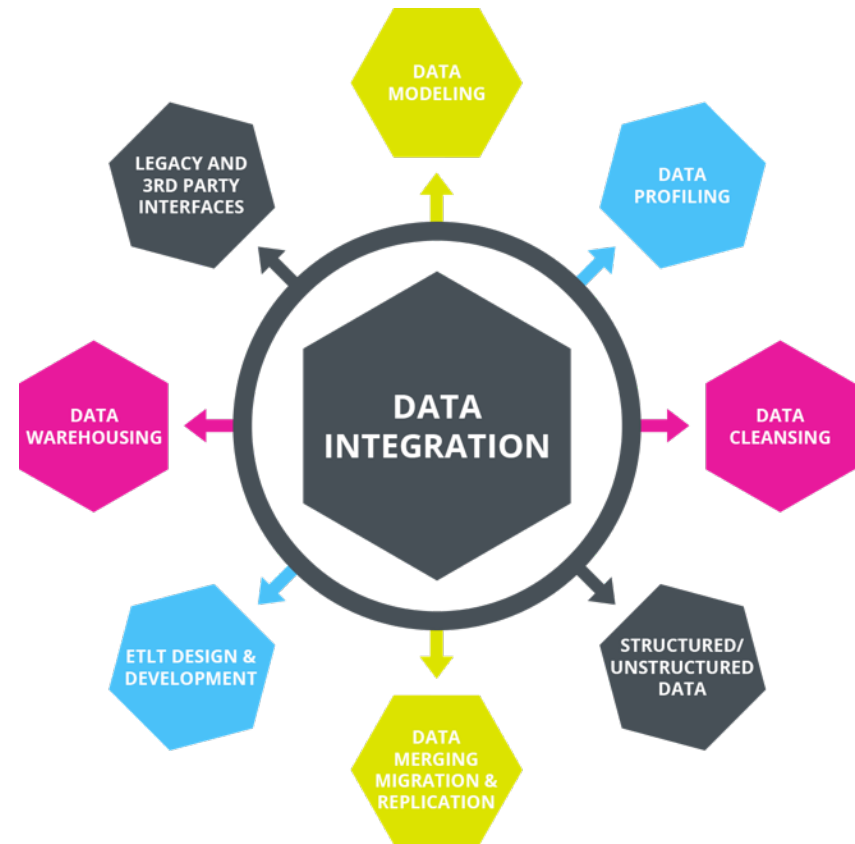
# Outline

- Data integration
  - Introduction
  - Current approaches
  - Apache Nifi
  - Hand-ons Apache Nifi
- Data preprocessing
  - Introduction
  - Data quality
  - Data preprocessing steps
  - Hand-ons Openrefine

# Data integration

# Data integration

- Provide uniform access to data available in multiple, autonomous, heterogeneous and distributed data sources
  - Uniform
  - Access to
  - Multiple
  - Autonomous
  - Heterogeneous
  - Distributed
  - Data Sources



# Why data integration

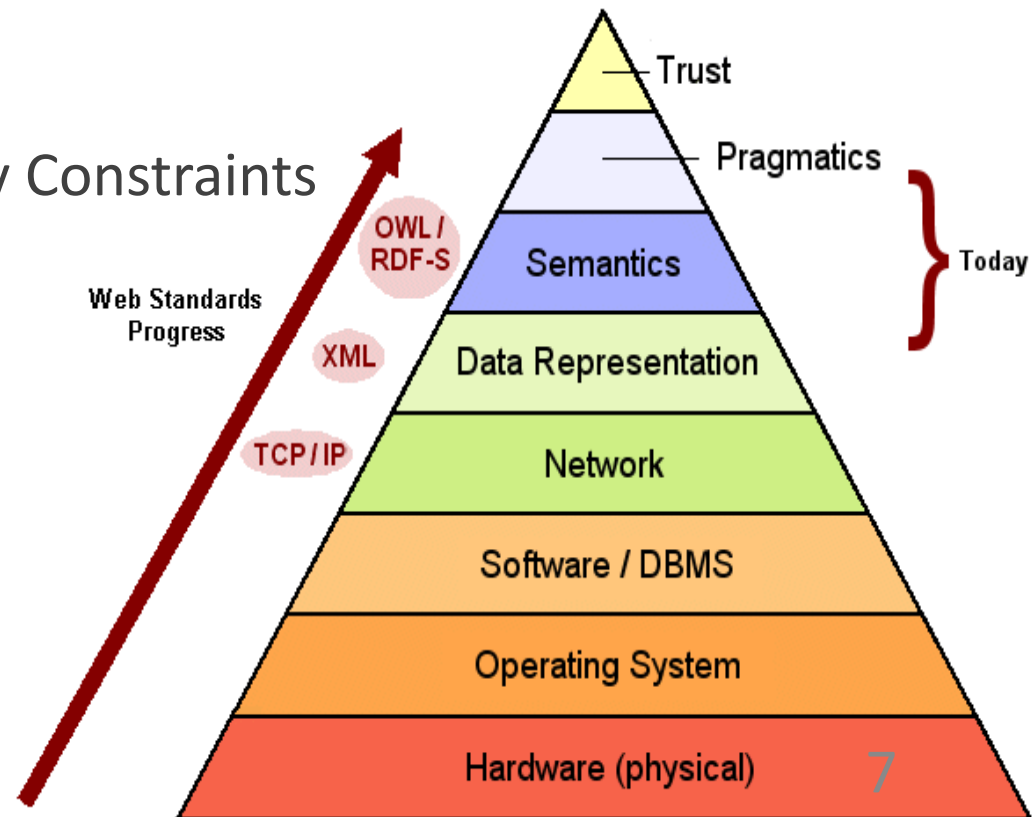
- To facilitate information access and reuse through a **single information access point**
- Data from different complementing information systems is **to be combined to gain a more comprehensive basis** to satisfy the need
  - Improve decision making
  - Improve customer experience
  - Increase competitiveness, Streamline operations
  - Increase productivity
  - Predict the future

# Data integration challenges

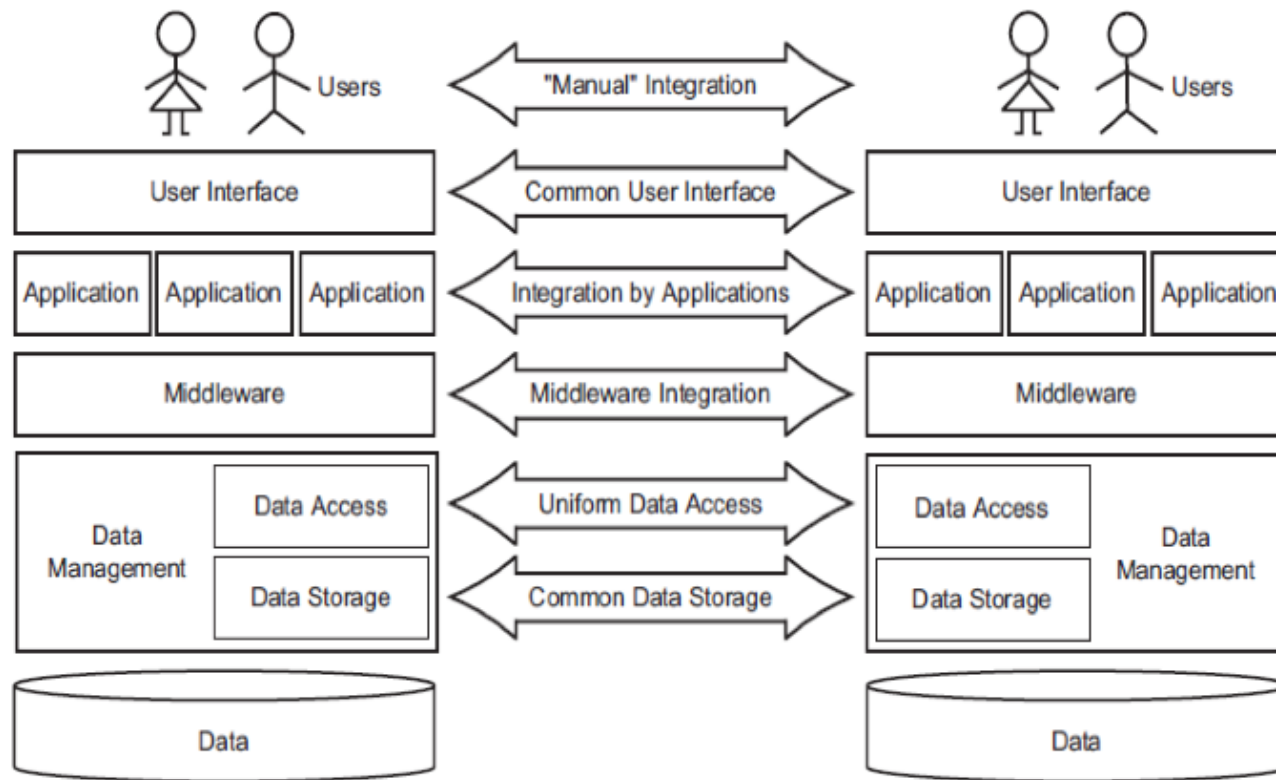
- Physical systems
  - Various hardwares, standards
  - Distributed deployment
  - Various data format
- Logical structures
  - Different data models
  - Different data schemas
- Business organization
  - Data security and privacy
  - Business rules and requirements
  - Different administrative zones in the business organization

# Kinds of Heterogeneity

- Hardware and Operating Systems
- Data Management Software
- Data Models, Schemas and Semantic
- Middle-ware
- User Interfaces
- Business Rules and Integrity Constraints



# Abstraction levels

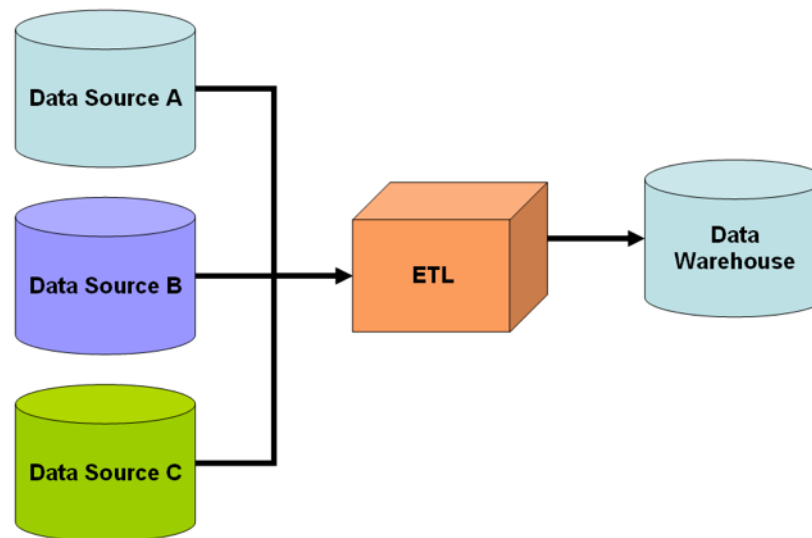




# Current approaches

- Data Warehouse

- Realize a common data storage approach
- Data from several operational sources (OLTP) are extracted, transformed, and loaded (ETL) into a data warehouse
- Analysis, such as OLAP, can be performed on cubes of integrated and aggregated data



# Getting data into DW

- How to load data into DW?
  - Scripts in linux shell, perl, python, ...
  - sqldr + SQL
  - Hardcoded in Java, C#, C
  - In-house built ETL tool
  - Off-the shelf ETL tool
- Aspects to be kept in mind
  - Manageability
  - Maintainability
  - Transparency
  - Scalability
  - Flexibility
  - Complexity
  - Auditing
  - Job restartability
  - Testing

# ETL process

- 70-80% of BI (DI or DW) project is reliable ETL process
- ETL = Extract – Transform – Load
- Extract
  - Get the data from source system as efficiently as possible
- Transform
  - Perform calculations on data
- Load
  - Load the data in the target storage

# Why is ETL (System) Important?

- Adds **value** to data
  - Removes mistakes and corrects data
  - Documented measures of confidence in data
  - Captures the flow of transactional data
  - Adjusts data from multiple sources to be used together (conforming)
  - Structures data to be usable by BI tools
  - Enables subsequent business / analytical data processing

# ETL market

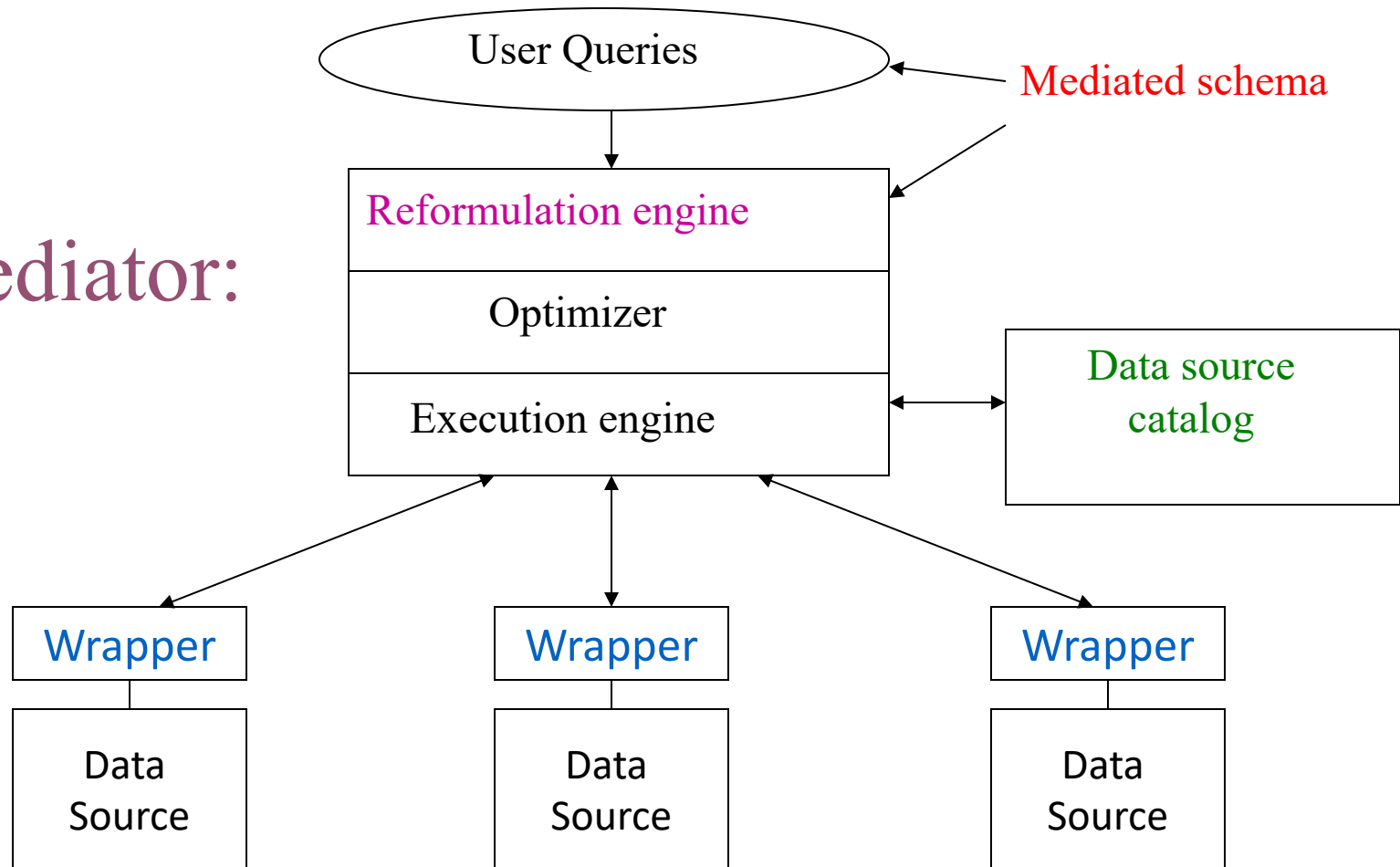


# Problems with DW approach

- Data has to be **cleaned** – different formats
- Needs to store all the data in all the data sources that will ever be asked for
  - Expensive due to data cleaning and space requirements
- Data needs to be updated periodically
  - Data sources are autonomous – content can change without notice
  - Expensive because of the large quantities of data and data cleaning costs

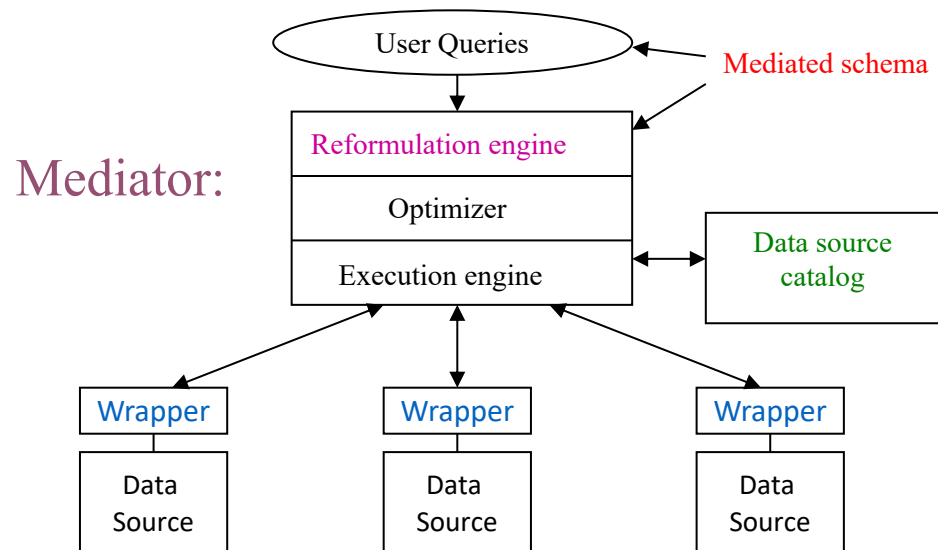
# Virtual integration approach

Mediator:



# Virtual integration: Architecture

- Leave the data in the data sources
- For every query over the mediated schema
  - Find the data sources that have the data (probably more than one)
  - Query the data sources
  - Combine results from different sources if necessary





# Challenges

- Designing a single mediated schema
  - Data sources might have different schemas, and might export data in different formats
- Translation of queries over the mediated schema to queries over the source schemas
- Query Optimization
  - No/limited/stale statistics about data sources
  - Cost model to include network communication cost
  - Multiple data sources to choose from

# Challenges (2)

- Query Execution

- Network connections unreliable – inputs might stall, close, be delayed, be lost
- Query results can be cached – what can be cached?

- Query Shipping

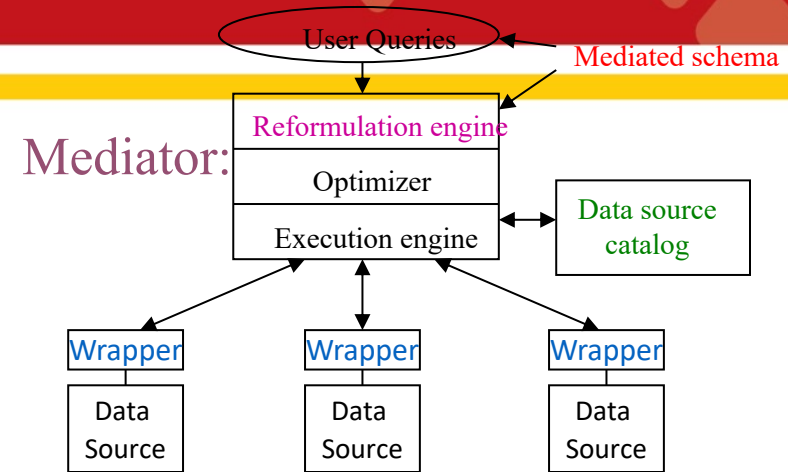
- Some data sources can execute queries – send them sub-queries
- Sources need to describe their query capability and also their cost models (for optimization)

- Incomplete data sources

- Data at any source might be partial, overlap with others, or even conflict
- Do we query all the data sources? Or just a few? How many? In what order?

# Wrappers

- Sources export data in different formats
- Wrappers are custom-built programs that transform data from the source native format to something acceptable to the mediator



XML

HTML

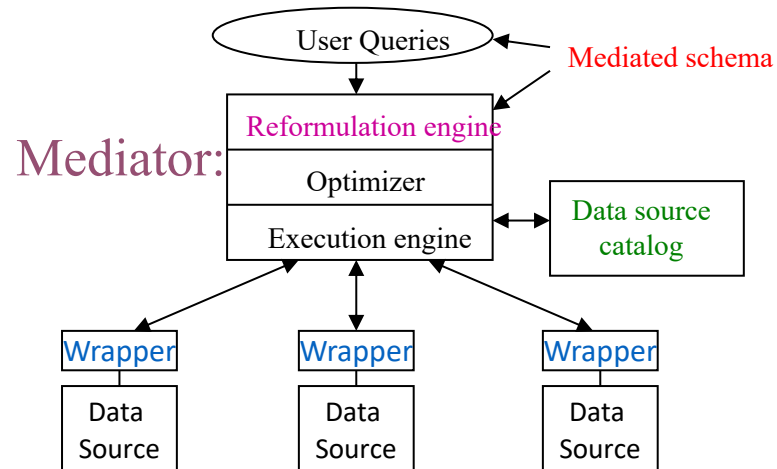
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<b> Introduction to DB </b>
<i> Phil Bernstein </i>
<i> Eric Newcomer </i>
Addison Wesley, 1999
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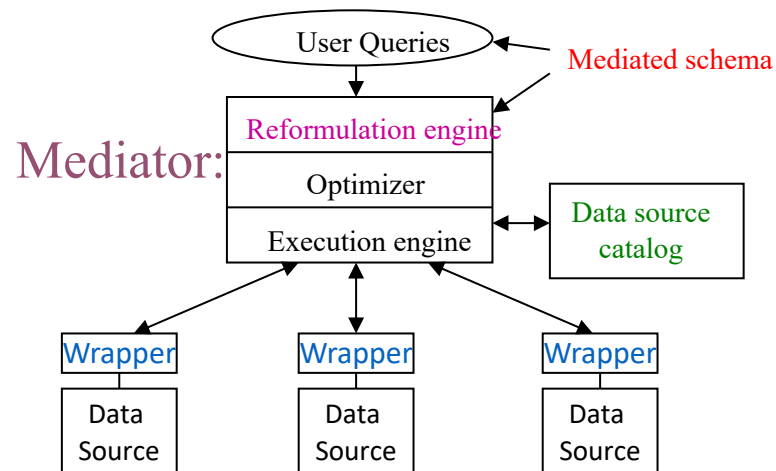
# Wrappers(2)

- Can be placed either at the source or at the mediator
- Maintenance problems
  - have to change if source interface changes



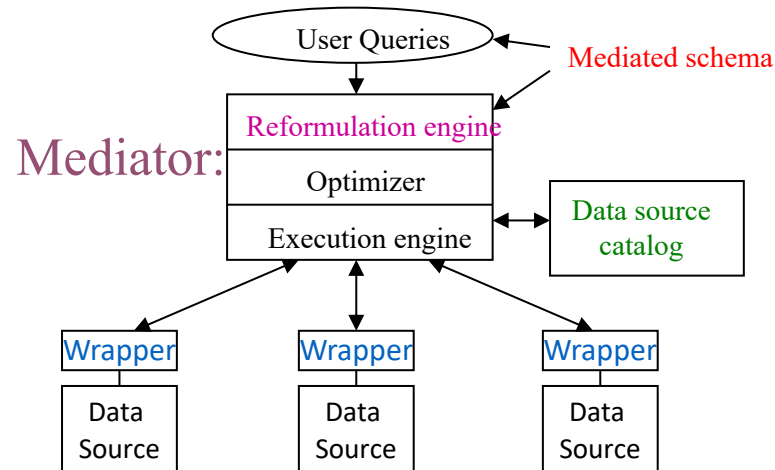
# Data Source Catalog

- Contains meta-information about sources
  - Logical source contents (books, new cars)
  - Source capabilities (can answer SQL queries)
  - Source completeness (has all books)
  - Physical properties of source and network
  - Statistics about the data (like in an RDBMS)
  - Source reliability
  - Mirror sources
  - Update frequency



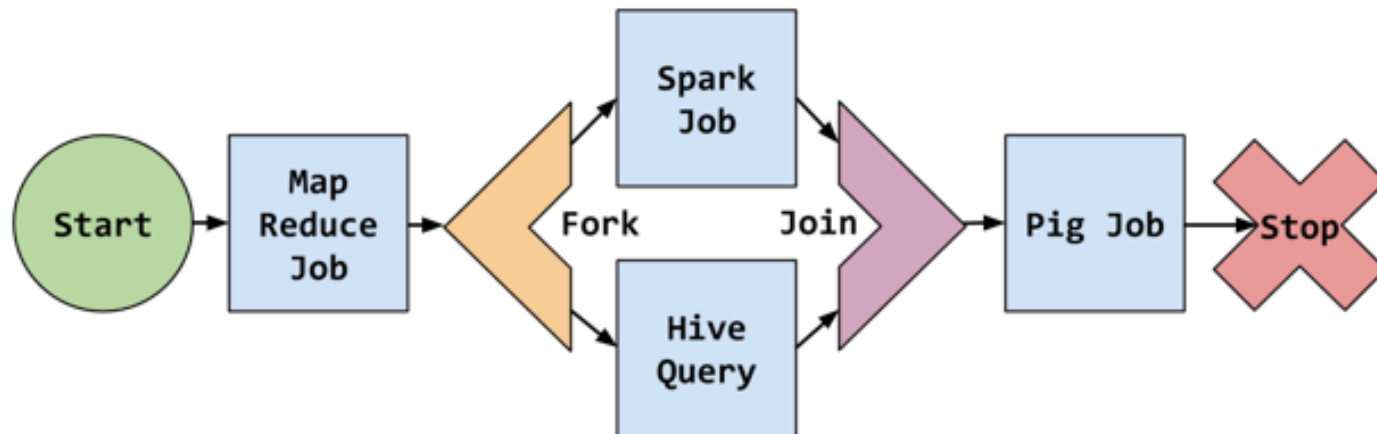
# Schema mediation

- Users pose queries over the **mediated schema**
- The data at a source is visible to the mediator is its **local schema**
- **Reformulation**: Queries over the mediated schema have to be rewritten as queries over the source schemas
- How would we do the reformulation?



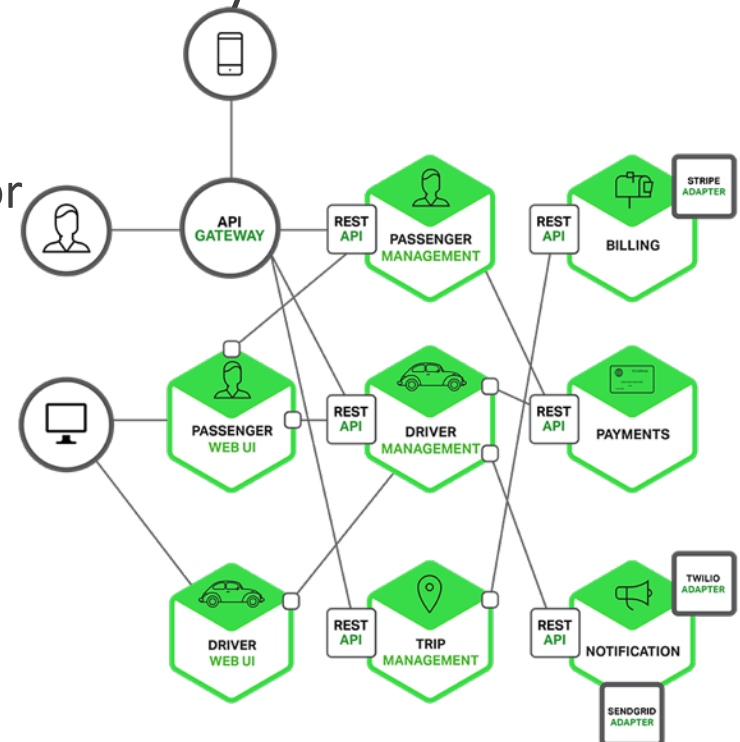
# Workflow management approach

- Represent an integration-by-application approach
- Allow to implement business processes where each single step is executed by a different application or user
- Support modeling, execution, and maintenance of processes that are comprised of interactions between applications and human users



# Web service approach

- Performs integration through software components (web services) that support machine-to-machine interaction by XML-based messages
- Depending on offered integration functionality either represent
  - a uniform data access approach, or
  - a common data access for later manual or
  - application-based integration





# Apache Nifi

- Introduction
- What is dataflow?
- What is NiFi?
- What's next?

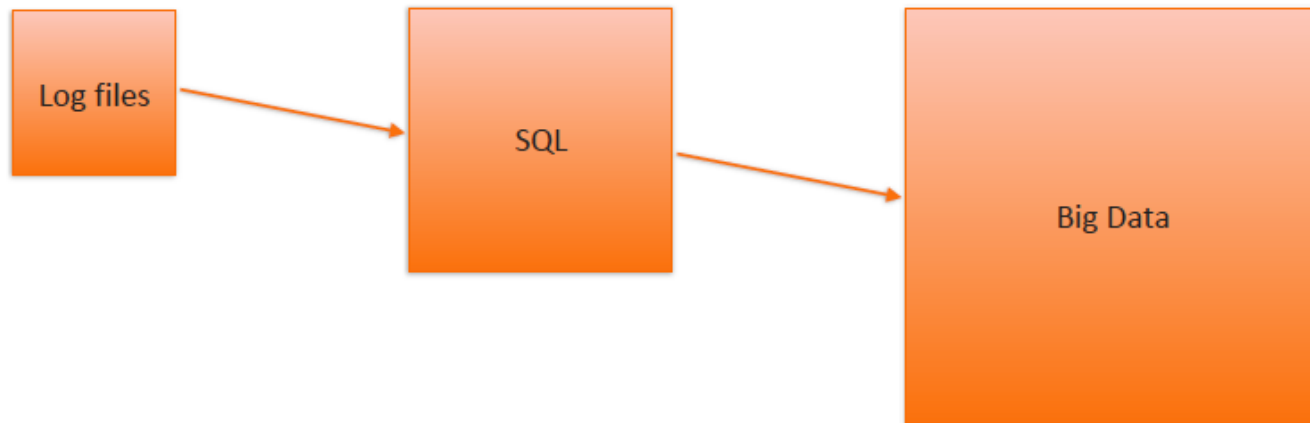


# What is dataflow?

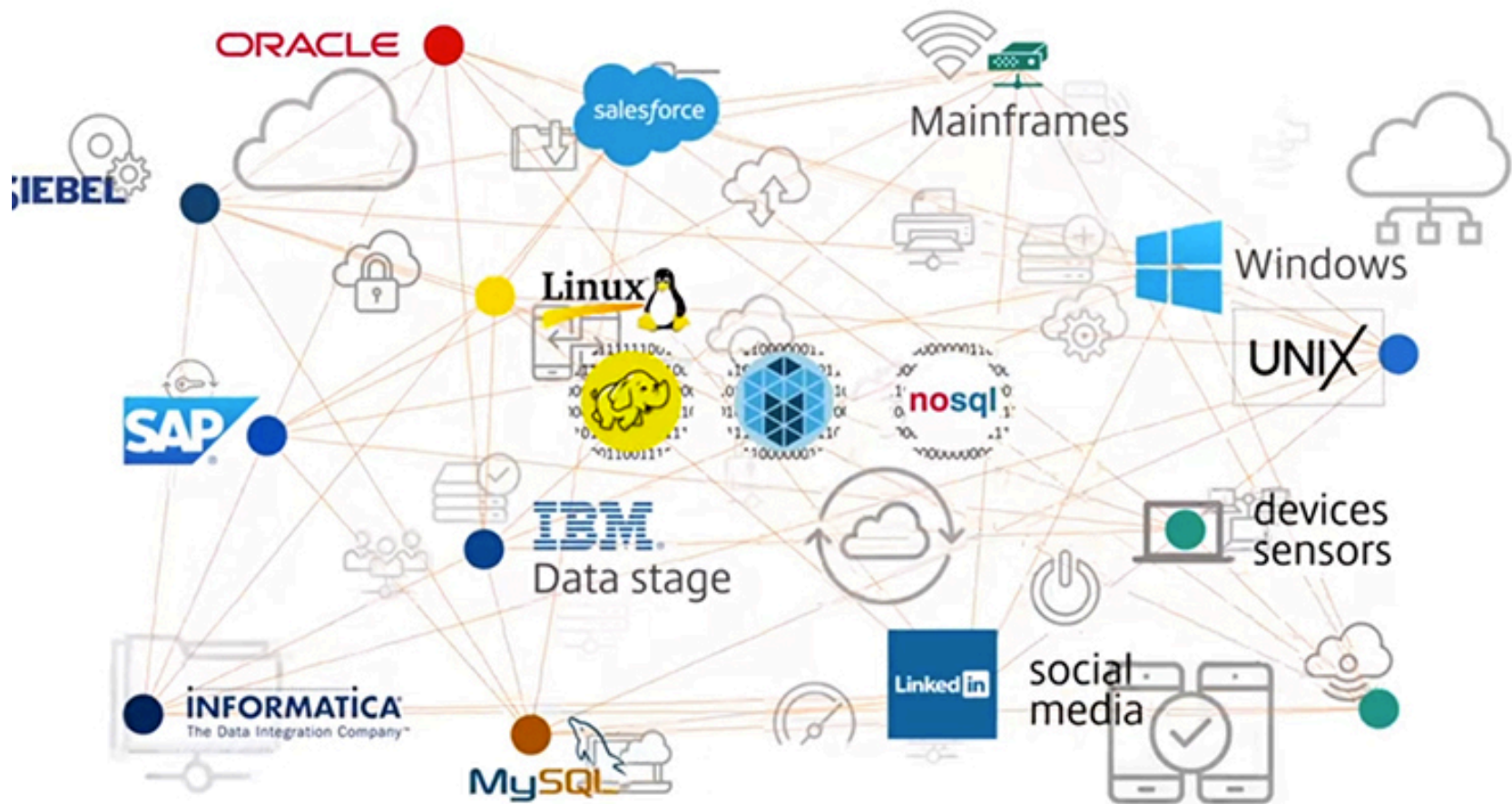
- Moving some content from A to B
- Content could be any bytes
  - Logs
  - HTTP
  - XML
  - CSV
  - Images
  - Video

# Connecting data points is easy

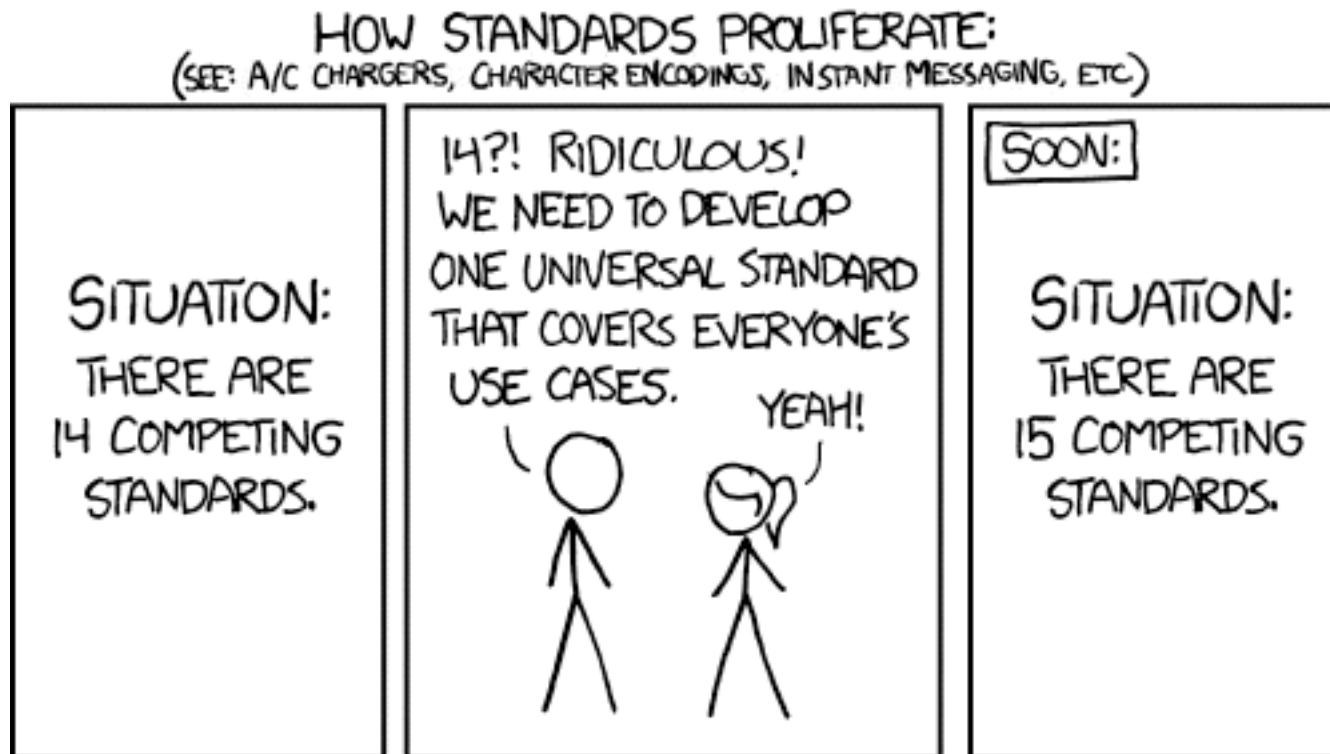
- Simple enough to write a process
  - Bash/Ruby/Python
  - SQL proc
  - etc.



# This approach doesn't scale



# Moving data effectively is hard



Standards: <http://xkcd.com/927/>

# Dataflow challenges in 3 categories

- Data

- Standards
- Formats
- Protocols
- Veracity
- Validity
- Schemas
- Partitioning/Bundling

- Infrastructure

- “Exactly Once” Delivery
- Ensuring Security
- Overcoming Security
- Credential Management
- Network

- People

- Compliance
- “That [person|team|group]”
- Consumers Change
- Requirements Change
- “Exactly Once” Delivery

# NiFi is based on Flow Based Programming (FBP)

FBP term	Niffi Term	Description
Information Packet	FlowFile	Each object moving through the system.
Black Box	FlowFile Processor	Performs the work, doing some combination of data routing, transformation, or mediation between systems.
Bounded Buffer	Connection	The linkage between processors, acting as queues and allowing various processes to interact at differing rates.
Scheduler	Flow Controller	Maintains the knowledge of how processes are connected, and manages the threads and allocations thereof which all processes use.
Subnet	Process Group	A set of processes and their connections, which can receive and send data via ports. A process group allows creation of entirely new component simply by composition of its components.

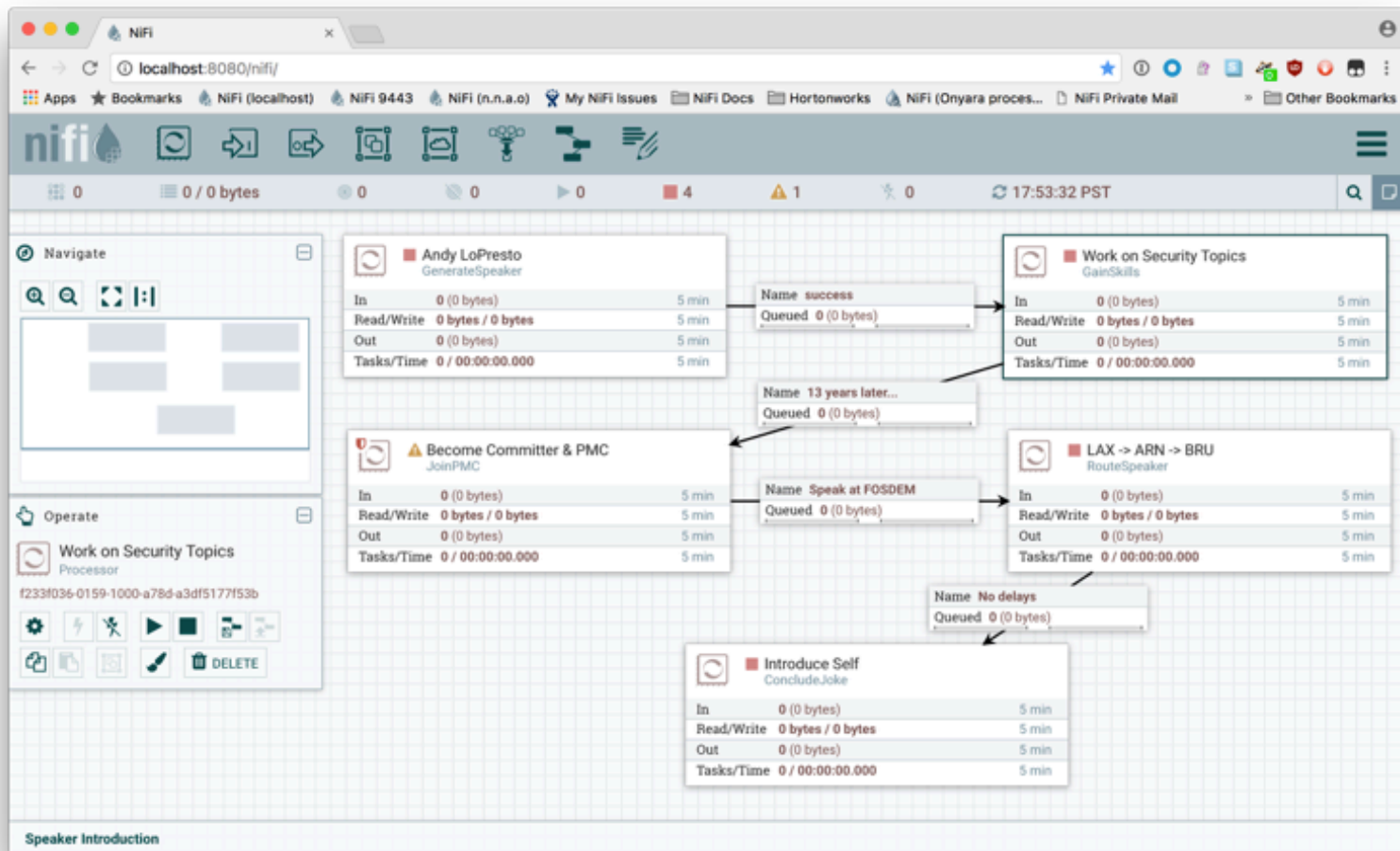
# Nifi key features

- Guaranteed delivery
- Prioritized queuing
- Flow specific QoS
  - Latency vs. throughput
  - Loss tolerance
- Data provenance
- Supports push and pull models
- Recovery/recording a rolling log of fine-grained history
- Visual command and control
- Flow templates
- Pluggable, multi-tenant security
- Designed for extension
- Clustering of Nifi instances





# User Interface



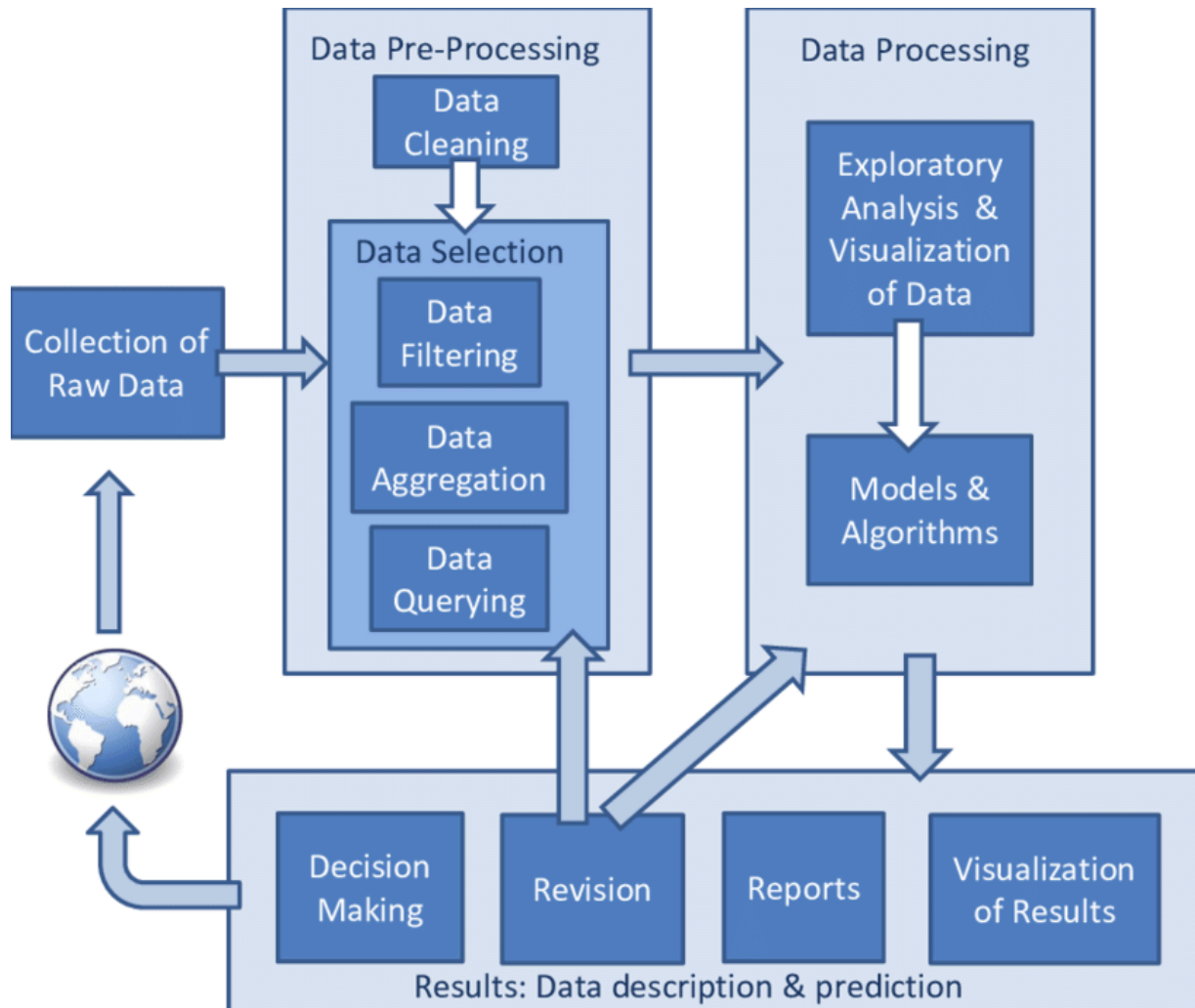
# Ecosystem Integration: 260+ Processors, 48 Controller Services



# Nifi demonstration

# Data Preprocessing

# Data science process

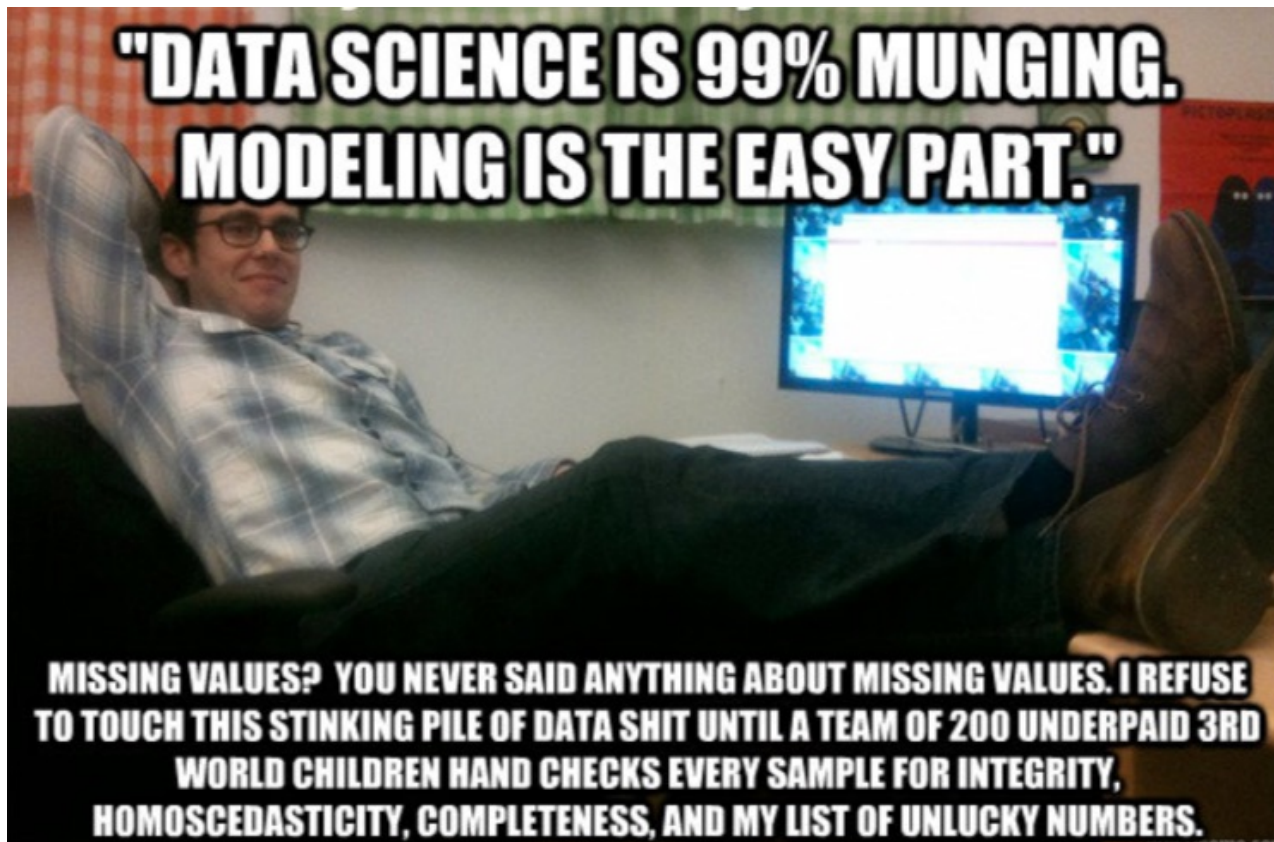


# Why data preprocessing?

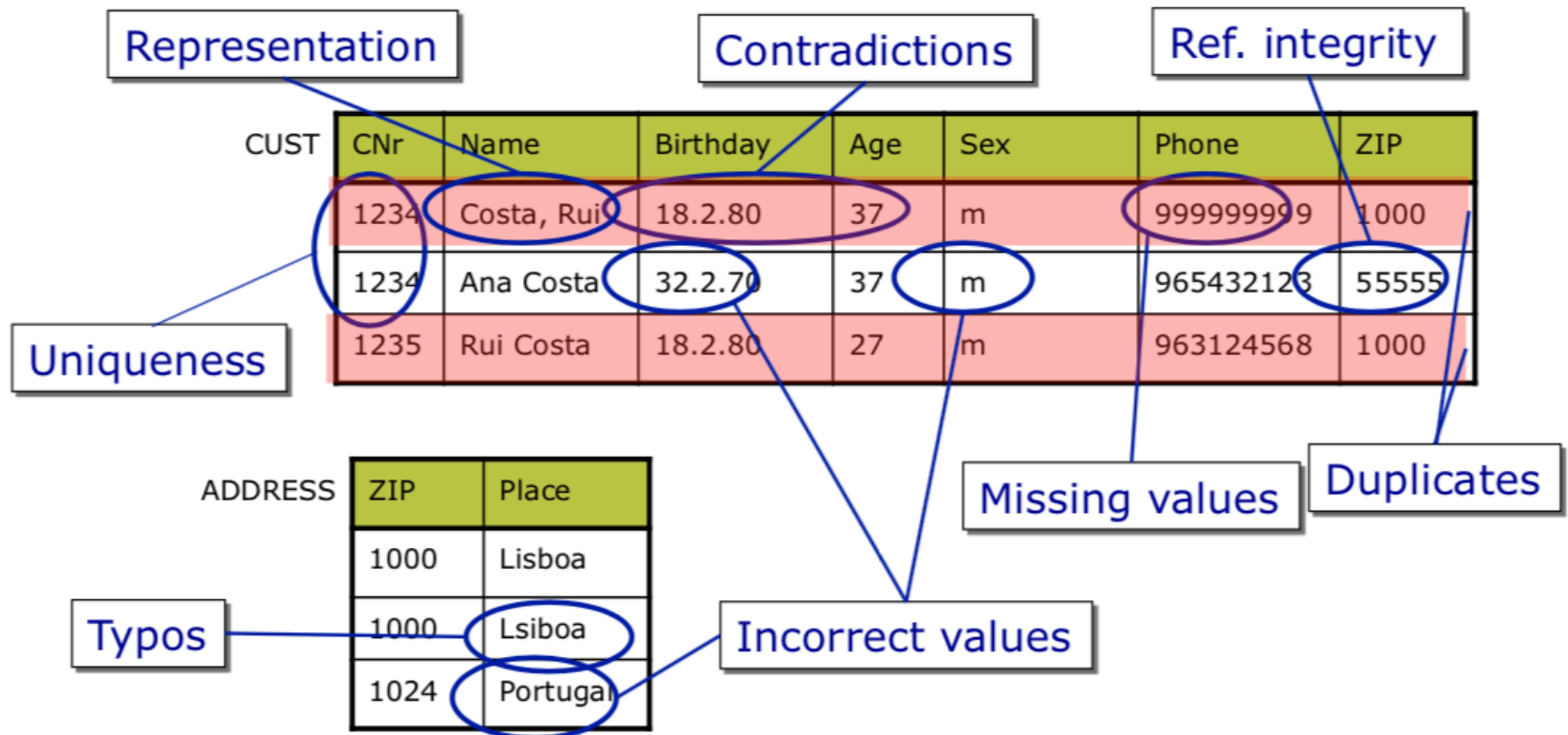
- Data in real world is dirty
- Incomplete (e.g name = "")
  - Lacking attribute values, lacking certain attributes of interest, or containing only aggregate data
  - Different considerations between the time when the data was collected and when it is analyzed
  - Human/hardware/software bugs
- Noisy (e.g. salary = '-10k')
  - Containing errors or outliers
  - Faulty data collection instruments
  - Human error at data entry
  - Error in data transmission
- Inconsistent (e.g., Age="20" Birthday="02/02/2000")
  - Different data sources
  - Functional dependency violation
- Duplicate records also need data cleaning

# Data preprocessing is costly

- Data extraction, cleaning, and transformation comprises the majority of the work of building a data warehouse



# Data quality problems





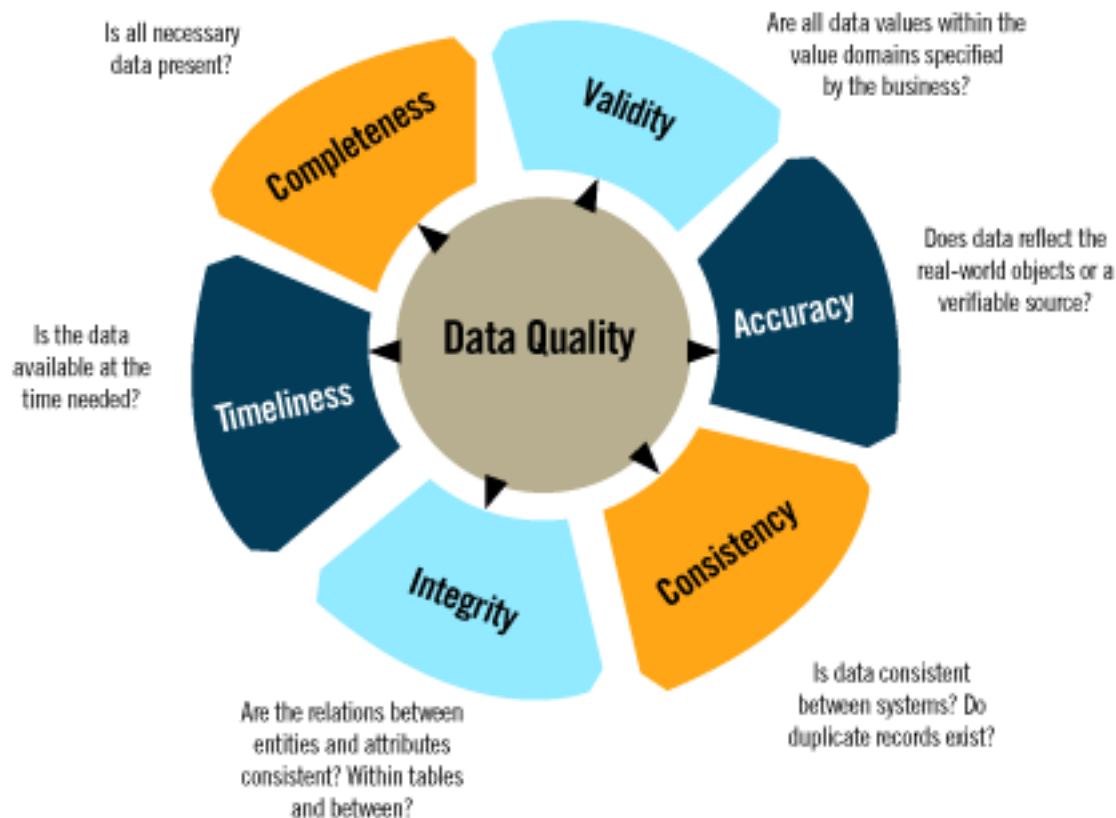
# No quality data, no quality mining results

- Quality decisions must be based on quality data
  - e.g., duplicate or missing data may cause incorrect or even misleading statistics.



# Data quality dimensions

- “Even though quality cannot be defined, you know what it is.”  
Robert Pirsig



# Taxonomy of data quality problems

- Value-level
- Value-set (attribute/column) level
- Record level
- Relation level
- Multiple relations level

# Value level

- Missing value: value not filled in a not null attribute
  - Ex:birthdate=""
- Syntax violation: value does not satisfy the syntax rule defined for the attribute
  - Ex:zipcode=27655-175;syntaxrule:xxxx-xxx
- Spelling error
  - Ex:city='Lsboa',insteadof'Lisbon'
- Domain violation: value does not belong to the valid domain set
  - Ex:age=240;age:{0,120}

# Value-set and record levels

- Value-set level

- Existence of synonyms: attribute takes different values, but with the same meaning
  - Ex: emprego = 'futebolista'; emprego = 'jogador futebol'
- Existence of homonyms: same word used with diff meanings
  - Ex: same name refers to different authors of a publication
- Uniqueness violation: unique attribute takes the same value more than once
  - Ex: two clients have the same ID number
- Integrity constraint violation
  - Ex: sum of the values of percent attribute is more than 100

- Record level

- Integrity constraint violation
  - Ex: total price of a product is different from price plus taxes

# Relation level

- Heterogeneous data representations: different ways of representing the same real world entity
  - Ex: name = 'John Smith'; name = 'Smith, John'
- Functional dependency violation
  - Ex: (2765-175, 'Estoril') and (2765-175, 'Oeiras')
- Existence of approximate duplicates
  - Ex: (1, André Fialho, 12634268) and (2, André Pereira Fialho, 12634268)!
- Integrity constraint violation
  - Ex: sum of salaries is superior to the max established

# Multiple tables level

- Heterogeneous data representations
  - Ex: one table stores meters, another stores inches
- Existence of synonyms
- Existence of homonyms
- Different granularities: same real world entity represented with diff. granularity levels
  - Ex: age:{0-30,31-60,>60};age:{0-25,26-40, 40-65, >65}
- Referential integrity violation
- Existence of approximate duplicates
- Integrity constraint violation

# Major tasks of data preprocessing

- Data cleaning
  - Fill in missing values, smooth noisy data, identify or remove outliers, and resolve inconsistencies
- Data integration
  - Integration of multiple databases, data cubes, files, or notes
- Data transformation
  - Normalization (scaling to a specific range)
  - Aggregation
- Data reduction
  - Obtains reduced representation in volume but produces the same or similar analytical results
  - Data discretization: with particular importance, especially for numerical data
  - Data aggregation, dimensionality reduction, data compression, generalization



# Data cleaning

- Tasks of Data cleaning
  - Fill in missing values
  - Identify outliers and smooth noisy data
  - Correct inconsistent data

# Manage missing data

- **Ignore the tuple:** usually done when class label is missing (assuming the task is classification—not effective in certain cases)
- **Fill in the missing value manually:** tedious + infeasible?
- Use **a global constant** to fill in the missing value: e.g., “unknown”, a new class?!
- Use the attribute **mean** to fill in the missing value
- Use the attribute **mean for all samples of the same class** to fill in the missing value: smarter
- Use the **most probable value** to fill in the missing value: inference based such as regression, Bayesian formula, decision tree

# Manage noisy data

- Binning method:
  - first sort data and partition into (equi-depth) bins
  - then one can smooth by bin means, smooth by bin median, smooth by bin boundaries, etc.
- Clustering:
  - detect and remove outliers
- Regression
  - Use regression functions
- Semi automated
  - Computer and manual intervention

# Manage inconsistent data

- Manual correction using external references
- Semi-automatic using various tools
  - To detect violation of known functional dependencies and data constraints
  - To correct redundant data

# Methodology for data cleaning

- Extraction of the individual fields that are relevant
- Standardization of record fields
- Correction of data quality problems at value level
  - Missing values, syntax violation, etc
- Correction of data quality problems at value-set level and record level
  - Synonyms, homonyms, uniqueness violation, integrity constraint violation, etc
- Correction of data quality problems at relation level
  - Violation of functional dependencies, duplicate elimination, etc
- Correction of data quality problems at multiple relations level
  - Referential integrity violation, duplicate elimination, etc
- User feedback
  - To solve instances of data quality problems not addressed by automatic methods
- Effectiveness of the data cleaning and transformation process must be always measured for a sample of the data set

# Data integration

- Data integration
  - combines data from multiple sources into a coherent store
- Schema integration: e.g.,  $A.cust-id = B.cust-\#$ 
  - Integrate metadata from different sources
- Entity identification problem
  - Identify and use real world entities from multiple data sources, e.g.,  
Bill Clinton = William Clinton
- Detecting and resolving data value conflicts
  - For the same real world entity, attribute values from different sources are different
  - Possible reasons: different representations, different scales, e.g.,  
metric vs. British units

# Handling redundancy in data integration

- Redundant data occur often when integration of multiple databases
  - Object identification: The same attribute or object may have different names in different databases
  - Derivable data: One attribute may be a “derived” attribute in another table, e.g., annual revenue
- Redundant attributes may be able to be detected by correlation analysis
- Careful integration of the data from multiple sources may help reduce/avoid redundancies and inconsistencies and improve mining speed and quality

# Data transformation

- Smoothing: remove noise from data
- Aggregation: summarization
- Generalization: concept hierarchy climbing
- Normalization: scaled to fall within a small, specified range
  - min-max normalization
  - z-score normalization
  - normalization by decimal scaling
- Attribute/feature engineering



# Data transformation: normalization

- Min-max normalization: transformation maps the values of a variable to a new range [NewMin, NewMax]

$$x'_i = \frac{x_i - \text{OriginalMin}}{\text{OriginalMax} - \text{OriginalMin}} \times (\text{NewMax} - \text{NewMin}) + \text{NewMin}$$

- Z-score normalization: ( $\mu$ : mean,  $\sigma$ : standard deviation):

$$v' = \frac{v - \mu_A}{\sigma_A}$$

- Normalization by decimal scaling: transformation moves the decimal point to ensure that  $x'_i$  is between 1 and  $-1$ 
  - where  $n$  is the number of digits of the maximum absolute value

# Data reduction

- Obtain a reduced representation of the data set that is much smaller in volume but yet produce the same (or almost the same) analytical results
  - Dimensionality reduction
    - Feature selection
    - Feature extraction (eg. PCA analysis)
  - Data Compression
    - Convert text to numbers
    - Data clustering
  - Discretization
    - Convert continuous data to categories



# Hands-on openrefine

<https://guides.library.illinois.edu/openrefine>

Or leverage Scikitlearn data transform

[https://scikit-learn.org/stable/data\\_transforms.html](https://scikit-learn.org/stable/data_transforms.html)

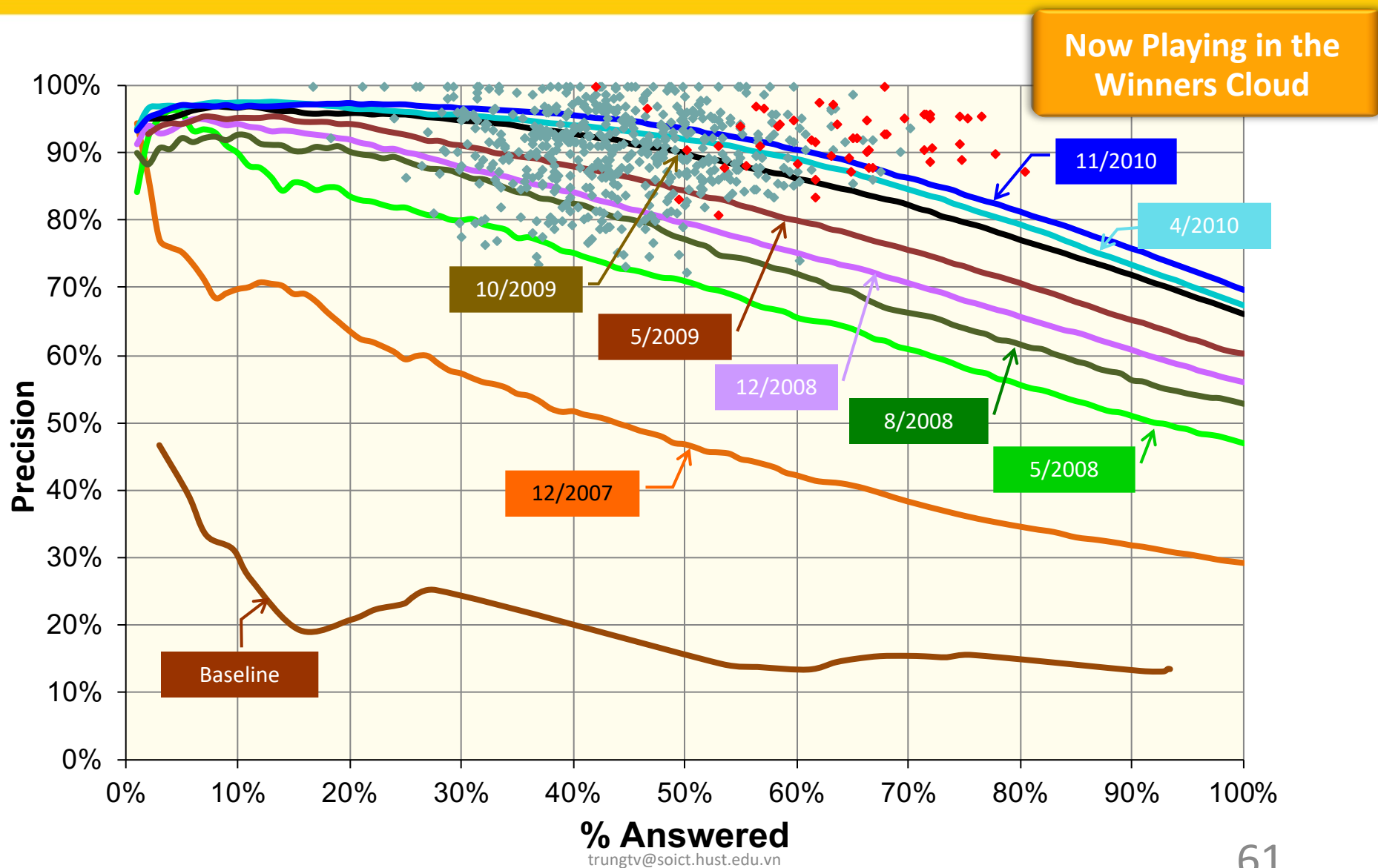
# Conclusion

- You have learnt
  - Data integration
  - Data preprocessing
- You have tried
  - Apache Nifi
  - Openrefine
- Garbage in, garbage out



# DeepQA: Incremental Progress in Precision and Confidence

6/2007-11/2010



# Appendix

# Correlation analysis (numerical data)

- Correlation coefficient (also called Pearson's product moment coefficient)

$$r_{A,B} = \frac{\sum (A - \bar{A})(B - \bar{B})}{(n-1)\sigma_A\sigma_B} = \frac{\sum (AB) - n\bar{A}\bar{B}}{(n-1)\sigma_A\sigma_B}$$

- where n is the number of tuples, and  $\bar{A}$  and  $\bar{B}$  are the respective means of A and B,  $\sigma_A$  and  $\sigma_B$  are the respective standard deviation of A and B, and  $\sum(AB)$  is the sum of the AB cross-product.
- If  $r_{A,B} > 0$ , A and B are positively correlated (A's values increase as B's). The higher, the stronger correlation.
- $r_{A,B} = 0$ : independent;
- $r_{A,B} < 0$ : negatively correlated

# Correlation analysis (categorical data)

- X2 (chi-square) test

$$\chi^2 = \sum_i \sum_j \frac{(\text{Observed} - \text{Expected})^2}{\text{Expected}}$$

- The larger the X2 value, the more likely the variables A, B are related (Observed is actual count of event (Ai,Bj))
- The cells that contribute the most to the X2 value are those whose actual count is very different from the expected count (based on totals)
- Correlation does not imply causality
  - # of hospitals and # of car-theft in a city are correlated
  - Both are causally linked to the third variable: population



# Chi-square calculation: An example

- $\chi^2$  (chi-square) calculation (numbers in parenthesis are expected counts calculated based on the data distribution in the two categories)
- It shows that like\_science\_fiction and play\_chess are correlated in the group

$$\chi^2 = \frac{(250 - 90)^2}{90} + \frac{(50 - 210)^2}{210} + \frac{(200 - 360)^2}{360} + \frac{(1000 - 840)^2}{840} = 507.93$$

	Play Chess	Don't play chess	Sum (Row)
Like science fiction	250(90)	200(360)	450
Don't Like science fiction	50(210)	1000(840)	1050
Sum (Column)	300	1200	1500