# Internet and Data

## Resources and Risks and Power

Kenneth W. Regan

CSE199, Fall 2023

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- [Week 1 Activity: Trying some SQL queries.]

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   - Hottest focus of consent, rights, and privacy issues. 2023 Example

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- Whichever, the Internet is in the "Zettabyte Epoch."

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- *Access* to data: *who* and *how*, is key.

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- Chicago Lakeside Technology Center, former champ at 1.1M sq. ft.

But for many users, where it lives virtually is in the Cloud.

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- Many data centers are augmented with **server farms** to do the processing.

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- Owner and/or provider are responsible for *structuring* data.

**Prime Directive**: Eliminate—or at least minimize—the one-off work a client needs to do to interface with your data.

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- The Cloud cannot serve *Random Access* on a large scale.

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  - **Locality.**
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  - **Locality.**
- Whole Net system architectures (MapReduce/Hadoop/Google File System, Amazon Elastic Compute Cloud...) are designed to ensure that data is *Stream-Friendly*.

# Data File Formats


- Positional formats typified by CSV, BMP
- Whereas TIFF tags images, XLSX adds markup to XLS…

# Markup

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- JavaScript Object Notation (**JSON**), Douglas Crockford, 2001.
- Now main alternative to XML, especially for *object serialization*.

## Markup Example: SGML (source, alt)

```
<recipe type="dessert" servings="6" preptime="10">  <!--Ten what?-->
<title>Haupia (Coconut Pudding)</title>
<ingredient-list>
<ingredient>
12 ounces coconut milk
</ingredient>      <!--Parser could allow omitting item close tag-->
<ingredient>
4 to 6 tablespoons sugar
...
</ingredient-list>
<instruction-list>
<step necessary="no">
Thoroughly wash and dry the pot you will use.
</step>
...
</instruction-list>
</recipe>
```

# Example: The First HTML Doc (lightly altered)

```
<TITLE>Tags used in HTML</TITLE>
<NEXTID 22>
<H1>HTML Tags</H1>This is a list of tags used in the
<A NAME=0 HREF=MarkUp.html#4>HTML</A> language.
Each tag starts with a tag opener (a less than sign) and ends
with a tag closer (a greater than sign).
Many tags have corresponding closing tags which
identical except for a slash after the tag opener.
(For example, the <A NAME=3 HREF=#2>TITLE</A> tag).<P>
Some tags take parameters, called attributes.
...
Opening list tags are:
<DL>
...
</DL>
the closing tag must obviously match the opening tag.
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Did not yet have `HEAD` and `BODY` structure. (Yes, word “are” is missing)

# Example: XML and JSON Compared

From https://www.w3schools.com/js/js_json_xml.asp, XML first:

```
<employees>
    <employee>
        <firstName>John</firstName> <lastName>Doe</lastName>
    </employee>
    <employee>
        <firstName>Anna</firstName> <lastName>Smith</lastName>
    </employee>
    <employee>
        <firstName>Peter</firstName> <lastName>Jones</lastName>
    </employee>
</employees>

{"employees":[
    { "firstName":"John", "lastName":"Doe" },
    { "firstName":"Anna", "lastName":"Smith" },
    { "firstName":"Peter", "lastName":"Jones" }
]}
```

# My Own Format Extending Chess “PGN” Standard

```
[GID "De Castellvi;Vinoles;Valencia;Valencia ESP;1475.??.??;?;1-0"]
[EID "Komodo-8-32bit"]
[Turn "6-w"]
[MovePlayed "h3"]
[EngineMove "Ne5"]
[Eval "+160"]
[Depth "12"]
...
        1    2    3    4    5    6    7    8    9   10   11   12
----------------------------------------------------------------
Ne5  n.a. n.a. n.a. n.a. n.a. +142 +142 +140 +132 +147 +146 +160
d3   +110 NREC NREC NREC +053 +095 NREC NREC NREC NREC NREC NREC
Bxf7 n.a. n.a. n.a. n.a. +107 +079 NREC NREC NREC NREC NREC NREC
...
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Mixes position-based and tagged elements. One [...] encloses tag and value.

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Non-hierarchical structure.

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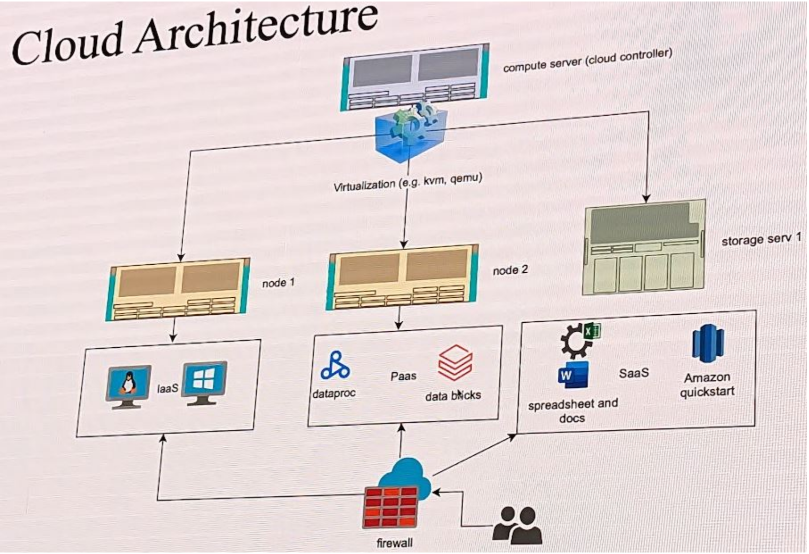
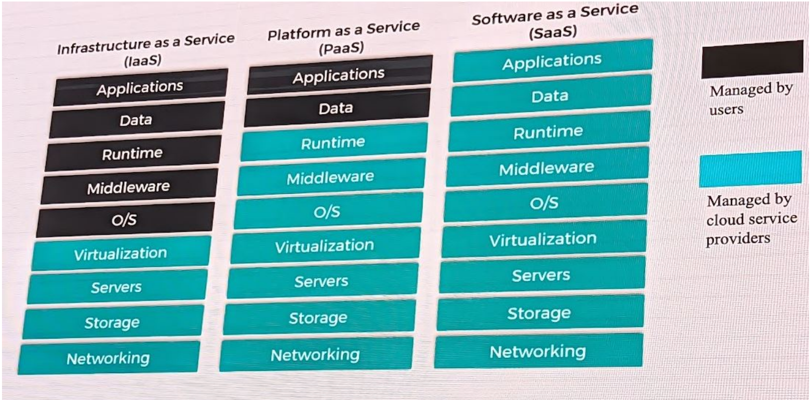
- (III) Select-all and mouse-copy the result into the left pane of DB-Fiddle. Click the "Run" triangle to verify.

# Three Extra Slides on the Cloud, by Asif Imran



# Levels of Using the Cloud




Source: https://www.inap.com/blog/iaas-paas-saas-differences/

# Cloud Platforms

## PaaS

- Platform to execute computing programs
- Hassle free since users do not need to set up the compilers, IDE, etc
- **Dataproc** is Google's cloud service for deploying Apache Spark and Apache Hadoop applications to a cloud environment [4]
- Integration with both Spark and Hadoop – take your applications as written for small clusters or single node, and scale to the cloud [4]
- Automatic scaling/resizing – elastic resource management can scale your application automatically as resources become available [4]
- Utilize existing Spark/Hadoop libraries for ML, SQL, Streaming, etc

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- (PGN and my AIF have no formal DTD, are minimally extensible.)

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Relational not positional. *Declarative* in that users are responsible only for data and queries, not algorithms or code.

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# Three Functions With Data—All Handled By SQL

1. Data Definition/Creation
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# Some SQL Commands

**CREATE**. Note that it creates a structure before you input data.

```
CREATE TABLE Games (
    gid             VARCHAR(128)       PRIMARY KEY,
    white_name      VARCHAR(50)        not null,
    black_name      VARCHAR(50)        not null,
    result          VARCHAR(7)         not null,
    white_rating    INTEGER
    black_rating    INTEGER
);
```

Here `TABLE` is a built-in SQL type, or rather template for the user-defined type `Games`. To kill it and all data you give both names:

```
DROP TABLE Games;
```

`TRUNCATE TABLE Games;` would destroy the entries but not the definition.

# Inserting, Updating, and Removing Data

```
INSERT INTO Games (white_name, black_name, result)
   VALUES ('DeCastellvi', 'Vinoles', '1-0');
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UPDATE Games SET gid = generate_game_id();
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SQL allows user-defined functions, here to generate the game ID.

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`DELETE FROM Games WHERE gid =` followed by the unique key removes just that game.

Can build by generating commands from data in XML/JSON/etc...

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(Yes, basic SQL needs that '`= 1`')

# Converting Data to SQL Entry (simplified)

```
<NFLTeams>
<Team code="ARI" teamName="Cardinals" region="Arizona"
      pop="4438000" lastPlayoffWin="2015"/>
<Team code="ATL" teamName="Falcons" region="Atlanta"
      pop="6462000" lastPlayoffWin="2016"/>
...
</NFLTeams>
```

```
CREATE TABLE NFLTeams (
   _code VARCHAR(3),
   _teamName VARCHAR(50),
   _region VARCHAR(50),
   _pop INT,
   _lastPlayoffWin INT
);
```

```
INSERT INTO NFLTeams VALUES ('ARI', 'Cardinals', 'Arizona', 4438000, 2015);
INSERT INTO NFLTeams VALUES ('ATL', 'Falcons', 'Atlanta', 6462000, 2016);
...
```

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- When "everything is data," those commands are data...and data is commands...

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- More about security in other weeks of this course...

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- Point is: we can't escape attention to low-level details.

# Fresh Example of Edge-Case Issues

My fantasy baseball league final matchup status after 4 MLB games on Monday 9/25/23:

**Shiftless Skonks**
KWRegan
155 - 98 - 11 | 1st

11 vs 0

**RockinRobin's Terrific Tigers**
RockinRobin
141 - 108 - 15 | 3rd

| Team | H/AB* | R | HR | RBI | SB | AVG | OPS | IP* | W | SV | K | HLD | ERA | WHIP | Score |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Shiftless Skonks | 4/7 | **2** | 0 | **1** | **1** | **.571** | **1.381** | 0.2 | **0** | **0** | **1** | **0** | **40.50** | **6.00** | **11** |
| RockinRobin's Terrific Tigers | 1/11 | 0 | 0 | 0 | 0 | .091 | .182 | - | - | - | - | - | - | - | 0 |

Because my opponent had no pitchers in those 4 games, his pitching scores were *null* not zero, and I got "credit" for 0 > *null*. (Never mind that 40.50 is a horrible ERA value—it still is considered to beat *null*.) This policy may nevertheless be correct on the simplest level.

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- Oct. 2022 Gulf of Mexico rescue via text message story.

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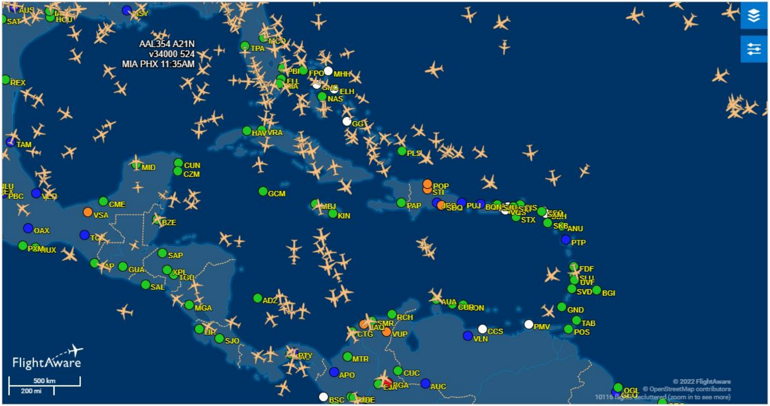
- **Unstructured Data** may not have been originally intended as data.

# A “Semi-Structred” Example (of Inferencing)

FlightAware Live Tracker, Monday 9/19/22, about 11am:

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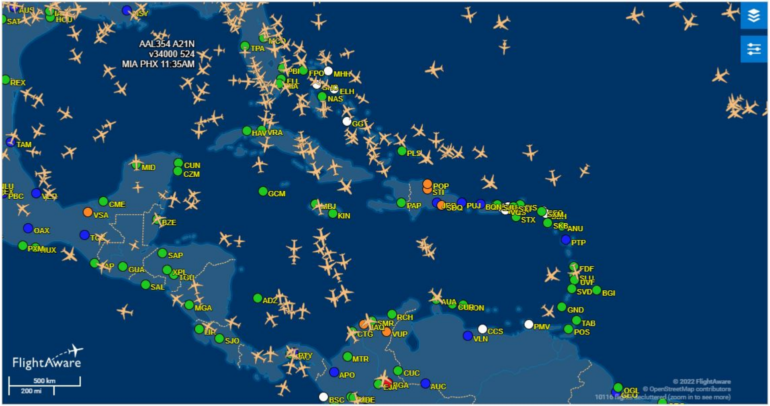


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And what about north of the Black Sea?

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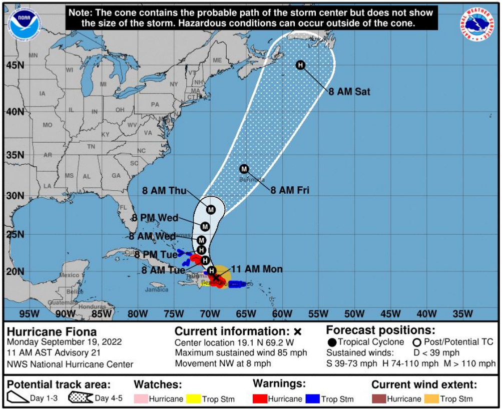


Note the error bars around the forecasted track.

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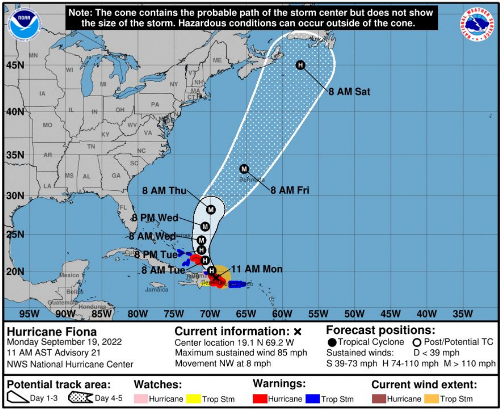


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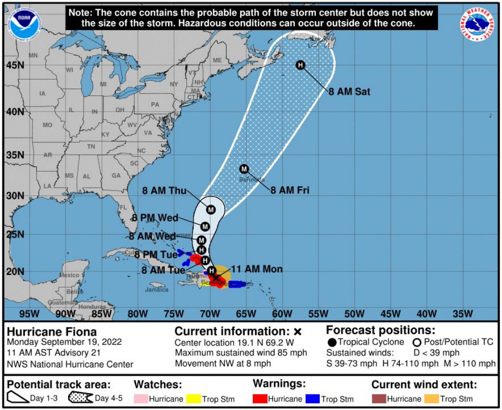


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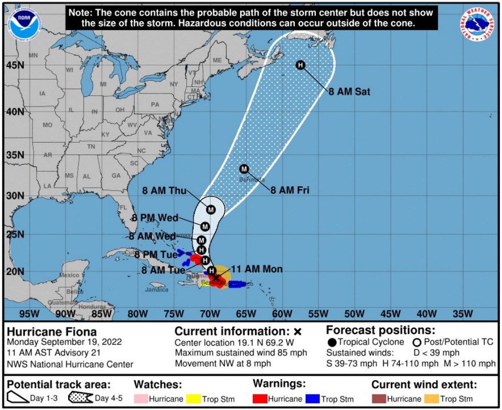


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**Abstraction in Modeling:** This is done at only $1km^2$ resolution.

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- Part of **OSINT**: Open-Source Intelligence. (Could discuss new Gaza examples.)

# Data, Metadata, and Privacy

A rough working definition of **metadata** is:

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| Data in XML headers and in `<tag ATTR=...>` attributes |

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• Major controversy over gathering metadata by law enforcement and intelligence.

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- Special research topic at UB CSE.

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- For misuse of Bram Cohen's BitTorrent—not so clear. Cut deal in 2005 with Motion Picture Association of America to follow DMCA.

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- Insofar as we are the training data for the Internet, the latter has baked in tangible amounts of racism and sexism.

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- Look at all these public datasets!

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- (Silly new example of correlation-versus-causation: do the KC Chiefs lose when Taylor Swift isn't at the game? Madden '24)

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- [show graphs from FanGraphs article, bottom of page.]
- Point is that the model can emulate/project the results of pitches by itself—when its projections go bad, the manager takes the actual flesh-and-blood pitcher out of the game. Like Blake Snell on 9/19/23!

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- **New 11/14/23**: Hurricane forecasting by AI, incl. Lee and Otis.

# Turing's Principle

**Alan Turing**: Besides his WWII work on the Enigma machine (featured in the movie *The Imitation Game*) and **Turing Machine** theory of computation in his 1936-38 PhD thesis under Alonzo Church, he is considered the **founder** of Artificial Intelligence.

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The **Church-Turing Thesis** is primarily stated in terms of the class of *computable functions*, but here is Turing's angle:

> **Anything that human beings can consistently deduce or classify can also be achieved by computers acting alone.**

The **Turing Test** involves computers trying to be indistinguishable from humans in ordinary life communications and transactions.

# Turing All the Possibilities

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Also defies the logical **contrapositive** of Turing's Principle:

If it is really hard for computers then it should be hard for humans.

What we fear when worrying that AI will take away our jobs is:

Stuff that is hard for humans but easy for computers.

The logical **converse** of Turing's Principle acts as a brake, however:

If $X$ is hard for humans—insofar as we can't consistently agree on answers—then $X$ is hard for computers too.

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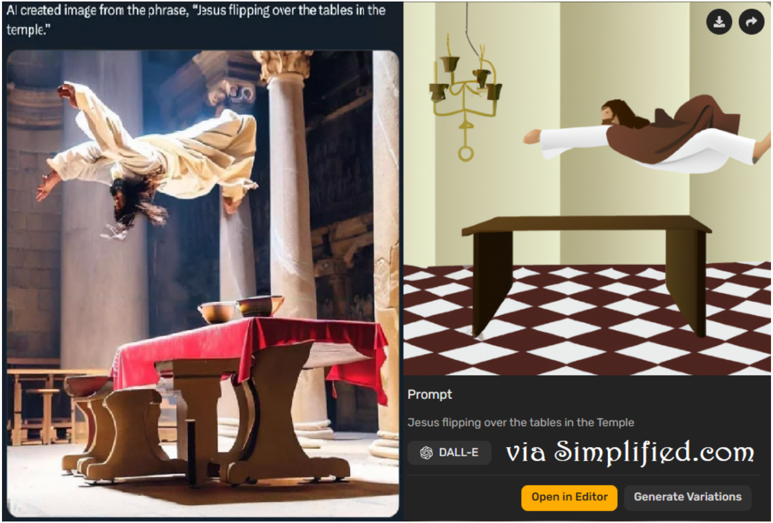
- But subject to **hallucinations** and other foibles—some shown by me here and here and here.

# AI Art Adventure

"Jesus flipping over the tables in the Temple." From the movie *Jesus Christ Superstar*—then try it on Cutout or NightCafe or Simplified:

# Two Results—one famous, one mine



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- (But possibly I already pushed it to the limits of its current data.)

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