Data Integration and Analysis
07 Data Provenane and Blockchain

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SCIENCE
PASSION
TECHNOLOGY

Last update: Nov 22, 2019

Announcements/Org

- **#1 Video Recording**
  - Link in TeachCenter & TUbe (lectures will be public)

- **#2 DIA Projects**
  - 13 Projects selected (various topics)
  - 3 Exercises selected (distributed data deduplication)

- **#3 CS Talks x6 (Nov 28, 5pm, Aula Alte Technik)**
  - Charlotte Han (NVIDIA, DL Marketing Manager)
  - Title: The Rise of AI and Robotics:
    How Will It Change the Way We Work and Live?

Agenda

- **Motivation and Terminology**
- **Data Provenance**
- **Blockchain Fundamentals**

Motivation and Terminology

Excursus: FAIR Data Principles

[https://www.go-fair.org/fair-principles/]

- **#1 Findable**
  - Metadata and data have globally unique **persistent identifiers**
  - Data describes w/ rich **meta data**; registered/indexes and searchable
- **#2 Accessible**
  - Metadata and data retrievable via open, free and universal **comm protocols**
  - Metadata accessible even when data no longer available
- **#3 Interoperable**
  - Metadata and data use a formal, **accessible, and broadly applicable format**
  - Metadata and data use FAIR vocabularies and qualified references
- **#4 Reusable**
  - Metadata and data described with plurality of accurate and relevant attributes
  - Clear license, **associated with provenance**, meets community standards

Terminology

- **Data Provenance**
  - Track and understand data origins and transformations of data (**where?**, **when?**, **who?**, **why?**, **how?**)

  - Contains meta data, context, and modifications (transform, enrichment)
  - Synonyms: **data lineage**, **data pedigree**

- **Data Catalogs** (curation/**governance**)
  - Directory of datasets including data provenance (meta data, artifacts)
  - Raw/original, curated datasets, derived data products

- **Blockchain**
  - Data structure logging transactions in **verifiable** and **permanent way**

Applications and Goals

a) High-Level Goals

- **#1 Versioning and Reproducibility** (analogy experiments)
- **#2 Explanability, Interpretability, Verification**

b) Low-Level Goals

- **#3 Full and Partial Reuse of Intermediates**
- **#4 Incremental Maintenance of MatViews, Models, etc**
- **#5 Tape/log of Executed Operations** → Auto Differentiation
- **#6 Recomputation for Caching / Fault Tolerance**
- **#7 Debugging via Lineage Query Processing**

Data Provenance

Overview Data Provenance

- **Def Data Provenance**
  - Information about the **origin** and **creation process** of data

- **Example**
  - Debugging suspicious query results

```
SELECT Customer, sum(O.Quantity*P.Price)
  FROM Orders O, Products P
  WHERE O.PID = P.PID
  GROUP BY Customer
```

Customer	Sum
A	**7620**
B	120
C	130
D	75

OID	Customer	Date	Quantity	PID
1	**A**	**2019-06-22**	**3**	**2**
2	B	2019-06-22	1	3
3	**A**	**2019-06-22**	**101**	**4**
4	C	2019-06-23	2	2
5	D	2019-06-23	1	4
6	C	2019-06-23	1	1

PID	Product	Price
1	X	100
2	**Y**	**15**
4	**Z**	**75**
3	W	120

Overview Data Provenance, cont.

- **An Abstract View**
  - **Data:** schema, structure → data items
  - **Data composition** (granularity): attribute, tuple, relation
  - **Transformation:** consumes inputs, produces outputs
  - **Hierarchical transformations:** query w/ views, query block, operators
  - **Additional:** env context (OS, libraries, env variables, state), users

[Boris Glavic: CS595 Data Provenance – Introduction to Data Provenance, **Illinois Institute of Technology, 2012**]

- **Goal: Tracing of Derived Results**
  - Inputs and parameters
  - Steps involved in creating the result
  - → Store and query data & provenance
  - General Data Protection Regulation (**GDPR**)?

[Zachary G. Ives: Data Provenance: Challenges, Benefits, Research, **NIH Webinar 2016**]


```
1. Read file1
2. Sort rows
3. Compute median
4. Write to file2
```

Prov.

Classification of Data Provenance

- **Overview**
  - Base query Q(D) = O with database D = {R_1, …, R_n}
  - **Forward lineage query:** $L_f(R_i'', O')$ from subset of input relation to output
  - **Backward lineage query:** $L_b(O', R_i)$ from subset of outputs to base tables
- **#1 Lazy Lineage Query Evaluation**
  - Rewrite (**invert**) lineage queries as relational queries over input relations
  - No runtime overhead but slow lineage query processing
- **#2 Eager Lineage Query Evaluation**
  - Materialize **annotations** (data/transforms) during base query evaluation
  - Runtime overhead but fast lineage query processing
  - Lineage capture: **Logical** (relational) vs **physical** (instrumented physical ops)

[Fotis Psallidas, Eugene Wu: Smoke: Fine-grained Lineage at Interactive Speed. **PVLDB 2018**]

Why-Provenance

[Boris Glavic: CS595 Data Provenance – Provenance Models and Systems, **Illinois Institute of Technology, 2012**]

- **Overview Why**
  - **Goal:** Which input tuples contributed to an output tuple t in query Q
  - Representation: Set of witnesses w for tuple t (**set semantics!**)
    - $w \subseteq I$ (subset of all tuples in instance I)
    - $t \in Q(w)$ (tuple in result of query over w)

- **Example Witnesses**

```
SELECT Customer, Product
  FROM Orders O, Products P
  WHERE O.PID=P.PID
```

	Customer	Date	PID
o1	A	2019-06-22	2
o2	B	2019-06-22	3
o3	A	2019-06-22	2

	PID	Product
p1	1	X
p2	2	Y
p3	4	Z
p4	3	W

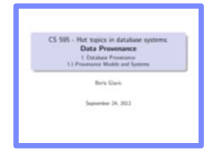
	Customer	Product
t1	A	Y
t2	B	W

  - **Witnesses** for **t1**:
    w1 = {o1,p2}, w2 = {o3,p2},
    w3 = {o1,p2,p3}, …, wn = I
  - Minimal witnesses for t1:
    w1 = {o1,p2}, w2 = {o3,p2}

Others: Where/How Provenance

How-Provenance

[Boris Glavic: CS595 Data Provenance – Provenance Models and Systems, **Illinois Institute of Technology, 2012**]



- **Overview**
  - Model how tuples where combined in the computation
  - **Alternative use:** need one of the tuples (e.g., union/projection)
  - **Conjunctive use:** need all tuples together (e.g., join)

- **Provenance Polynomials**
  - **Semiring annotations** to model provenance $(\mathbb{N}[I], +, \times, 0, 1)$

- **Examples**
  - $q = \pi_a(R)$

	a	b
r1	1	2
r2	1	3

→

a
1

r1 + r2

Provenance Polynomials

  - $q = \pi_b(R \bowtie S)$

	a	b
r1	1	P
r2	2	G
	3	M

	c	a
s1	S	1
s2	S	2
s3	W	2

→

b
P
G

r1 x s1

(r2 x s2) + (r2 x s3)

Why Not?-Provenance

[Adriane Chapman, H. V. Jagadish: **Why not? SIGMOD 2009**]

- **Overview**
  - Why are items not in the results
  - **Example Problem:**
    "Window-display-books < $20"
    → (Euripides, Medea).
    → **Why not** (Hrotsvit, Basilius)?

>= 20$?

Bug in the query / system?

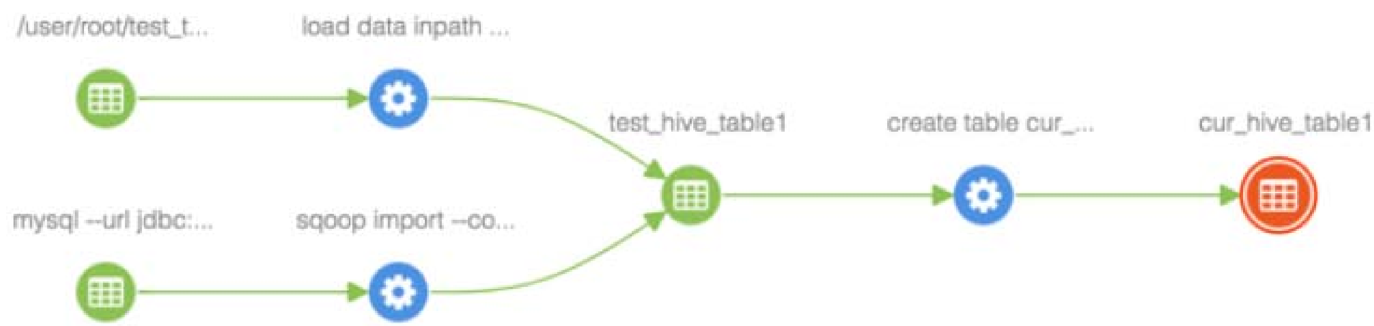
Not in book store?

Author	Title	Price	Publisher
	Epic of Gilgamesh	$150	Hesperus
Euripides	Medea	$16	Free Press
Homer	Iliad	$18	Penguin
Homer	Odyssey	$49	Vintage
Hrotsvit	Basilius	$20	Harper
Longfellow	Wreck of the Hesperus	$89	Penguin
Shakespeare	Coriolanus	$70	Penguin
Sophocles	Antigone	$48	Free Press
Virgil	Aeneid	$92	Vintage

- **Evaluation Strategies**
  - Given a user question (why no tuple satisfies predicate S), dataset D, result set R, and query Q, leverage **why lineage**
  - **#1 Bottom-Up:** from leafs in topological order to find last op eliminating $d \in S$
  - **#2 Top-Down:** from result top down to find last op, **requires stored lineage**

Apache Atlas

- **Apache Atlas Overview**
  - Metadata management and governance capabilities
  - Build catalog (data classification, cross-component lineage)
- **Example**
  - Configure Atlas hooks w/ Hadoop components
  - Automatic tracking of lineage and side effects



[https://www.cloudera.com/tutorials/cross-component-lineage-with-apache-atlas-across-apache-sqoop-hive-kafka-storm/.html]

Provenance for ML Pipelines (fine-grained)

- **DEX: Dataset Versioning**
  - **Versioning of datasets, stored with delta encoding**
  - Checkout, intersection, union queries over deltas
  - Query optimization for finding efficient plans

[Amit Chavan, Amol Deshpande: DEX: Query Execution in a Delta-based Storage System. **SIGMOD 2017**]

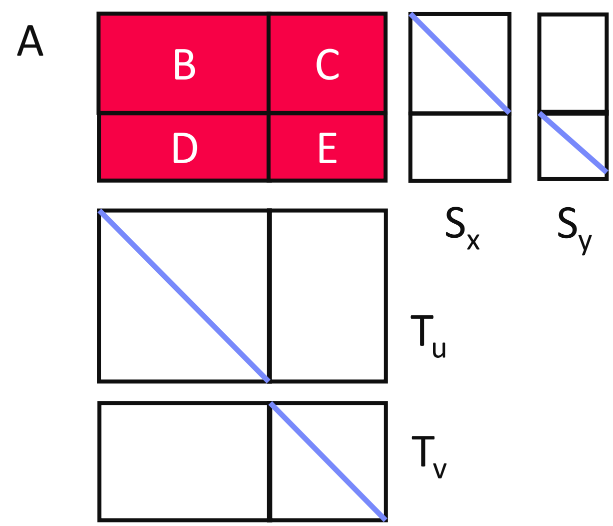
- **MISTIQUE: Intermediates of ML Pipelines**
  - Capturing, storage, querying of intermediates
  - **Lossy deduplication and compression**
  - Adaptive querying/materialization for finding efficient plans

[Manasi Vartak et al: MISTIQUE: A System to Store and Query Model Intermediates for Model Diagnosis. **SIGMOD 2018**]

- **Linear Algebra Provenance**
  - Provenance propagation by decomposition
  - Annotate parts w/ provenance polynomials (identifiers of contributing inputs + impact)

$$A = S_x B T_u + S_x C T_v + S_y D T_u + S_y E T_v$$

[Zhepeng Yan, Val Tannen, Zachary G. Ives: Fine-grained Provenance for Linear Algebra Operators. **TaPP 2016**]



Provenance for ML Pipelines (coarse-grained)

- **MLflow**
  - Programmatic API for tracking parameters, experiments, and results
  - **autolog()** for specific params

[**Credit:** https://databricks.com/blog/2018/06/05]

```
import mlflow
mlflow.log_param("num_dimensions", 8)
mlflow.log_param("regularization", 0.1)
mlflow.log_metric("accuracy", 0.1)
mlflow.log_artifact("roc.png")
```

- **Flor (on Ground)**
  - DSL embedded in python for managing the workflow development phase of the ML lifecycle
  - DAGs of Actions, Artifacts, and Literals
  - Data context generated by activities in Ground

[Credit: https://rise.cs.berkeley.edu/projects/jarvis/]

[Joseph M. Hellerstein et al: Ground: A Data Context Service. **CIDR 2017**]

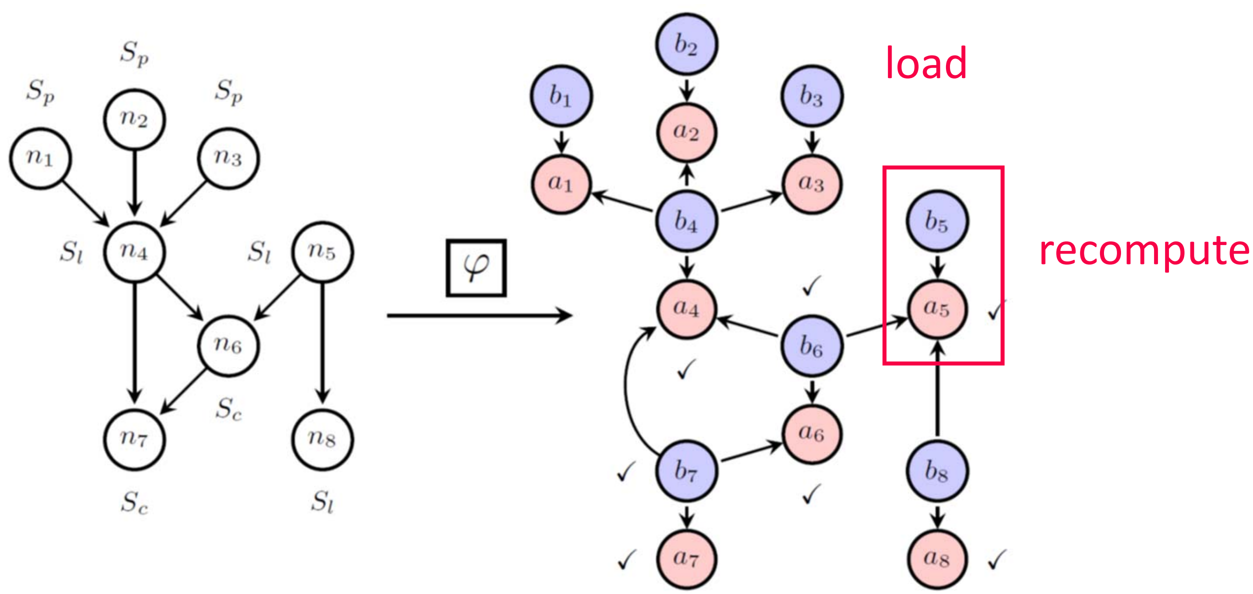
- **Dataset Relationship Management**
  - **Reuse**, **reveal**, **revise**, **retarget**, **reward**
  - Code-to-data relationships (data provenance)
  - Data-to-code relationships (potential transforms)

[Zachary G. Ives, Yi Zhang, Soonbo Han, Nan Zheng,: Dataset Relationship Management. **CIDR 2019**]

Provenance for ML Pipelines (coarse-grained), cont.

- **HELIX**
  - Goal: focus on iterative development w/ small modifications (trial & error)
  - Caching, reuse, and recomputation
  - Reuse as Max-Flow problem → NP-hard → heuristics
  - Materialization to disk for future reuse

[Doris Xin, Stephen Macke, Litian Ma, Jialin Liu, Shuchen Song, Aditya G. Parameswaran: Helix: Holistic Optimization for Accelerating Iterative Machine Learning. **PVLDB 2018**]



Fine-grained Lineage in SystemDS

- **Problem**
  - **Exploratory data science** (data preprocessing, model configurations)
  - **Reproducibility** and **explanability** of trained models (data, parameters, prep)

  ➔ **Lineage/Provenance as Key Enabling Technique:**
  Model versioning, reuse of intermediates, incremental maintenance, auto differentiation, and debugging (query processing over lineage)

- **a) Efficient Lineage Tracing**
  - Tracing of inputs, literals, and **non-determinism**
  - **Trace lineage of logical operations** for all live variables, store along outputs, program/output reconstruction possible:

```
X = eval(deserialize(serialize(lineage(X))))
```

  - **Proactive deduplication** of lineage traces for loops

Fine-grained Lineage in SystemDS, cont.

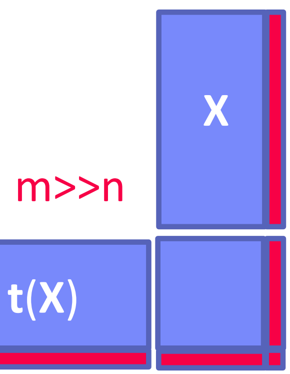
- **b) Full Reuse of Intermediates**
  - Before executing instruction, probe output lineage in cache `Map<Lineage, MatrixBlock>`
  - Cost-based/heuristic caching and eviction decisions (compiler-assisted)

$O(k(mn^2+n^3)) \rightarrow O(mn^2+kn^3)$

```
for( i in 1:numModels )
  R[,i] = lm(X, y, lambda[i,], ...)
```

```
m_lmDS = function(...) {
  l = matrix(reg,ncol(X),1)
  A = t(X) %*% X + diag(l)
  b = t(X) %*% y
  beta = solve(A, b) ...}
```

- **c) Partial Reuse of Intermediates**
  - **Problem:** Often partial result overlap
  - Reuse partial results via dedicated rewrites (compensation plans)
  - Example: steplm



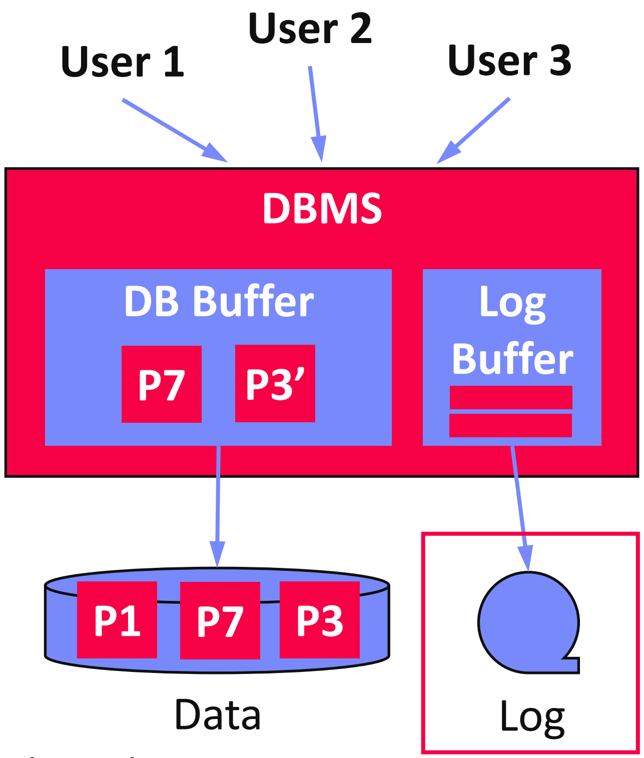

```
m_steplm = function(...) {
  while( continue ) {
    parfor( i in 1:n ) {
      if( !fixed[1,i] ) {
        Xi = cbind(Xg, X[,i])
        B[,i] = lm(Xi, y, ...)
    } }
    # add best to Xg
    # (AIC)
} }
```

$O(n^2(mn^2+n^3)) \rightarrow O(n^2(mn+n^3))$

Blockchain Fundamentals

Recap: Database (Transaction) Log

- **Database Architecture**
  - Page-oriented storage on disk and in memory (DB buffer)
  - Dedicated **eviction algorithms**
  - Modified in-memory pages marked as dirty, flushed by cleaner thread
  - Log: append-only TX changes
  - Data/log often placed on different devices and periodically archived (backup + truncate)



- **Write-Ahead Logging (WAL)**
  - The log records representing changes to some (dirty) data page must be on **stable storage before the data page** (UNDO - atomicity)
  - Force-log on commit or full buffer (REDO - durability)
  - **Recovery:** forward (REDO) and backward (UNDO) processing
  - Log sequence number (LSN)

[C. Mohan, Donald J. Haderle, Bruce G. Lindsay, Hamid Pirahesh, Peter M. Schwarz: ARIES: A Transaction Recovery Method Supporting Fine-Granularity Locking and Partial Rollbacks Using Write-Ahead Logging. **TODS 1992**]

Bitcoin and Blockchain

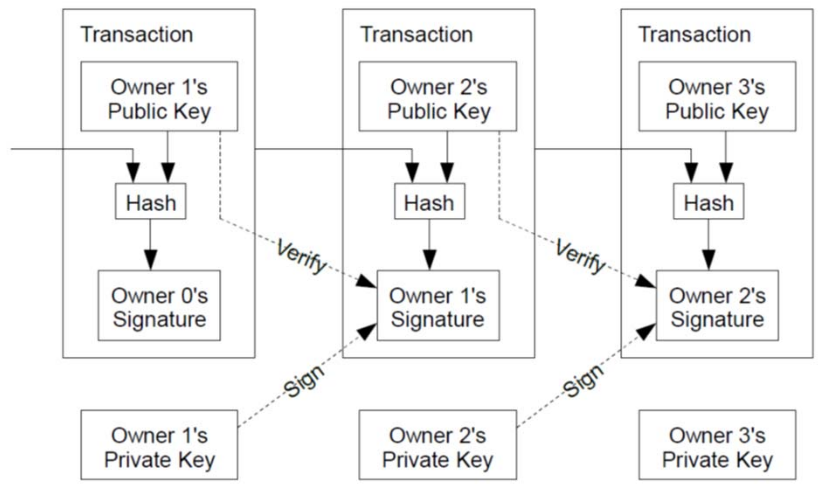
[**Satoshi Nakamoto**: Bitcoin: A Peer-to-Peer Electronic Cash System, **White paper 2008**]

- **Motivation**
  - Peer-to-peer (decentralized, anonymous) electronic cash/payments
  - **Non-reversible transactions** w/o need for trusted third party
  - **Statistics** Nov 21:

Market Price (USD)	Average Block Size	Transactions per Day	Mempool Size
$7,862.72 USD	1.16 Megabytes	303,921 Transactions	11,304,890 Bytes

[https://www.blockchain.com/charts]

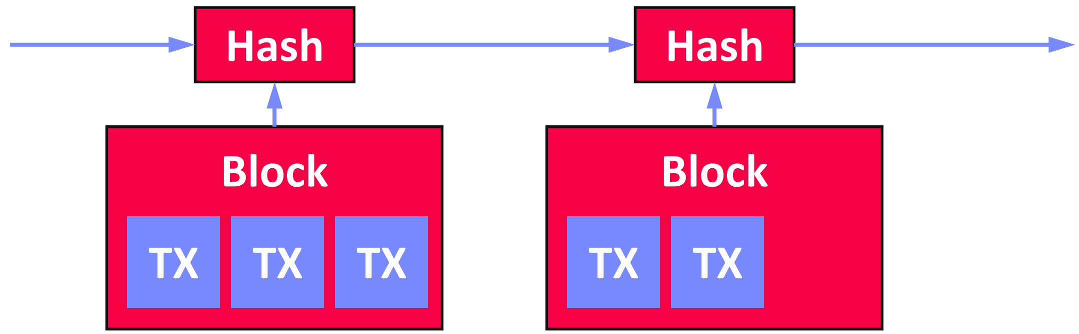
- **Transaction Overview**
  - Electronic coin defined as chain of digital signatures
  - Transfer by signing hash of previous TX and public key of next owner
  - **Double-spending problem** (without global verification)



Blockchain Data Structure

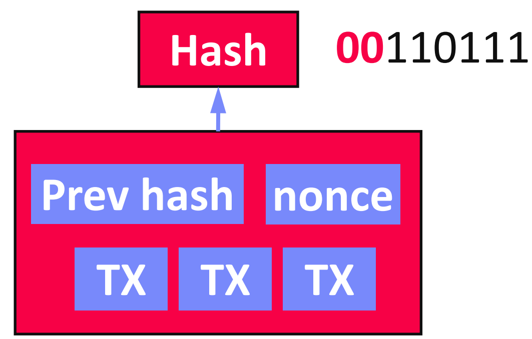
[**Satoshi Nakamoto**: Bitcoin: A Peer-to-Peer Electronic Cash System, **White paper 2008**]

- **Timestamp Server**
  - Decentralized timestamp server: chain of hashes ➔ **public ledger**



Enforces order dependency ➔ No double-spending

- **Proof-of-Work**
  - Scanning for value (nonce) which **SHA-256 hash** begins with a number of zero bits
    → exponential in number of zeros
  - # zero bits determine by MA of avg blocks/hour
  - Hard to recompute for chain, easy to check
  - **Majority decision:** CPU time, longest chain



Merkel tree (hash tree)

Blockchain Data Structure, cont.

- **Bitcoin Mining**
  - HW: from CPU to GPUs/FPGAs/ASICs (**10-70 TH/s** @ 2-3KW)
  - Usually mining pools → **"mining cartels"**

- **Hash Rate of Bitcoin Network**
  - **~10 min per block** (144 blocks per day)

Blockchain Communication

[**Satoshi Nakamoto**: Bitcoin: A Peer-to-Peer Electronic Cash System, **White paper 2008**]

- **Networking Protocol**
  - New **TXs are broadcast** to all nodes
  - Each node collects new **TXs into a block**
  - Each node works on finding **proof-of-work** for its block
    → **Incentive:** 1st TX in block new coin
    (**12.5 BTC** haves every 210k block) for the block creator / TX fees
  - When a node finds a proof-of-work, **broadcast the block** to all nodes
  - Nodes accept the block if **all TXs are valid** (double spending)
  - Nodes express **acceptance by working on next block** in the chain, using the hash of the accepted block as the previous hash

- **Fault Tolerance**
  - **TX broadcasts:** no need to reach all but many → next block contains it
  - **Block broadcast:** no need to reach all → next block references it

Smart Contracts (Ethereum)

- **Motivation**
  - **Problem:** Bitcoin TXs for transferring X $BTC from Alice to Bob (exchange as assets)
  - **Goals:** voting, auctions, games, bets, legal agreements (notary)
- **Ethereum**
  - Decentralized platform that allows creation, management, and execution of smart contracts
  - Ether cryptocurrency, block mining rate: seconds (5 ETH/block)

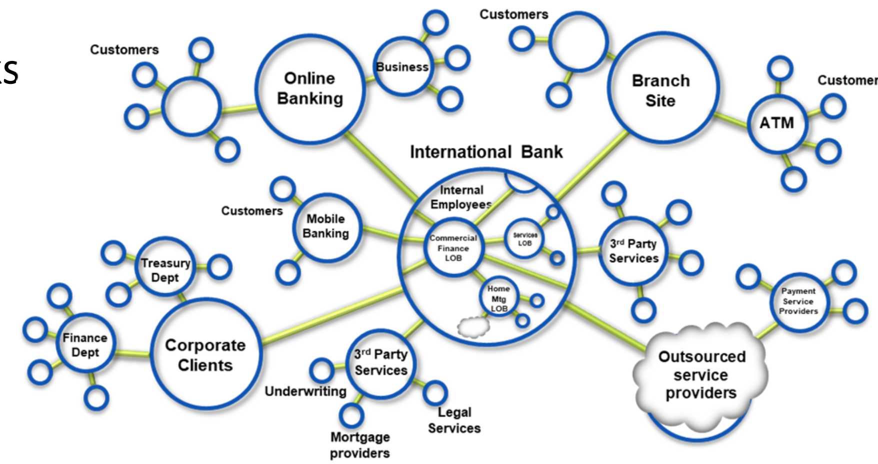
[**Credit:** Shana Hutchison]

- **Smart Contract**
  - Store smart contract (turing-complete programs) on the blockchain
  - **On transfer/trigger:** run smart contract (in) in Ethereum Virtual Machine
  - Language: Serpent/Solidity (deterministic, w/ control flow and function calls)
    ➔ Problem: while(true) → EVM gas and fees (start gas, gas price)
  - Immutability guarantees persistence

Permissioned/Private Blockchains

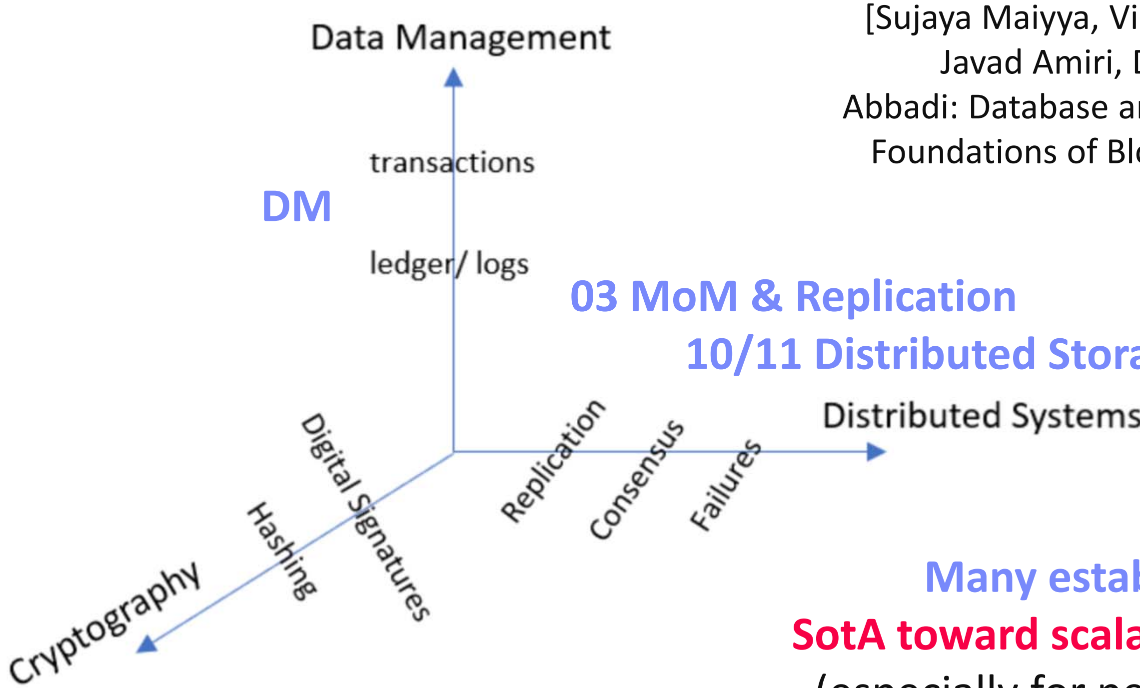
- **Private Setup**
  - Business Networks connect businesses
  - **Participants with Identity**
  - Assets flow over business networks
  - Transactions describe exchange or change of states of assets
  - **Smart contracts** underpin transactions
  - Blockchain as shared, replicated, permissioned ledger (TX log): **consensus**, **provenance**, **immutability**

[**C. Mohan:** State of Permissionless and Permissioned Blockchains: Myths and Reality, **2019**]



- **Hyperledger Fabric (https://github.com/hyperledger/)**
  - IBM, Oracle, Baidu, Amazon, Alibaba, Microsoft, JD, SAP, Huawei, Tencent
  - **Blockchain-as-a-Service** (BaaS) offerings: distributed ledger, libs, tools

Discussion Blockchain



DM

03 MoM & Replication

10/11 Distributed Storage/Compute

[Sujaya Maiyya, Victor Zakhary, Mohammad Javad Amiri, Divyakant Agrawal, Amr El Abbadi: Database and Distributed Computing Foundations of Blockchains. **SIGMOD 2019**]

Many established techniques

SotA toward scalable/efficient blockchains

(especially for permissioned blockchains)

➔ **Recommendation: Investigate business requirements/context, decide on technical properties and acceptable trade-offs**

Summary and Q&A

- **Motivation and Terminology**
- **Data Provenance**
- **Blockchain Fundamentals**

- **Projects and Exercises**
  - 13 projects + 3 exercises (3/13 discussions scheduled)
  - **Nov 29:** 2pm – 4.30pm in groups → **invites tonight**

- **Next Lectures**
  - **Nov 29:** no lecture → start with project (before DIA-part B)
  - **08 Cloud Computing Foundations** [**Dec 06**]
  - **09 Cloud Resource Management and Scheduling** [**Dec 13**]
  - **10 Distributed Data Storage** [**Jan 10**]