CSCE 581: Introduction to Trusted AI

Lectures 5 and 6: AI, ML and Supervised ML

PROF. BIPLAV SRIVASTAVA, AI INSTITUTE

28TH AND 30TH JAN 2025

Carolinian Creed: “I will practice personal and academic integrity.”

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Organization of Lectures 5, 6

- Introduction Section
  - Recap from Week 2 (Lectures 3 and 4)
- Main Section
  - L5: Complete discussion on open data and knowledge graph
  - L6: Common ML methods
  - L6: Supervised ML
- Concluding Section
  - About next week – Lectures 7, 8
  - Ask me anything

Introduction Section

A Lesson in Trust

Weather alerts and Closing campus, Canceling classes

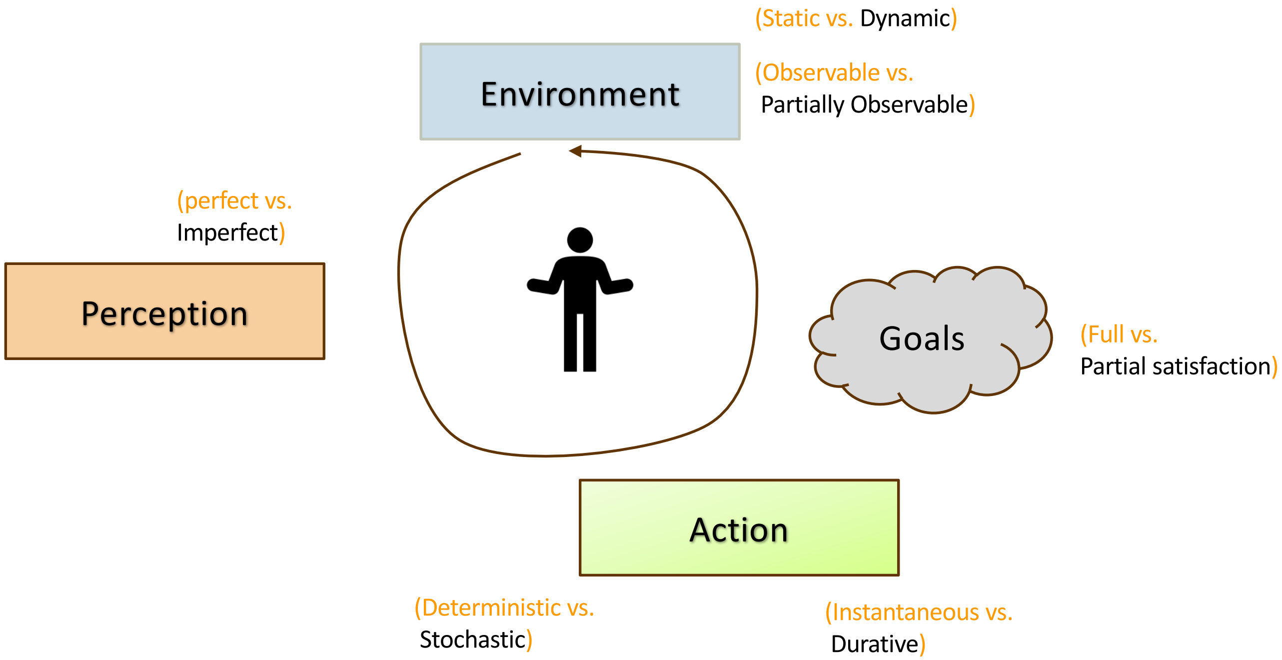
- Event order and response by actors // Choice 1 (Actual): Trustable ??
  - Alert1 -> Close campus -> Cancel class
  - Alert2 -> Unclose (Open) campus -> Uncancel (Normal) class
  - Alert3 -> Close campus -> Cancel class
  - …
- Event order and response by actors // Choice 2: A more trustable way ??
  - Alert1 -> Close campus -> Online class (or recorded) OR CANCEL class
  - Alert2 -> Unclose (Open) campus -> *No Change*
  - Alert3 -> Close campus -> *No Change*
  - …
- *Which one would you have preferred, and WHY?*

Recap from Week 2 (Lectures 3, 4)

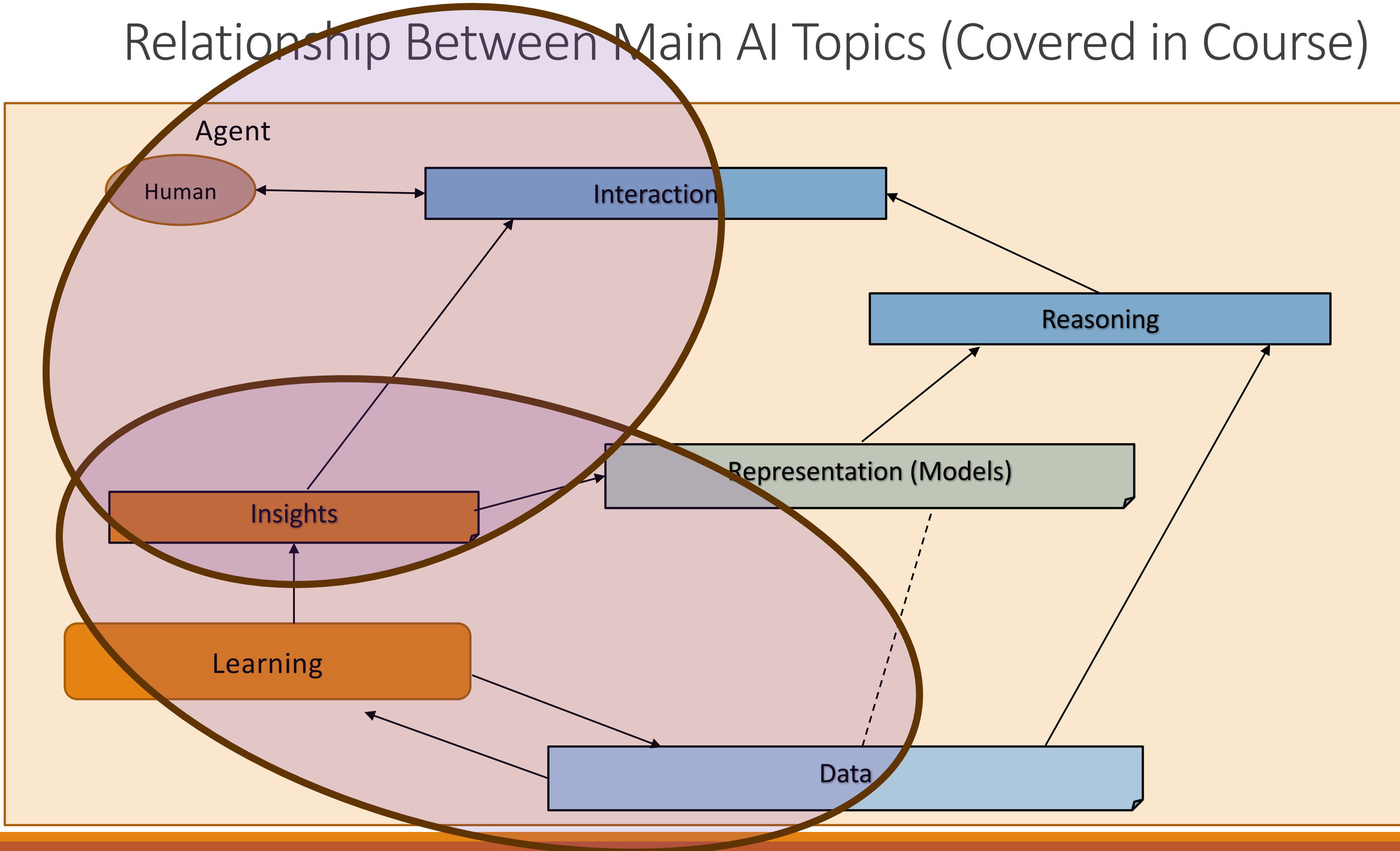
Week 1: Introduction to Trusted AI

- Week 2
  - Expectations survey
  - Trusted decisions, data
  - Paper reading (Joy Buolamwini, Timnit Gebru. Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification. In Sorelle A. Friedler, Christo Wilson, editors, Conference on Fairness, Accountability and Transparency, FAT 2018, 23-24 February 2018, New York, NY, USA. Volume 81 of Proceedings of Machine Learning Research, pages 77-91, PMLR, 2018.)

Intelligent Agent Model



Relationship Between Main AI Topics (Covered in Course)



High Level Semester Plan (Adapted, Approximate)

CSCE 581 –

- Week 1: Introduction
- Week 2: Background: AI - Common Methods
- Week 3: The Trust Problem
- Week 4: Machine Learning (Structured data) - Classification
- Week 5: Machine Learning (Structured data) - Classification – Trust Issues
- Week 6: Machine Learning (Structured data) – Classification – Mitigation Methods
- Week 7: Machine Learning (Structured data) – Classification – Explanation Methods
- Week 8: Machine Learning (Text data, **vision**) – Classification, **Large Language Models**
- Week 9: Machine Learning (Text data) - Classification – Trust Issues, LLMs
- Week 10: Machine Learning (Text data) – Classification – Mitigation Methods
- Week 11: Machine Learning (Text data) – Classification – Explanation Methods
- Week 12: Emerging Standards and Laws, **Real world applications**
- Week 13: Project presentations
- Week 14: Project presentations, Conclusion

AI/ ML topics and with a focus on fairness, explanation, Data privacy, reliability

Main Section

Gender Shades paper

1. Joy Buolamwini, Timnit Gebru. Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification. In Conference on Fairness, Accountability and Transparency, FAT 2018, 23-24 February 2018, New York, NY, USA. Volume 81 of Proceedings of Machine Learning Research, pages 77-91, PMLR, 2018.

2. http://gendershades.org/overview.html

Dataset

a. Megaface, which to date is the largest publicly available set of facial images, was composed utilizing Head Hunter to select one million images from the Yahoo Flicker 100M image dataset
b. LFW, a dataset composed of celebrity faces which has served as a gold standard benchmark for face recognition, was estimated to be 77.5% male and 83.5% White. Performance not broken down by gender or race
c. Intelligence Advanced Research Projects Activity (IARPA) released the IJB-A dataset as the most geographically diverse set of collected face.
d. As of 2017, The National Institute of Standards and Technology is starting another challenge to spur improvement in face gender classification by expanding on the 2014-15 study.

Pilot Parliament Benchmark

- They also used IJB-A and Adience for comparison.
- One author labeled each image with one of six Fitzpatrick skin types and provided gender annotations for the IJB-A dataset.
- The Adience benchmark was already annotated for gender.
- These preliminary skin type annotations on existing datasets were used to determine if a new benchmark was needed. For PPB, 3 annotators including the authors provided gender and Fitzpatrick labels.
- A board-certified surgical dermatologist provided the definitive labels for the Fitzpatrick skin type.
- Gender labels were determined based on the name of the parliamentarian, gendered title, prefixes such as Mr or Ms, and the appearance of the photo.

Inequality in Misclassification

a. The gender misclassification rates on the Pilot Parliaments Benchmark replicate this trend across all classifiers. The differences between female and male classification error rates range from 8. 1% to 20. 6%.
b. **Even though darker females make up 21.3% of the PPB benchmark, they constitute between 61.0% to 72.4.1% of the classification error**
c. COTS1 and COTS2 APIs solely output single labels indicating whether the face was classified as female or male. COTS3's API outputs an additional number which indicates the confidence with which the classification was made. The authors note that giving crisp class labels does not give users the ability to analyze true positive (TPR) and false positive (FPR) rates for various subgroups if different thresholds were to be chosen.
d. Errors do not seem to happen because of image quality. They consider South African photos of similar image quality as Europeans.

Discussion: What is Right (Fair)?

- Equal errors?
- Equal accuracy?
- Errors on individual faces?
- …

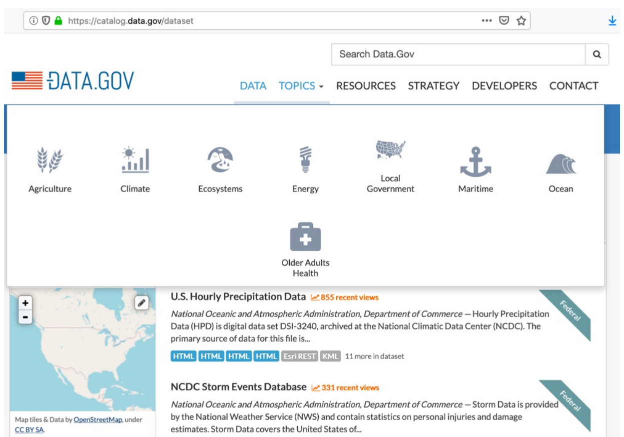
Open Data

"Open data and content can be **freely used, modified, and shared** by **anyone** for **any purpose**"

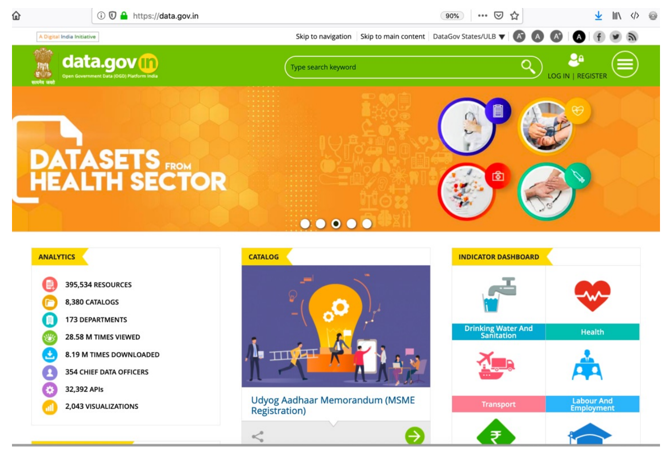
http://opendefinition.org/od/2.1/en/

Open Data is an Old Concept in a New Setting

- Open data is the notion that data should not be hidden, but made available to everyone to **reuse**. The idea is not new.
- Scientific publications follow this: “standing on the shoulders of giants”
- Data quality and open publishing process is critical



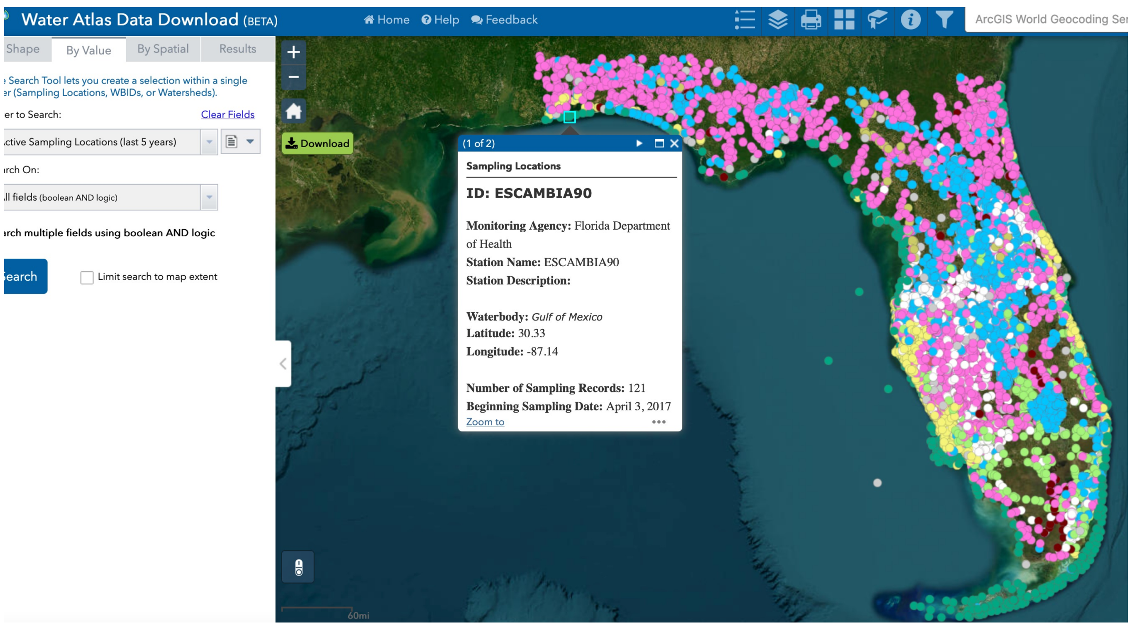
USA



India

Open Data Should Not to Be Confused With Orthogonal Trend – Big Data

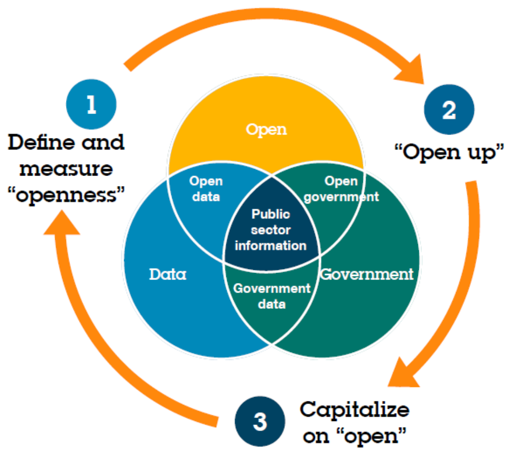
- Volume
- Variety
- Velocity
- Veracity
- …



Cartoon critical of big data application,
by T. Gregorius
http://upload.wikimedia.org/wikipedia/commons/thumb/b/b3/Big_data_cartoon_t_gregorius.jpg/220px-Big_data_cartoon_t_gregorius.jpg

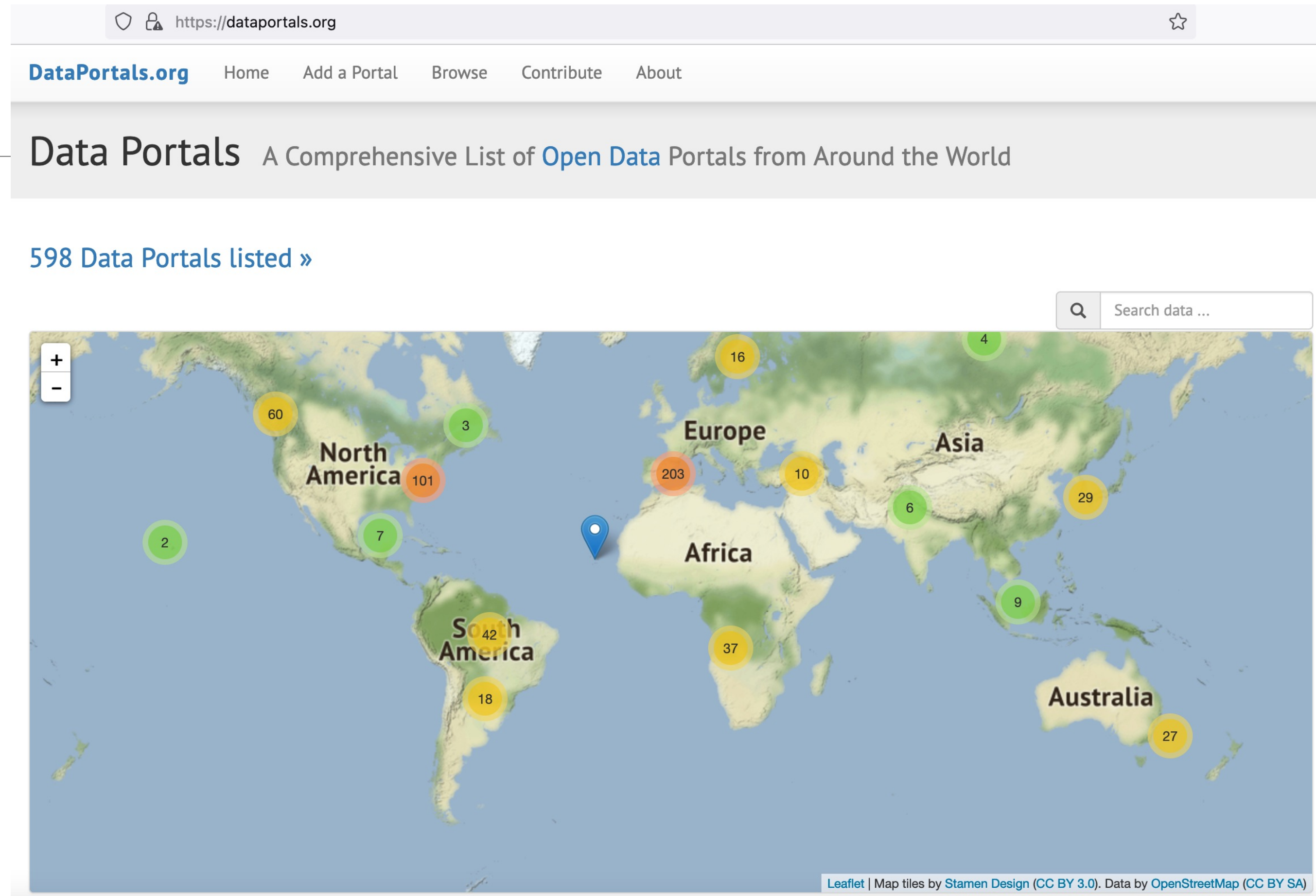
Data: https://github.com/biplav-s/course-tai/tree/main/sample-code/common-data/water

~600 Data Catalogs of Open Data



Source: IBM Institute for Business Value.

As on 26 Aug 2024



Demo: US Open Data

- Site: https://data.gov
- Tools: https://resources.data.gov/categories/data-tools/

Open Datasets

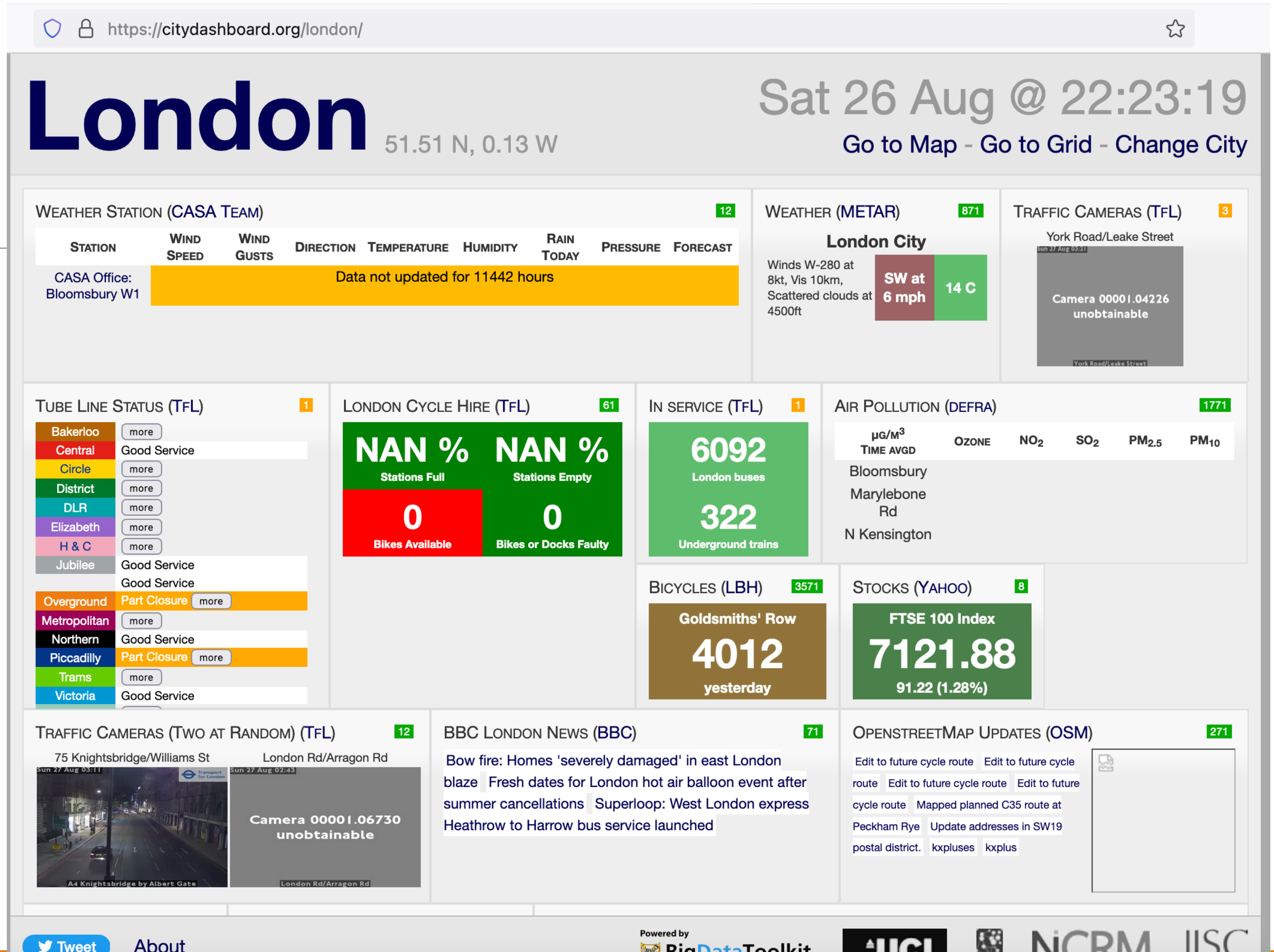
- data.gov OF ANY COUNTRY
  - Portal: https://dataportals.org/
  - US: https://www.data.gov/ or any US state
  - India: https://data.gov.in
- Text of legislations - LegiScan, https://legiscan.com/
- Kaggle datasets: https://www.kaggle.com/datasets
- Google datasets search: https://datasetsearch.research.google.com/

City Dashboard - London

CityDashboard aggregates simple spatial data for cities around the UK and displays the data on a dashboard and a map.

http://citydashboard.org/london/
http://citydashboard.org/about.php

- Birmingham
- Brighton
- Cardiff
- Edinburgh
- Glasgow
- Leeds
- London
- Manchester



Attempt for Dashboards - Amsterdam

[2016] http://citydashboard.waag.org/

Exercise 1 - Explore

1. Google data search tool: https://datasetsearch.research.google.com/

2. US open data: https://www.data.gov/

3. Select a problem domain and search for data

4. Discuss your experience

Accessing Data

Example: Open 311 (http://open311.org/)

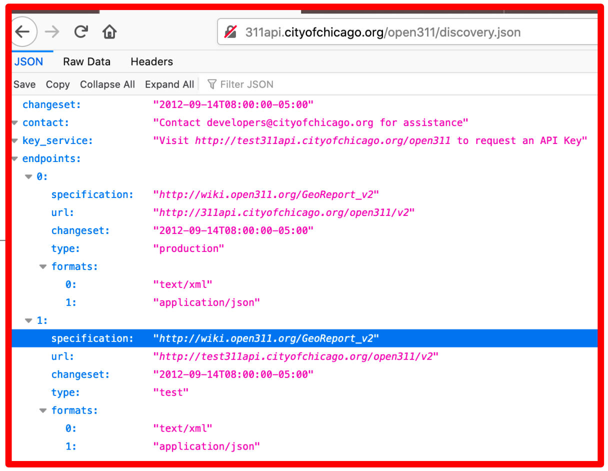
Refers to non-emergency events like graffiti, garbage, down trees, abandoned car, …

- Not human life threatening
- 60+ cities support it world-wide

Discovering Open 311 of a City

http://311api.cityofchicago.org/open311/discovery.json

changeset	"2012-09-14T08:00:00-05:00"
contact	"Contact developers@cityofchicago.org for assistance"
key_service	"Visit http://test311api.cityofchicago.org/open311 to request an API Key"
endpoints	
0	
specification	"http://wiki.open311.org/GeoReport_v2"
url	"http://311api.cityofchicago.org/open311/v2"
changeset	"2012-09-14T08:00:00-05:00"
type	"production"
formats	
0	"text/xml"
1	"application/json"
1	
specification	"http://wiki.open311.org/GeoReport_v2"
url	"http://test311api.cityofchicago.org/open311/v2"
changeset	"2012-09-14T08:00:00-05:00"
type	"test"
formats	
0	"text/xml"
1	"application/json"



Demonstration: Open 311

List of services

- http://311api.cityofchicago.org/open311/v2/services.json
- Result

[{"service_code":"4ffa4c69601827691b000018","service_name":"Abandoned Vehicle","description":"Abandoned vehicles are taken to auto pound 3S or 3N where they are -- if not redeemed by the owners -- sold for scrap.","metadata":true,"type":"batch","keywords":"code:SKA","group":"Streets & Sanitation"},

{"service_code":"4ffa9cad6018277d4000007b","service_name":"Alley Light Out","description":"One or more alley lights out, on a wooden pole in the alley itself, are reported under this service request type. Important information needed when reporting alley lights out includes: the exact address that the light/lights are behind, how many lights are out, and if the light(s) are completely out or if they blink on and off intermittently. Alley light repairs are done during the day when the lights are not on, so this information is essential to expedite the repair work.","metadata":true,"type":"batch","keywords":"code:SFA","group":"Transportation"},

…]

Details of a service

- http://311api.cityofchicago.org/open311/v2/services/4ffa4c69601827691b000018.json
- Result

{"service_code":"4ffa4c69601827691b000018",
 "attributes":
  [{"variable":true,"code":"FQSKA1",
    "datatype":"singlevaluelist","required":false,"order":1,
    "description":"Vehicle Make/Model",
    "values":
      [{"key":"ASVEAV","name":"(Assembled From Parts,Homemade)"},
       {"key":"HOMDCYL","name":"(Homemade Motorcycle, Moped.Etc.)"},
       {"key":"HMDETL","name":"(Homemade Trailer)"}, …]
…]}

Demonstration: Open 311

http://311api.cityofchicago.org/open311/v2/services/4ffa9cad6018277d4000007b.json

Result

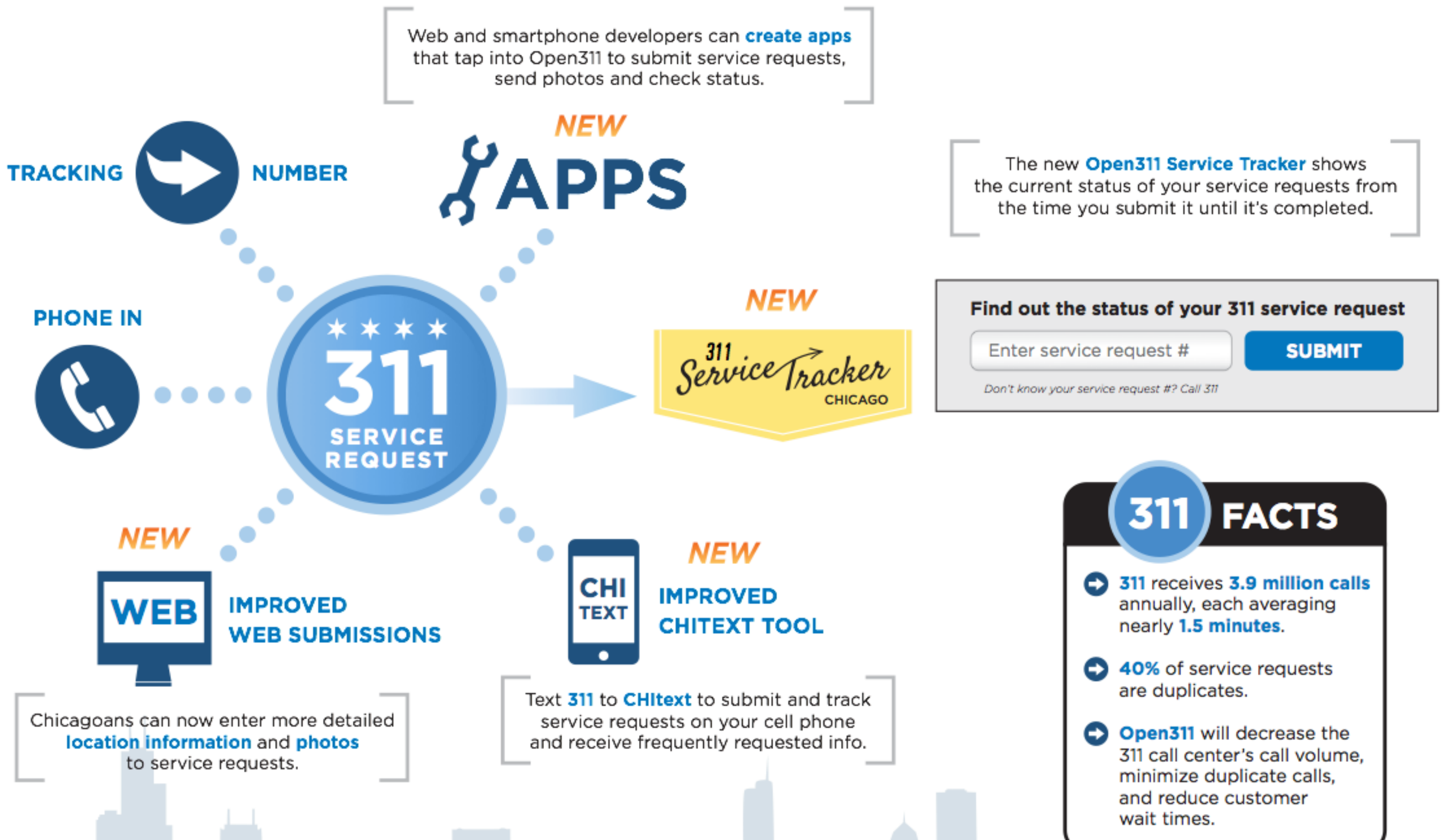
{"service_code":"4ffa9cad6018277d4000007b",
"attributes":
[{"variable":true,"code":"ISTHELI2",
"datatype":"singlevaluelist","required":true,"order":1,
"description":"Is the light located in your alley or the street?",
"values":[{"key":"ALLEY","name":"Alley"},
{"key":"STREET","name":"Street"}]},

{"variable":true,"code":"POLEWORM",
"datatype":"singlevaluelist","required":true,"order":2,
"description":"Is the pole wooden or metal?",
"values":[{"key":"METAL","name":"Metal"},
{"key":"WOODEN","name":"Wooden"}]},

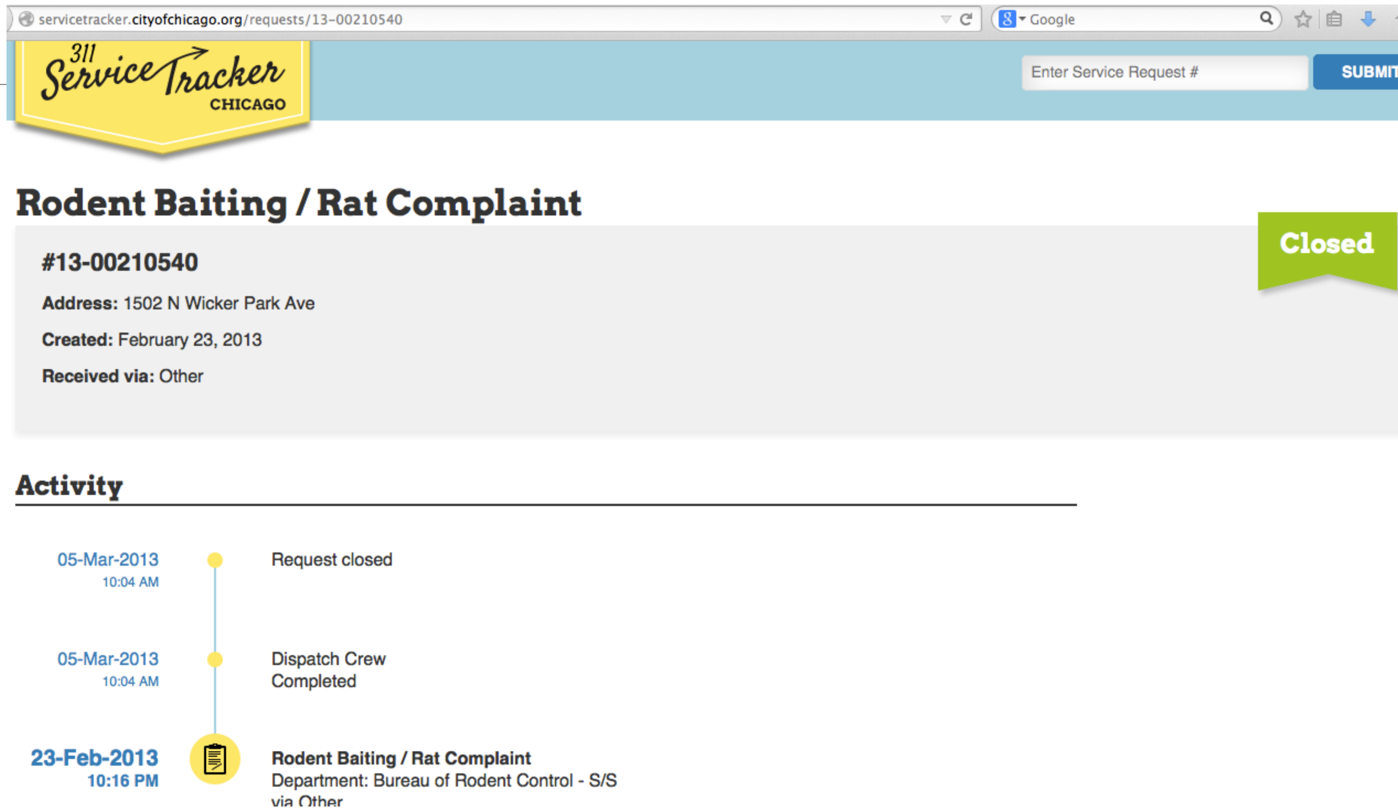
{"variable":true,"code":"ISTHELI3",
"datatype":"singlevaluelist","required":true,"order":3,
"description":"Is the light directly behind this address?",
"values":[{"key":"NO","name":"No - Light Not Directly Behind Address"}
,{"key":"YES","name":"Yes - Light Directly Behind Address"}]},

{"variable":true,"code":"A511OPTN",
"datatype":"string","required":false,
"datatype_description":"Enter number as 999-999-9999","order":4,
"description":"Input mobile # to opt-in for text updates. If already opted-in, add mobile # to contact info."}]}

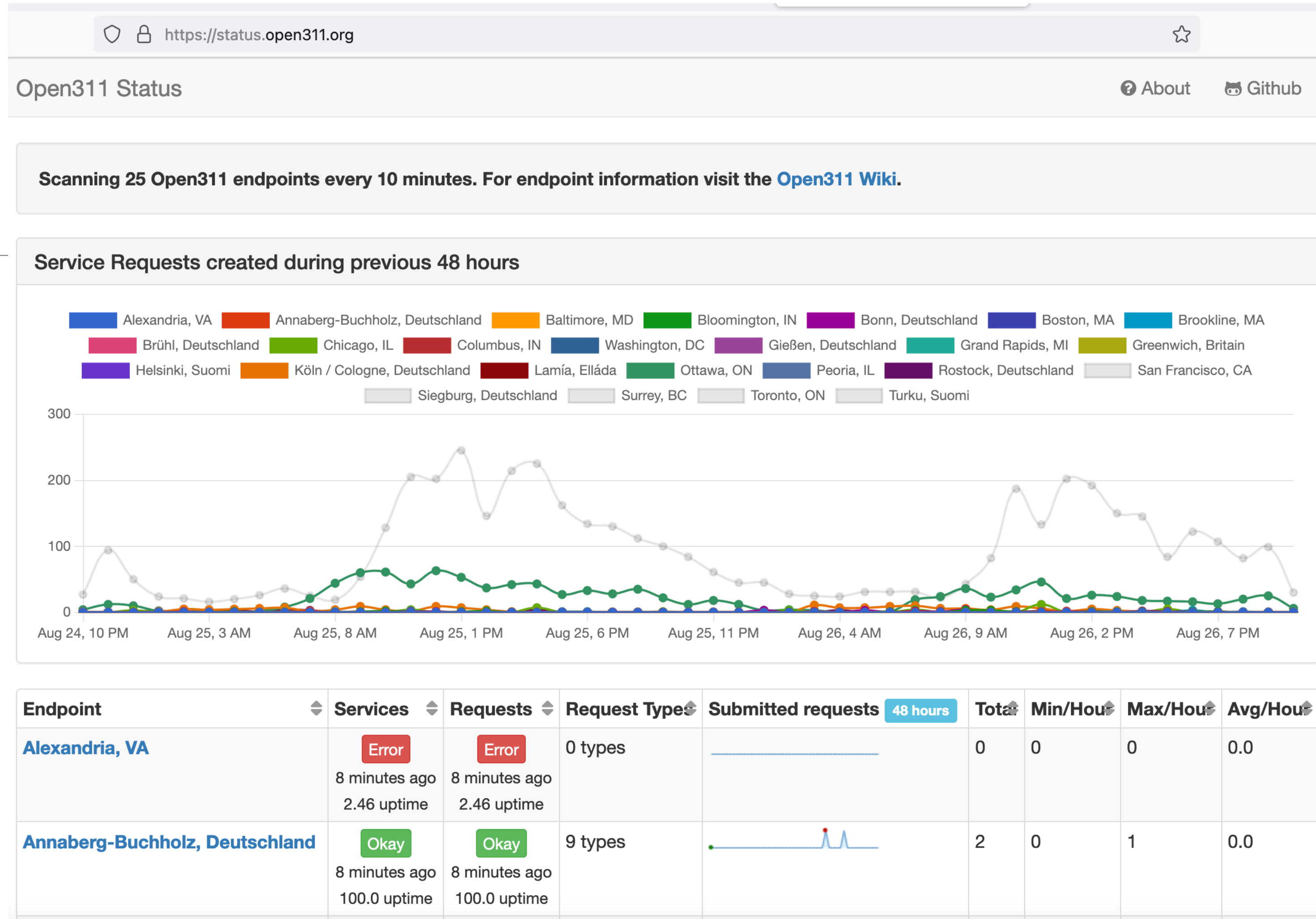
Chicago: Service Tracking



Example: Application over Open Data (Chicago)



Scaling with Open 311



https://status.open311.org/

Exercise 2 – Programmatically Access Data

1. See sample code on GitHub:
   - https://github.com/biplav-s/course-d2d-ai/blob/main/sample-code/l2-opendata/Explore%20OpenData.ipynb

2. Explore APIs of another city of your choice

Exercise 3 – Programmatically Access Data

1. Water data
2. Text data

Code samples: https://github.com/biplav-s/course-ai-tai-f23/blob/main/sample-code/Class2-data.md

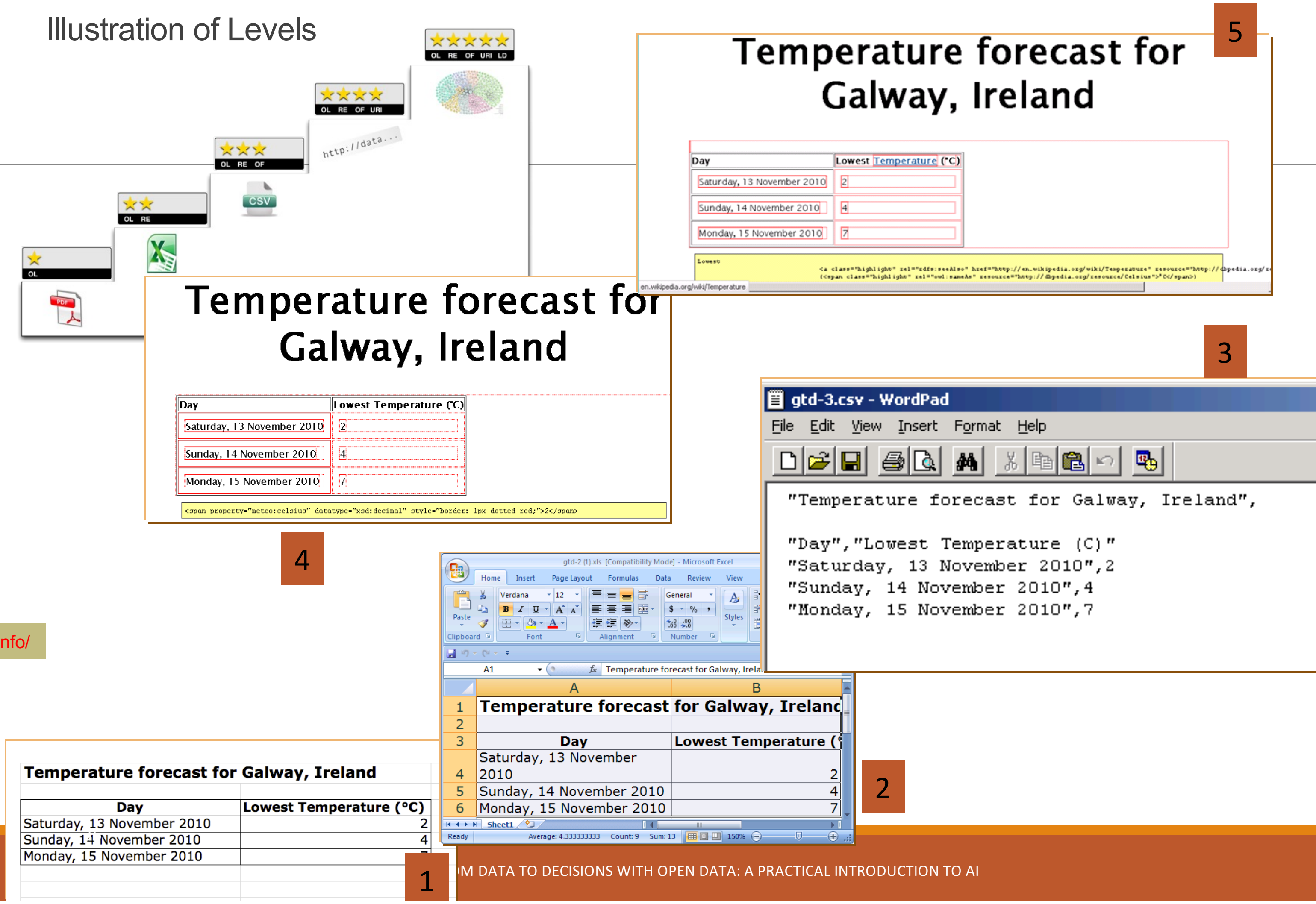
Text Data

- Text of legislations - LegiScan, https://legiscan.com/
- Voter FAQs - https://github.com/ai4society/election-dataset
- Compendium of benchmarks and datasets:
  - https://zilliz.com/learn/popular-datasets-for-natural-language-processing,
  - UCI dataset – https://archive.ics.uci.edu/datasets?search=&Types=Text
  - Kaggle - https://www.kaggle.com/datasets?search=text
- NLP task specific -
  - https://paperswithcode.com/task/named-entity-recognition-ner/
  - …

Quality of Data

Does Opening Data Make It Reusable? No

Illustration of Levels

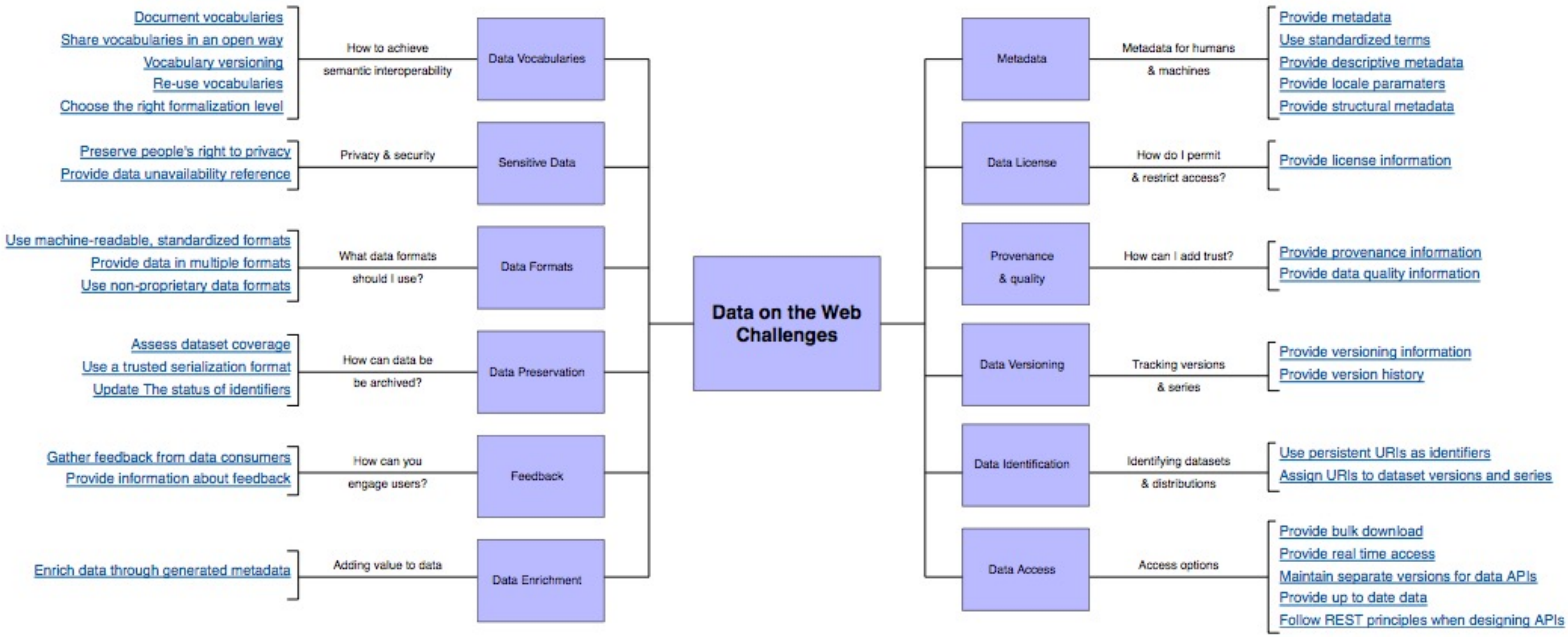


Source: http://5stardata.info/

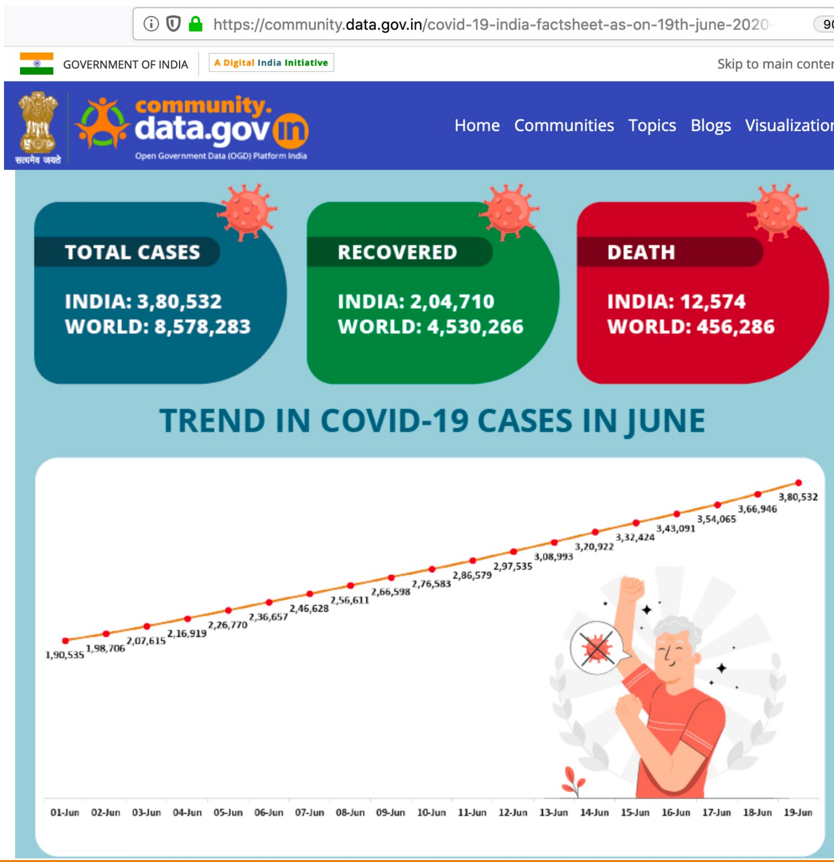
Helping Publish Good Quality Open Data is Key

Have data policy in place
Publish with best practices, have semantics, promote reuse

Figure courtesy: http://www.w3.org/TR/2015/WD-dwbp-20150625/



Data Quality of Public Data in India



Right to Information

- Not even 1*
- Information available to requester, but no one else

Data.gov.in

- 2-3*
- Available in CSV, etc but not uniquely referenceable

Open data movements are moving to linked data form for semantics

Annotated – Indian Open Data

Vocabulary services: http://vocab.nic.in/index.php

- Authoritative
- Standardized codes

Examples

- States in the Union: http://vocab.nic.in/rest.php/states/json
- Districts in a state (“UP”): http://vocab.nic.in/rest.php/district/up/json
- State legislatures: http://vocab.nic.in/rest.php/orgn/sg/legislature/json
- Union government offices in a state (“TN”): http://vocab.nic.in/rest.php/orgn/ug/state/tn/json

Quality of Data in SC

- Data
  - https://sc.gov/data-and-transparency
  - https://rfa.sc.gov/data-research/population-demographics/census-state-data-center/housing-units-in-structure-2015-2019
  - Comment: Lots of pds and reports: combines/ confounds data with presentation
- Quality of data
  - 1-3 star
  - Not easily amenable for analysis

Guideline: Human Impact of Data and AI

- We study technology (AI) but it works with data
- Data, when from people or about people, can have issues like bias
  - **Example**: data reveals a view which is influenced by data collection practices
  - **Difference**: World as it is, world according to data and **world as it should be**

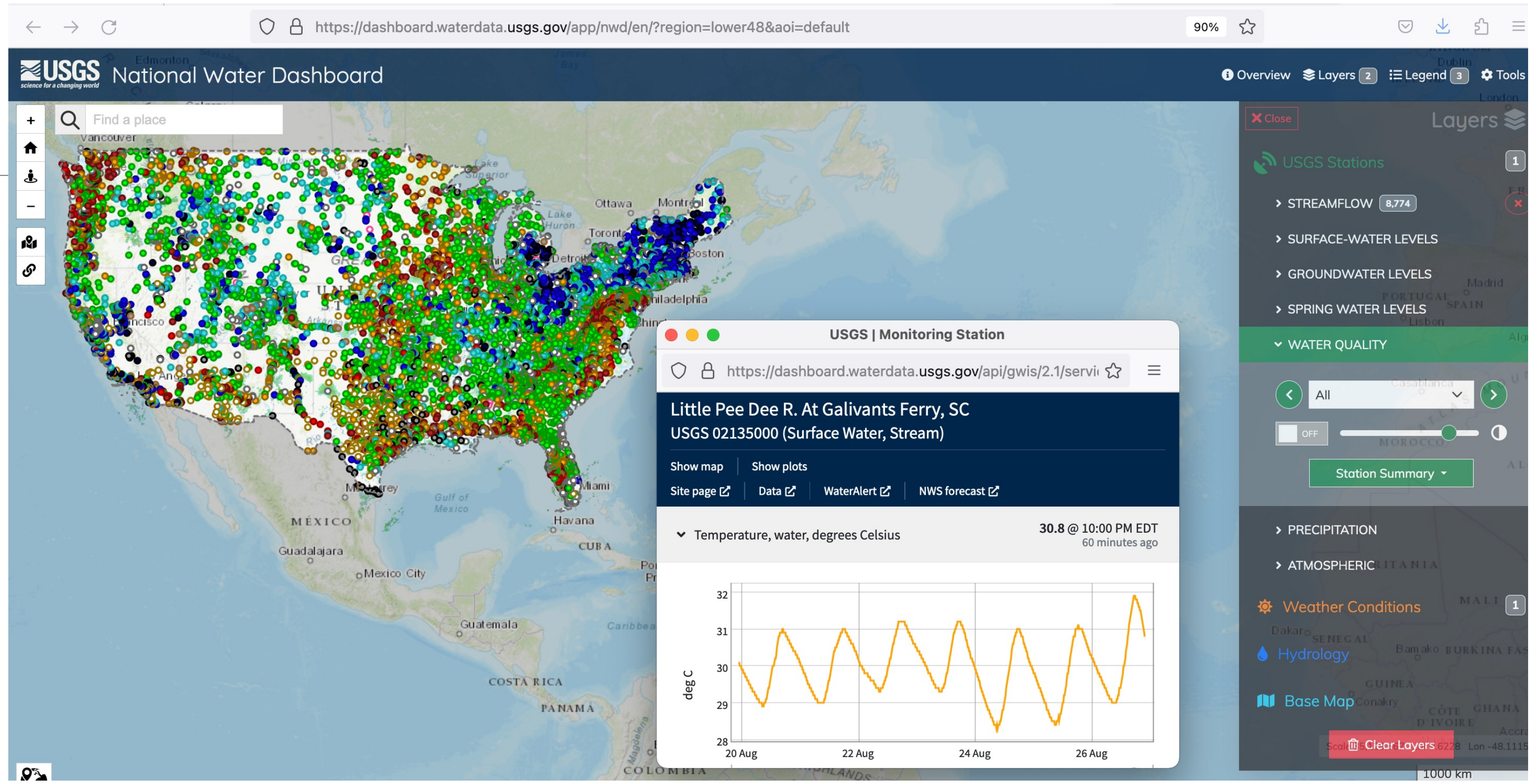
- The course and instructor believes in
  - Not promoting bias of any kind
  - Respecting everyone regardless of background

Discussion Exercise: Your Resumes

- What does a (Google) search tell about you?
- What does a LLM/ ChatGPT tell about you?
- Task:
  - Put your resume at: <TBD>
- Course task: We will analyze them as part of AI/ data science activity in a later class

Working With Data – Preparing and Organizing Information

Water Data



https://dashboard.waterdata.usgs.gov/app/nwd/en/?region=lower48&aoi=default

Claims data from 13,000 locations online on 26 Aug 2023

How Do We Start Working With This?

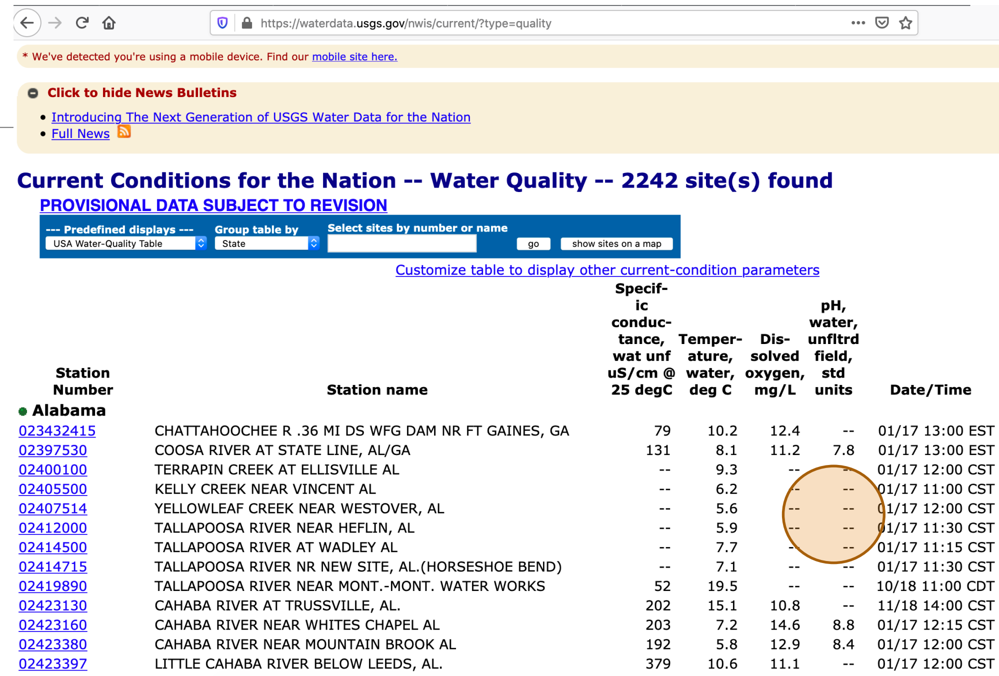
- Access and licensing (Class 3)
- Cleaning, organizing and finding related information (Class 4 – this class)
- Representing formally (in logic) to draw insights (using inferencing) – (Class 4 – this class)

Is this important ? YES !

- Understanding impact of hurricanes
- Planning during regular times – homes, schools, roads; hospital services; electricity, …
- Economic development

Common Problem: Missing Value

- Occurrence
  - Missing completely at random
  - Missing at random (a group not wanting to participate)
  - Missing not at random (a group not able to participate)
- What does it mean?
  - The value was not provided
  - The value does not exist or has no practical interpretation
  - The value is being hidden (redaction)
  - Others: The value is not reliable, …
- How to detect it?
  - By checking for specific values: NA, Not applicable, out-of-range value, 0, -1, “”.


https://waterdata.usgs.gov/nwis/current/?type=quality

* We've detected you're using a mobile device. Find our mobile site here.

Click to hide News Bulletins
- Introducing The Next Generation of USGS Water Data for the Nation
- Full News

Current Conditions for the Nation -- Water Quality -- 2242 site(s) found

PROVISIONAL DATA SUBJECT TO REVISION

--- Predefined displays --- USA Water-Quality Table | Group table by State | Select sites by number or name | go | show sites on a map

Customize table to display other current-condition parameters

Station Number	Station name	Specific conductance, wat unf uS/cm @ 25 degC	Temperature, water, deg C	Dissolved oxygen, mg/L	pH, water, unfltrd field, std units	Date/Time
Alabama						
023432415	CHATTAHOOCHEE R .36 MI DS WFG DAM NR FT GAINES, GA	79	10.2	12.4	--	01/17 13:00 EST
02397530	COOSA RIVER AT STATE LINE, AL/GA	131	8.1	11.2	7.8	01/17 13:00 EST
02400100	TERRAPIN CREEK AT ELLISVILLE AL	--	9.3	--	--	01/17 12:00 CST
02405500	KELLY CREEK NEAR VINCENT AL	--	6.2	--	--	01/17 11:00 CST
02407514	YELLOWLEAF CREEK NEAR WESTOVER, AL	--	5.6	--	--	01/17 12:00 CST
02412000	TALLAPOOSA RIVER NEAR HEFLIN, AL	--	5.9	--	--	01/17 11:30 CST
02414500	TALLAPOOSA RIVER AT WADLEY AL	--	7.7	--	--	01/17 11:15 CST
02414715	TALLAPOOSA RIVER NR NEW SITE, AL.(HORSESHOE BEND)	--	7.1	--	--	01/17 11:30 CST
02419890	TALLAPOOSA RIVER NEAR MONT.-MONT. WATER WORKS	52	19.5	--	--	10/18 11:00 CDT
02423130	CAHABA RIVER AT TRUSSVILLE, AL.	202	15.1	10.8	--	11/18 14:00 CST
02423160	CAHABA RIVER NEAR WHITES CHAPEL AL	203	7.2	14.6	8.8	01/17 12:15 CST
02423380	CAHABA RIVER NEAR MOUNTAIN BROOK AL	192	5.8	12.9	8.4	01/17 12:00 CST
02423397	LITTLE CAHABA RIVER BELOW LEEDS, AL.	379	10.6	11.1	--	01/17 12:00 CST

Missing Value – Handling

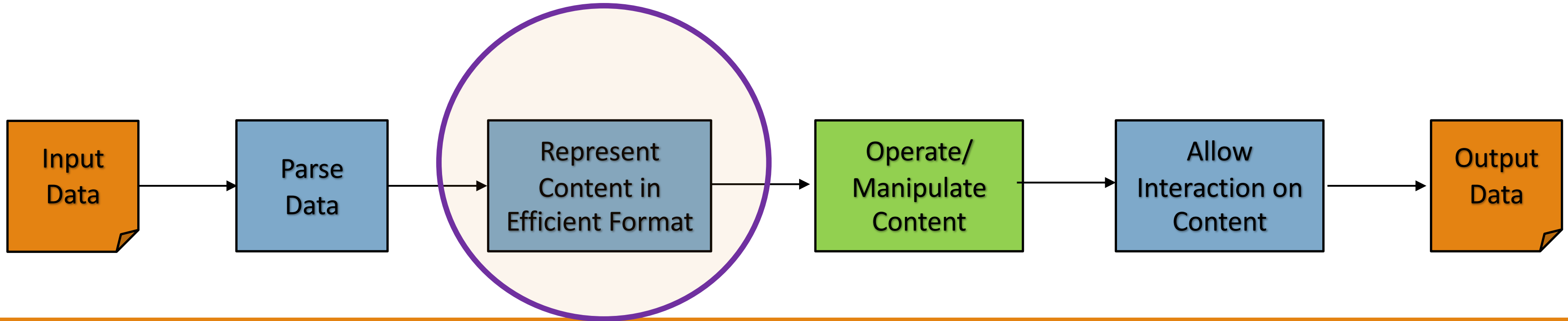
- Ignoring missing value (Omission)
  - Reduces available data
- Impute new value (Imputation)
  - Mean or median
  - Default value
- Analysis techniques which are robust against missing value
  - Expectation maximization

Code Examples

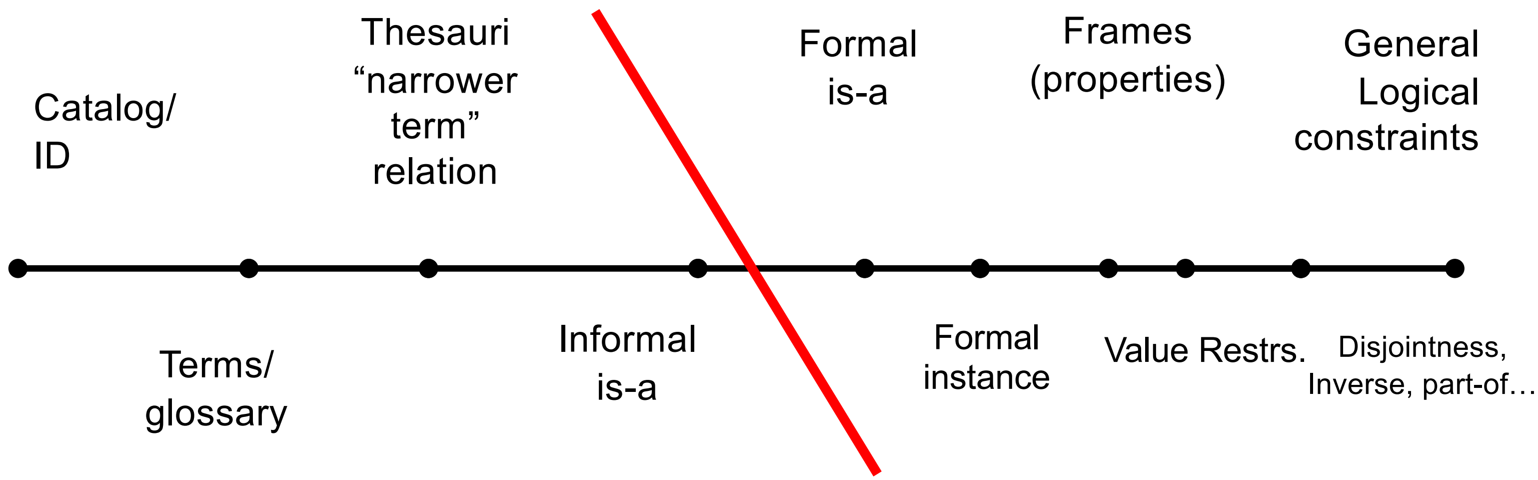
https://github.com/biplav-s/course-d2d-ai/blob/main/sample-code/l5-dataprep/

- Basic concepts: **DataPreparation-Numeric.ipynb**
- An illustration: **Clean-RealSample.ipynb**

Annotation: Knowledge Graphs and Ontology



The Spectrum of Annotation Methods



Ontologies Come of Age McGuinness, 2001, and From AAAI Panel 99 – McGuinness, Welty, Uschold, Gruninger, Lehmann
Plus basis of Ontologies Come of Age – McGuinness, 2003

Thesaurus – Authoritative Entities and Relationships

Countries: https://en.wikipedia.org/wiki/List_of_ISO_3166_country_codes

ISO 3166[1]			ISO 3166-1[2]			ISO 3166-2[3]	
Country name[5]	Official state name[6]	Sovereignty[6][7][8]	Alpha-2 code[5]	Alpha-3 code[5]	Numeric code[5]	Subdivision code links[3]	Internet ccTLD[9]
Afghanistan	The Islamic Republic of Afghanistan	UN member state	AF	AFG	004	ISO 3166-2:AF	.af
Akrotiri and Dhekelia – See United Kingdom, The							
Åland Islands	Åland	Finland	AX	ALA	248	ISO 3166-2:AX	.ax
Albania	The Republic of Albania	UN member state	AL	ALB	008	ISO 3166-2:AL	.al
Algeria	The People's Democratic Republic of Algeria	UN member state	DZ	DZA	012	ISO 3166-2:DZ	.dz
American Samoa	The Territory of American Samoa	United States	AS	ASM	016	ISO 3166-2:AS	.as
Andorra	The Principality of Andorra	UN member state	AD	AND	020	ISO 3166-2:AD	.ad
Angola	The Republic of Angola	UN member state	AO	AGO	024	ISO 3166-2:AO	.ao
Anguilla	Anguilla	United Kingdom	AI	AIA	660	ISO 3166-2:AI	.ai
Antarctica[a]	All land and ice shelves south of the 60th parallel south	Antarctic Treaty	AQ	ATA	010	ISO 3166-2:AQ	.aq
Antigua and Barbuda	Antigua and Barbuda	UN member state	AG	ATG	028	ISO 3166-2:AG	.ag
Argentina	The Argentine Republic	UN member state	AR	ARG	032	ISO 3166-2:AR	.ar

(Unique) US Counties Information

In COVID sample code: https://github.com/biplav-s/course-d2d-ai/blob/main/sample-code/l3-health/CovidExploration.ipynb,

reference made to **FIPS** code

References:

- https://www.nrcs.usda.gov/wps/portal/nrcs/detail/national/home/?cid=nrcs143_013697
- https://github.com/kjhealy/fips-codes/blob/master/county_fips_master.csv

Question: how many Richland counties are there in US ?

Answer: 14

County FIPS Codes

FIPS	Name	Stat
01001	Autauga	AL
01003	Baldwin	AL
01005	Barbour	AL
01007	Bibb	AL
01009	Blount	AL
01011	Bullock	AL
01013	Butler	AL
01015	Calhoun	AL
01017	Chambers	AL
01019	Cherokee	AL
01021	Chilton	AL
01023	Choctaw	AL
01025	Clarke	AL
01027	Clay	AL
01029	Cleburne	AL
01031	Coffee	AL
01033	Colbert	AL
01035	Conecuh	AL

Is-a Relationship

List of Countries, States, … (County), City

- United Nations: https://unece.org/trade/cefact/unlocode-code-list-country-and-territory
- US Source: https://github.com/grammakov/USA-cities-and-states

Schema.org

- Website: https://schema.org/docs/about.html
- GitHub: https://github.com/schemaorg/schemaorg

- An organization of metadata information for entities found on the web. Mostly backed by web search companies.
- Explore
  - Thing: https://schema.org/Thing
  - Product:

Schema.org

Example 2

No Markup | Microdata | RDFa | JSON-LD | Structure

Example notes or example HTML without markup.

```
<img src="dell-30in-lcd.jpg" alt="A Dell UltraSharp monitor" />
Dell UltraSharp 30" LCD Monitor

87 out of 100 based on 24 user ratings

$1250 to $1495 from 8 sellers

Sellers:
<a href="save-a-lot-monitors.com/dell-30.html">
  Save A Lot Monitors - $1250</a>
<a href="jondoe-gadgets.com/dell-30.html">
  Jon Doe's Gadgets - $1350</a>
...
```

No structure

Schema.org

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...
```

No structure

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No Markup | Microdata | RDFa | JSON-LD | Structure

Example encoded as JSON-LD in a HTML script tag.

```
<script type="application/ld+json">
{
  "@context": "https://schema.org",
  "@type": "Product",
  "aggregateRating": {
    "@type": "AggregateRating",
    "bestRating": "100",
    "ratingCount": "24",
    "ratingValue": "87"
  },
  "image": "dell-30in-lcd.jpg",
  "name": "Dell UltraSharp 30\" LCD Monitor",
  "offers": {
    "@type": "AggregateOffer",
    "highPrice": "$1495",
    "lowPrice": "$1250",
    "offerCount": "8",
    "offers": [
      {
        "@type": "Offer",
        "url": "save-a-lot-monitors.com/dell-30.html"
      },
      {
        "@type": "Offer",
        "url": "jondoe-gadgets.com/dell-30.html"
      }
    ]
  }
}
</script>
```

Structure in JSON-LD format

Schema.org

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<script type="application/ld+json">
{
  "@context": "https://schema.org",
  "@type": "Product",
  "aggregateRating": {
    "@type": "AggregateRating",
    "bestRating": "100",
    "ratingCount": "24",
    "ratingValue": "87"
  },
  "image": "dell-30in-lcd.jpg",
  "name": "Dell UltraSharp 30\" LCD Monitor",
  "offers": {
    "@type": "AggregateOffer",
    "highPrice": "$1495",
    "lowPrice": "$1250",
    "offerCount": "8",
    "offers": [
      {
        "@type": "Offer",
        "url": "save-a-lot-monitors.com/dell-30.html"
      },
      {
        "@type": "Offer",
        "url": "jondoe-gadgets.com/dell-30.html"
      }
    ]
  }
}
</script>
```

Structure in JSON-LD format

Example 2

No Markup | Microdata | RDFa | JSON-LD | **Structure**

Structured representation of the JSON-LD example.

@type	Product
name	Dell UltraSharp 30" LCD Monitor
offers	
@type	AggregateOffer
offerCount	8
lowPrice	$1250
highPrice	$1495
offers	
@type	Offer
url	http://example.org/jondoe-gadgets.com/dell-30.html
offers	
@type	Offer
url	http://example.org/save-a-lot-monitors.com/dell-30.html
image	http://example.org/dell-30in-lcd.jpg
aggregateRating	
@type	AggregateRating
ratingValue	87
ratingCount	24
bestRating	100

Induced Structure

Schema.org - continued

- **Exploration Exercise**
  - Services: https://schema.org/Service
  - Event: https://schema.org/Event

- Benefit:
  - Easy to incorporate annotations
  - Uses popular development tools and technologies (JSON, Microformat)
- Disadvantage
  - Cannot perform deep inferencing
  - Popular in certain communities

Formalizing Knowledge in an Ontology

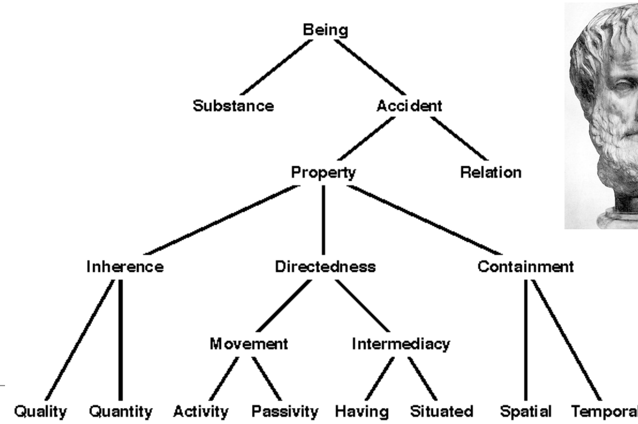
Sources:
Achille Fokoue, Anastasios Kementsietsidis Tutorial
SCRIBE presentation by Rosario Usceda Sosa, Biplav Srivastava, Bob Schloss

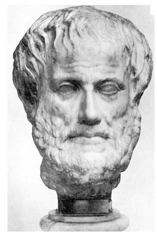
- https://github.com/rschloss/ismp ,
- https://researcher.watson.ibm.com/researcher/view_group.php?id=2505

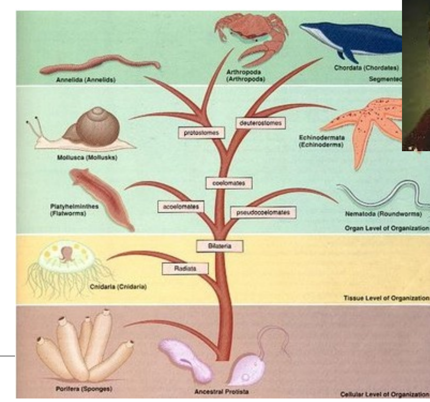
What is an ontology, anyway?

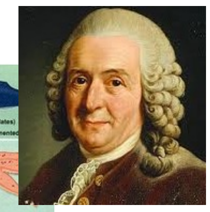
In Computer Science, “An ontology is a formal explicit description of concepts in a domain of discourse (**classes** (sometimes called concepts)), **properties** of each concept describing various features and **attributes** of the concept (slots (sometimes called roles or properties)), and **restrictions** on slots (facets (sometimes called role restrictions)). An ontology together with a set of individual instances of classes constitutes a knowledge base. In reality, there is a fine line where the ontology ends and the knowledge base begins.” [Noy, 2000]

Not to be confused with ontologies (and/or taxonomies) in Philosophy or Life Sciences







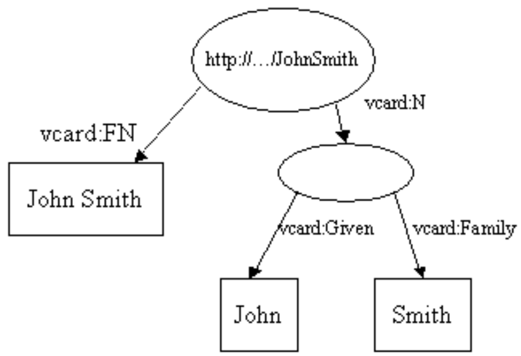


In a Smart City domain, we’re concerned with modeling the *city data* (city activity data, city departments, assets, KPIs), not the city itself (the full set of spatial and temporal relations between people and objects in the city) Ontologies help us to structure and reason about city *events*, *entities* and *services*.

Ontology = Class + Relations + Constraints

Knowledge Base = Ontology + instances + (Standard) Inference and rules

RDF / Turtle Example




```
---- Turtle ----
<http://somewhere/JohnSmith>
    <http://www.w3.org/2001/vcard-rdf/3.0#FN>
         "John Smith" ;
    <http://www.w3.org/2001/vcard-rdf/3.0#N>
         [ <http://www.w3.org/2001/vcard-
    rdf/3.0#Family>
               "Smith" ;
          <http://www.w3.org/2001/vcard-
    rdf/3.0#Given>
               "John"
         ] .
```

```
<rdf:RDF
  xmlns:rdf="http://www.w3.org/1999/02/22-rdf-
 syntax-ns#"
  xmlns:vcard="http://www.w3.org/2001/vcard-
 rdf/3.0#" >
 <rdf:Description rdf:nodeID="A0">
  <vcard:Given>John</vcard:Given>
  <vcard:Family>Smith</vcard:Family>
 </rdf:Description>
 <rdf:Description
 rdf:about="http://somewhere/JohnSmith">
  <vcard:FN>John Smith</vcard:FN>
  <vcard:N rdf:nodeID="A0"/>
 </rdf:Description>
</rdf:RDF>
```

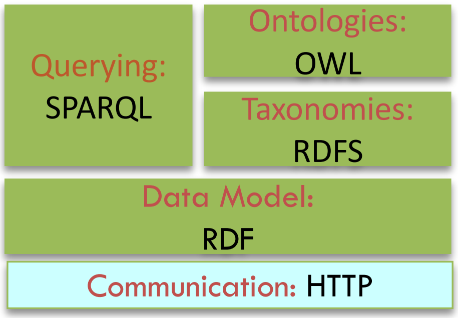
OWL extends RDF…

RDF-schema
- Class, subclass
- Property, subproperty

+ Restrictions
- Range, domain
- Local, global
- Existential
- Cardinality

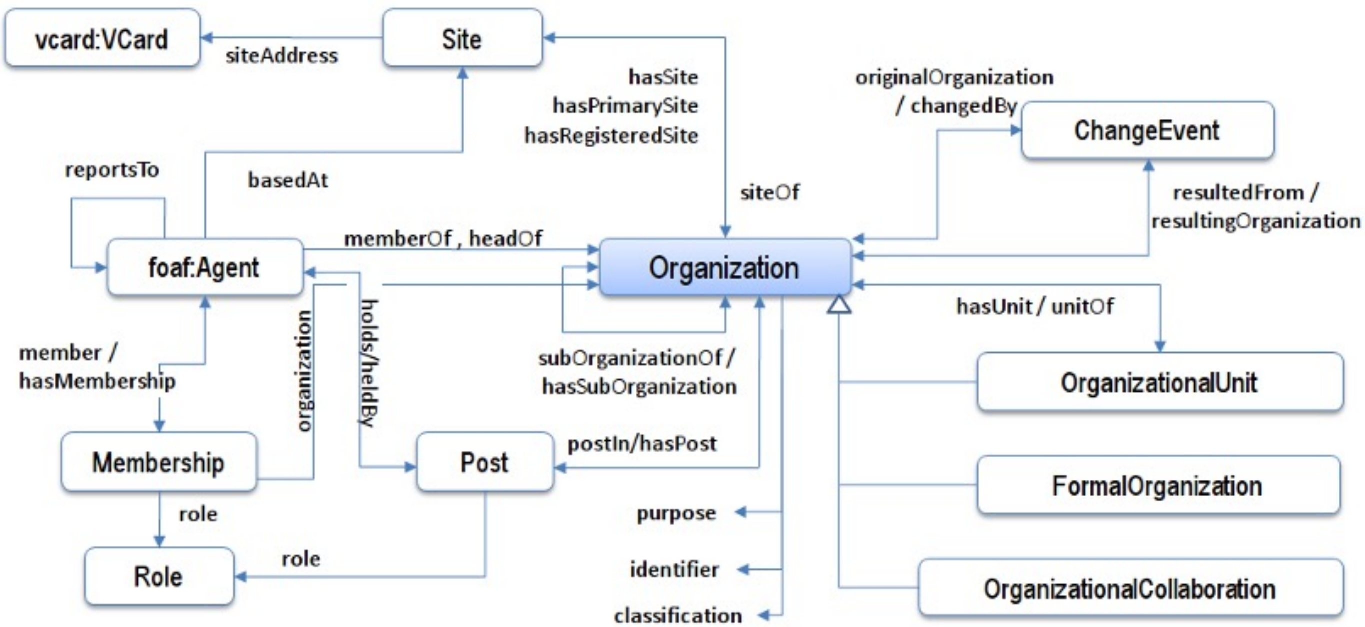
+ Combinators
- Union, Intersection
- Complement
- Symmetric, transitive

+ Mapping
- Equivalence
- Inverse



Source: Achille Fokoue, Anastasios Kementsietsidis Tutorial

Larger Example: Organization Ontology



Ontology description: http://www.w3.org/TR/vocab-org/

Ontology: http://www.w3.org/ns/org.ttl

Larger Ontology

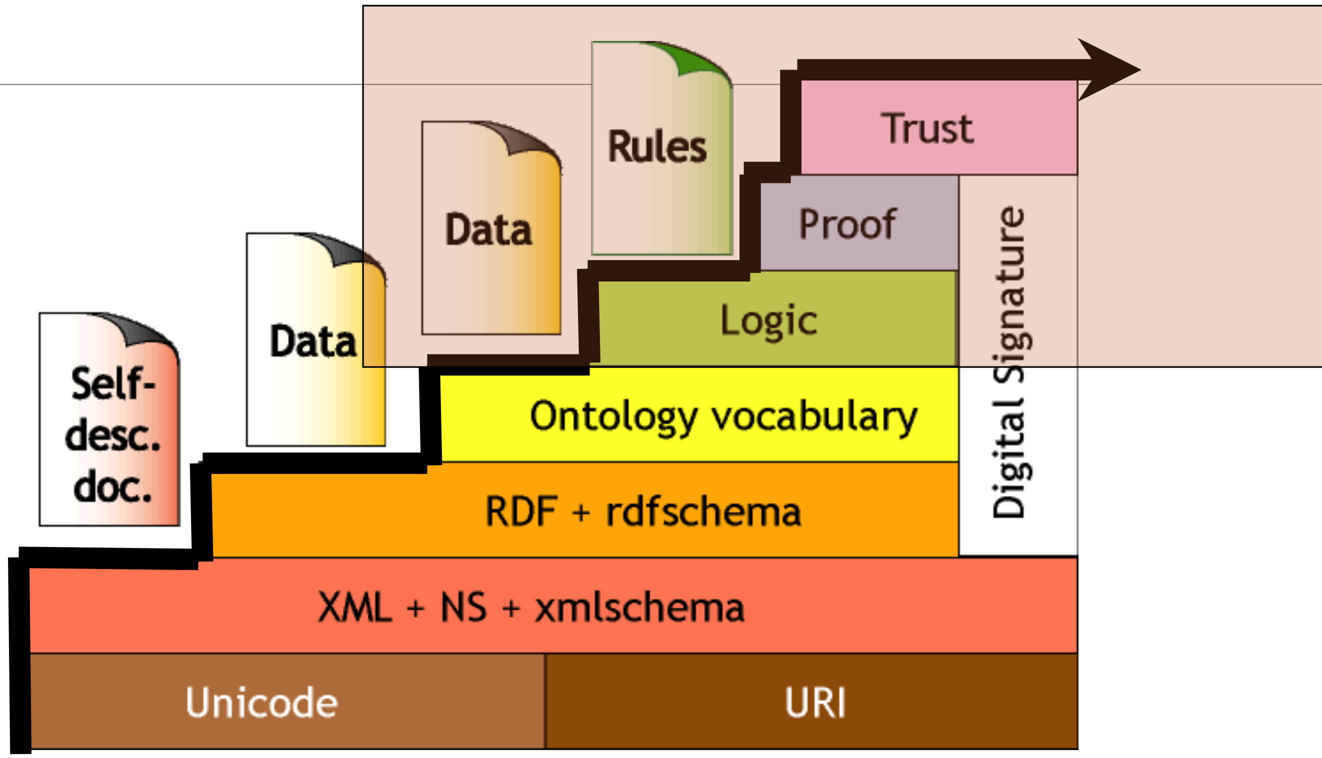
http://www.w3.org/ns/org.ttl

```
@prefix rdf:        <http://www.w3.org/1999/02/22-rdf-syntax-ns#> .
@prefix rdfs:       <http://www.w3.org/2000/01/rdf-schema#> .
@prefix owl:        <http://www.w3.org/2002/07/owl#> .
@prefix xsd:        <http://www.w3.org/2001/XMLSchema#> .
@prefix skos:       <http://www.w3.org/2004/02/skos/core#> .
@prefix foaf:       <http://xmlns.com/foaf/0.1/> .
…
@prefix :           <http://www.w3.org/ns/org#> .

# -- Meta data -----------------------------------------------------------

<http://www.w3.org/ns/org#>
    a owl:Ontology;
    owl:versionInfo "0.7";
    rdfs:label "Core organization ontology"@en;
    rdfs:comment "Vocabulary for describing organizational structures, specializable to a broad variety of types of organization."@en;
    dct:created "2010-05-28"^^xsd:date;
    dct:modified "2010-06-09"^^xsd:date;
    dct:modified "2010-10-08"^^xsd:date;
…
    rdfs:seeAlso <http://www.w3.org/TR/vocab-org/> ;
    .

# -- Organizational structure ---------------------------------------------

org:Organization a owl:Class, rdfs:Class;
    rdfs:subClassOf  foaf:Agent;
    owl:equivalentClass foaf:Organization;
    rdfs:label "Organization"@en;
    rdfs:label "Organisation"@fr;
    owl:hasKey (org:identifier) ;
    rdfs:comment """Represents a collection of people organized together into a community or other social, commercial or political structure. … Alternative names: _Collective_ _Body_ _Org_ _Group_"""@en;
    rdfs:comment """Représente un groupe de personnes organisées en communauté où tout autre forme de structure sociale, commerciale ou politique. … code provenant d'une liste de code."""@fr;
    rdfs:isDefinedBy <http://www.w3.org/ns/org> ;
    .
```

```
- <rdf:RDF xmlns:rdf="http://www.w3.org/1999/02/22-rdf-syntax-ns#"
    xmlns:skos="http://www.w3.org/2004/02/skos/core#" xmlns:foaf="http://xmlns.com/foaf/0.1/"
    xmlns:org="http://www.w3.org/ns/org#" xmlns:gr="http://purl.org/goodrelations/v1#"
    xmlns:owl="http://www.w3.org/2002/07/owl#" xmlns:dct="http://purl.org/dc/terms/"
    xmlns:prov="http://www.w3.org/ns/prov#" xmlns:owlTime="http://www.w3.org/2006/time#"
    xmlns:xsd="http://www.w3.org/2001/XMLSchema#" xmlns:vcard="http://www.w3.org/2006/vcard/ns#"
    xmlns:rdfs="http://www.w3.org/2000/01/rdf-schema#">
  + <owl:Ontology rdf:about="http://www.w3.org/ns/org#">
  + <rdfs:Class rdf:about="http://www.w3.org/ns/org#Organization">
  - <rdfs:Class rdf:about="http://www.w3.org/ns/org#Role">
      <rdfs:label xml:lang="fr">Rôle</rdfs:label>
    - <owl:disjointWith>
        <owl:Class rdf:about="http://www.w3.org/ns/org#ChangeEvent" />
      </owl:disjointWith>
      <rdfs:subClassOf rdf:resource="http://www.w3.org/2004/02/skos/core#Concept" />
    - <owl:disjointWith>
        <owl:Class rdf:about="http://www.w3.org/ns/org#Site" />
      </owl:disjointWith>
      <rdfs:comment xml:lang="fr">Indique le rôle qu'une Personne ou un autre Agent peut avoir dans une
        Organisation. Les instances de cette classe décrivent le rôle dans l'absolu; pour indiquer une personne
        ayant ce rôle spécifique dans une Organisation, utilisez une instance de `org:Membership`. Il est
        courant que les rôles soient organisés dans une sorte de taxonomie, ce qui peut être représenté avec
        SKOS. Les propriétés de libellés standards de SKOS devraient être utilisées pour libeller le Rôle.
        D'autres propriétés additionnelles pour ce rôle, comme une fourchette de Salaire peuvent être ajoutées
        par une extension de ce vocabulaire.</rdfs:comment>
    - <owl:disjointWith>
        <owl:Class rdf:about="http://www.w3.org/ns/org#Membership" />
      </owl:disjointWith>
      <rdfs:label xml:lang="en">Role</rdfs:label>
      <rdfs:isDefinedBy rdf:resource="http://www.w3.org/ns/org" />
      <rdf:type rdf:resource="http://www.w3.org/2002/07/owl#Class" />
      <rdfs:comment xml:lang="en">Denotes a role that a Person or other Agent can take in an organization.
        Instances of this class describe the abstract role; to denote a specific instance of a person playing that
        role in a specific organization use an instance of `org:Membership`. It is common for roles to be
```

http://www.w3.org/ns/org

Moving to the future of the web



Semantic Web LayerCake (Berners-Lee, 99;Swartz-Hendler, 2001)

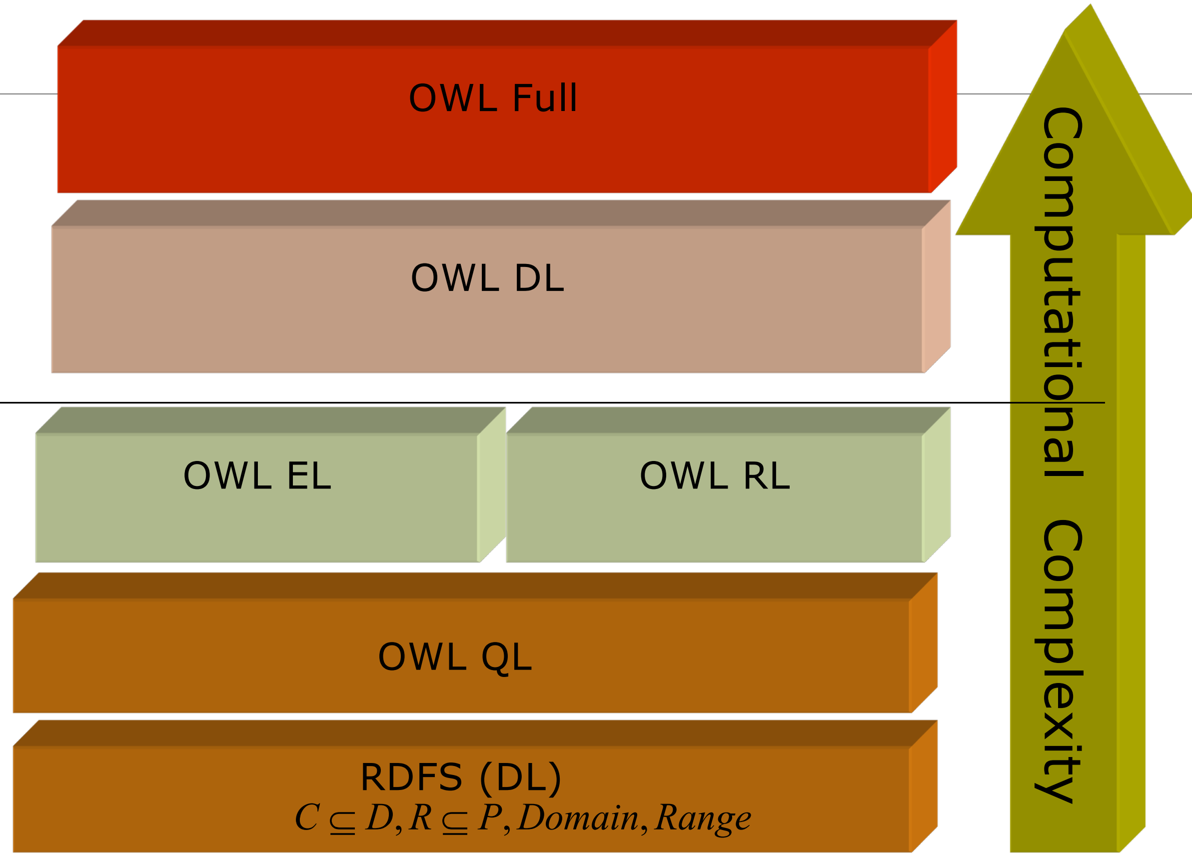
Challenge of Reasoning on Ontologies

•Undecidable

•Data Complexity open (NP-hard)
• Optimized tableau-based reasoners

• PTime-complete Data Complexity
• Efficient implementation on top of rule engine

• LogSpace Data Complexity
• Efficient evaluation on top of RDBMS



What makes a good ontology for data integration?

A *good* ontology is a *useful* ontology, an ontology that *both* humans and systems can process.

Human Usability

Communicable. Naming, natural language support, etc.

Concise. A simple way to describe the key entities of the model and yet able to infer many facts

Consistent. Naming conventions and modeling patterns

Authoritative to domain experts

Documented, not just descriptions, but also provenance

Managed and maintained by people throughout the model lifecycle.

Reusable in similar domains, for similar instances.

System Usability

Scalable so large amounts of data can be parsed, stored and retrieved.

Efficient query and inferencing

Programmable solutions, both in open and closed data paradigms.

Open infrastructure and tools

- ***Formal*** *representation of* ***knowledge*** *in a particular domain*
- *Formally defines key* ***concepts*** *and* ***relations*** *in the domain*
- *Specifies relationships between those key concepts and relations*
- *Supports* ***automated reasoning*** *about entities in the domain*

Using Ontology

- Visually via tools like Protégé - https://protege.stanford.edu/
- Programmatically with APIs like
  - Jena (Java) - https://jena.apache.org/documentation/ontology/
  - OwlReady2 (Python) - https://bitbucket.org/jibalamy/owlready2/src/master/
  - Rdflib (Python) - https://github.com/RDFLib/OWL-RL

- A compendium of resources - https://github.com/totogo/awesome-knowledge-graph

Code Illustration

On Github:
https://github.com/biplav-s/course-nl/blob/master/l11-ontology/Exploring%20ontologies.ipynb

Knowledge Graph

- No clear definition
  - "Towards a Definition of Knowledge Graphs," by Lisa Eherlinger and Wolfram Wöß, CEURWorkshop Proceedings. 2016, http://ceur-ws.org/Vol-1695/paper4.pdf
  - For practical purposes, concepts and their relationships; not constraints
  - Driven by applications in search and information integration
  - See discussion at: http://accidental-taxonomist.blogspot.com/2019/05/knowledge-graphs-and-ontologies.html
- But ontology as knowledge graph widely used in industries
  - Industry-Scale Knowledge Graphs: Lessons and Challenges, CACM 2019, https://cacm.acm.org/magazines/2019/8/238342-industry-scale-knowledge-graphs/fulltext

KG Usage

	Data model	Size of the graph	Development stage
Microsoft	The types of entities, relations, and attributes in the graph are defined in an ontology.	~2 billion primary entities, ~55 billion facts	Actively used in products
Google	Strongly typed entities, relations with domain and range inference	1 billion entities, 70 billion assertions	Actively used in products
Facebook	All of the attributes and relations are structured and strongly typed, and optionally indexed to enable efficient retrieval, search, and traversal.	~50 million primary entities, ~500 million assertions	Actively used in products
eBay	Entities and relation, well-structured and strongly typed	Expect around 100 million products, >1 billion triples	Early stages of development and deployment
IBM	Entities and relations with evidence information associated with them.	Various sizes. Proven on scales documents >100 million, relationships >5 billion, entities >100 million	Actively used in products and by clients

Figure courtesy: Industry-Scale Knowledge Graphs: Lessons and Challenges, CACM 2019

Machine Learning

Credit: Retrieved from internet

Machine Learning – Insights from Data

- Descriptive analysis
  - Describe a past phenomenon
  - **Methods**: classification (feedback from label), clustering, dimensionality reduction, anomaly detection, neural methods, reinforcement learning (feedback from hint/ reward)
- Predictive analysis
  - Predict about a new situation
  - **Methods**: time-series, neural networks
- Prescriptive analysis
  - What an agent should do
  - **Methods**: simulation, reinforcement learning, reasoning
- New areas
  - Counterfactual analysis
  - Causal Inferencing
  - Scenario planning

Nomenclature

Column, Attribute, Feature

Row, Item

1	PID	ST_NUM	ST_NAME	OWN_OCCUPIED	NUM_BEDROOMS	NUM_BATH	SQ_FT
2	100001000	104	PUTNAM	Y	3	1	1000
3	100002000	197	LEXINGTON	N	3	1.5	--
4	100003000		LEXINGTON	N	n/a	1	850
5	100004000	201	BERKELEY	12	1	NaN	700
6		203	BERKELEY	Y	3	2	1600
7	100006000	207	BERKELEY	Y	NA	1	800
8	100007000	NA	WASHINGTON		2	HURLEY	950
9	100008000	213	TREMONT	Y	1	1	
10	100009000	215	TREMONT	Y	na	2	1800

Types of Attributes/ Columns

- Numeric: has number as value in computational sense; all mathematical functions are valid.
  - Example: SQ_FT
- Categorical: has distinct values
  - Nominal: each value is incomparable with other
    - Example: OWN_OCCUPIED, ST_NAME
  - Ordinal: the values can be ordered
    - Example: ST_NUM, NUM_BEDS
- Comment:
  - Q: what type is a binary variable?
  - A: depends on the semantics – nominal (gender), ordinal (number basements).

1	PID	ST_NUM	ST_NAME	OWN_OCCUPIED	NUM_BEDROOMS	NUM_BATH	SQ_FT
2	100001000	104	PUTNAM	Y	3	1	1000
3	100002000	197	LEXINGTON	N	3	1.5	--
4	100003000		LEXINGTON	N	n/a	1	850
5	100004000	201	BERKELEY	12	1	NaN	700
6		203	BERKELEY	Y	3	2	1600
7	100006000	207	BERKELEY	Y	NA	1	800
8	100007000	NA	WASHINGTON		2	HURLEY	950
9	100008000	213	TREMONT	Y	1	1	
10	100009000	215	TREMONT	Y	na	2	1800

Why is Type of Variable Important

- Handling of missing values
- Distance between
  - Values
  - Data items
- Used for measuring accuracy, error
- Guiding the learning process
  - Selection of algorithms

Concepts

- **Input data**: data available
  - **Training data**: used for training a learning algorithm and get a model
    - [Optional] **Validation data**: used to tune parameters
  - **Test data**: used to test a learning model

- **Classification problem**
  - Separating data into classes (also called labels, categorical types)
  - One of the attributes is the class label we are trying to learn
  - Class label is the **supervision**
- **Clustering problem**
  - We are trying to learn grouping of data
  - There is no attribute indicating membership in the groups (hence, **unsupervised**)
- **Prediction problem**
  - Learning value of a continuous variable

Reference: https://machinelearningmastery.com/difference-test-validation-datasets/
https://www2.seas.gwu.edu/~bell/csci243/lectures/classification.pdf

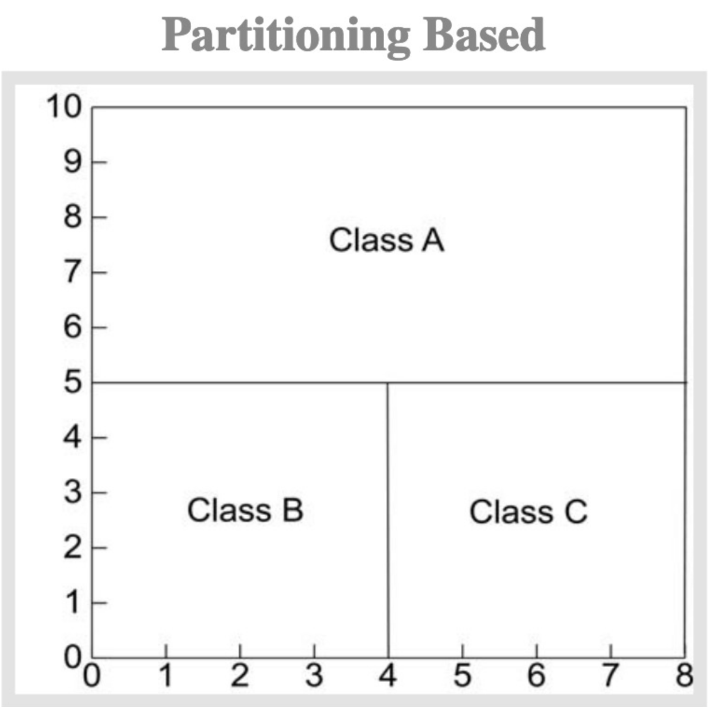
Sample Learning Task

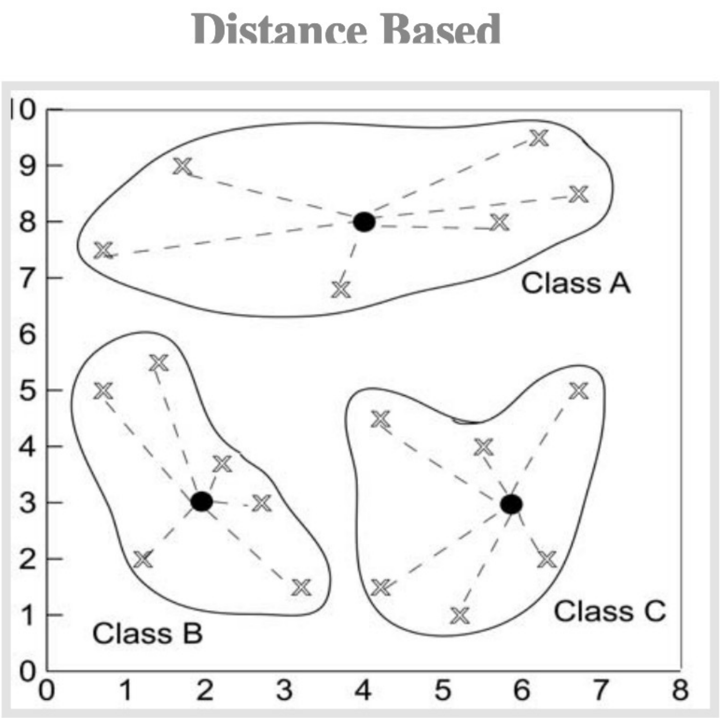
- COVID-19 data

Notebook: https://github.com/biplav-s/course-d2d-ai/blob/main/sample-code/l6-l7-l8-supervised-ml/Supervised-Regression-Classification.ipynb

-

Methods for Classification

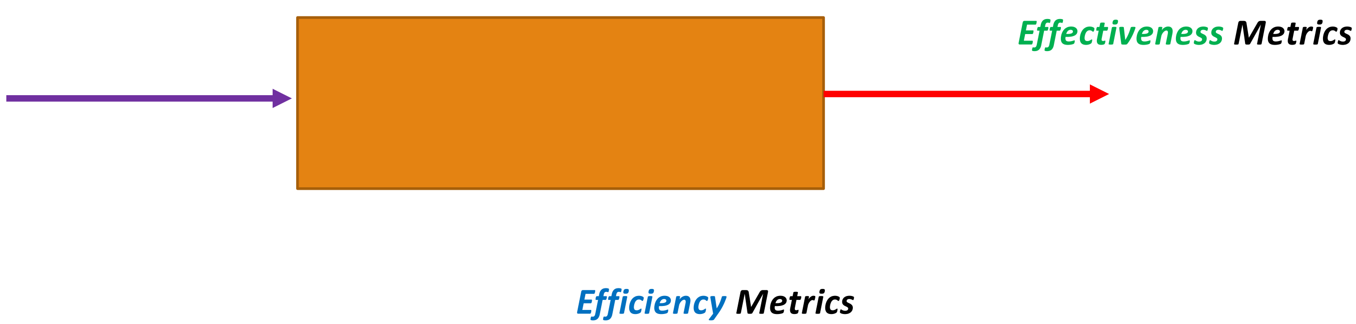




Source: https://www2.seas.gwu.edu/~bell/csci243/lectures/classification.pdf

Metric Types

- **Effectiveness**: what the **user** of a system sees, primarily cares about
- **Efficiency**: what the **executor** in a system sees, primarily cares about



Example: Predicting COVID cases

- **Effectiveness**: what the **user** of a system sees, primarily cares about
  - *How accurate (high) is the prediction?*
  - *How low is the error?*
- **Efficiency**: what the **executor** in a system sees, primarily cares about
  - *How low is the error?*
  - *How fast was prediction made?*
  - *How stable is the prediction to change in data?*

Example: Detecting Spam in Email

- **Effectiveness**: what the **<u>user</u>** of a system sees, primarily cares about
  - *How many spams identified?*
  - *How many spams missed?*
- **Efficiency**: what the **<u>executor</u>** in a system sees, primarily cares about
  - *How fast were spams detected?*
  - *How much memory was used per million emails processed ?*

Comparing Classification Methods

- Predictive accuracy
- Interpretability: providing insight
- Robustness: handling noisy data

- Speed
- Scalability: large volume of data

Source: Data Mining: Concepts and Techniques, by Jiawei Han and Micheline Kamber

Metrics: Accuracy, Precision, Recall

	Predicted class		
Actual Class		Class = Yes	Class = No
	Class = Yes	True Positive	False Negative
	Class = No	False Positive	True Negative

Accuracy =
(TP+TN)/
(TP+FP+FN+TN)

Precision =
(TP)/
(TP+FP)

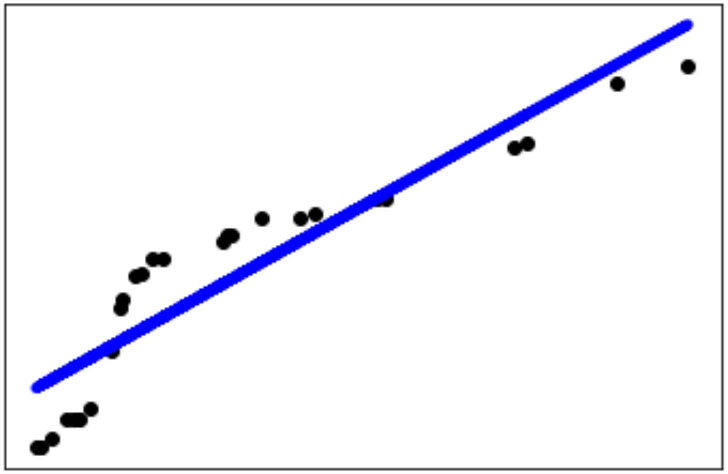
Recall =
(TP)/
(TP+FN)

F1 Score: *Harmonic Mean*

1/F1 = 1/Precision + 1/Recall

F1 = 2*(Recall * Precision) /
(Recall + Precision)

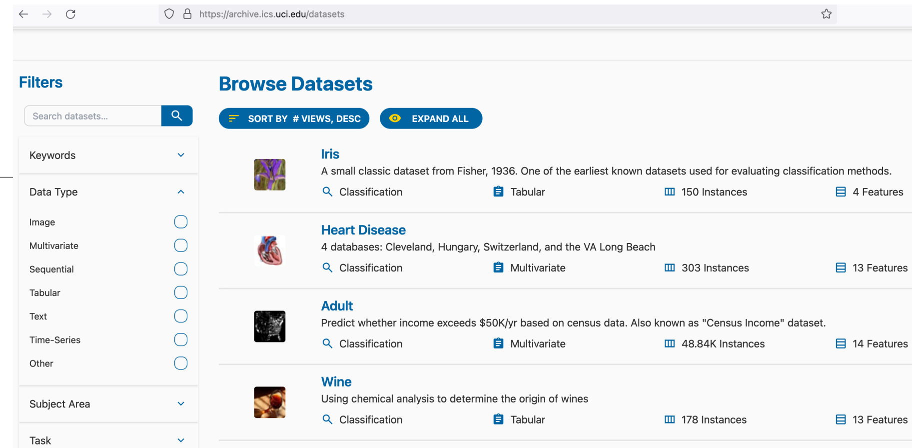
Linear Regression

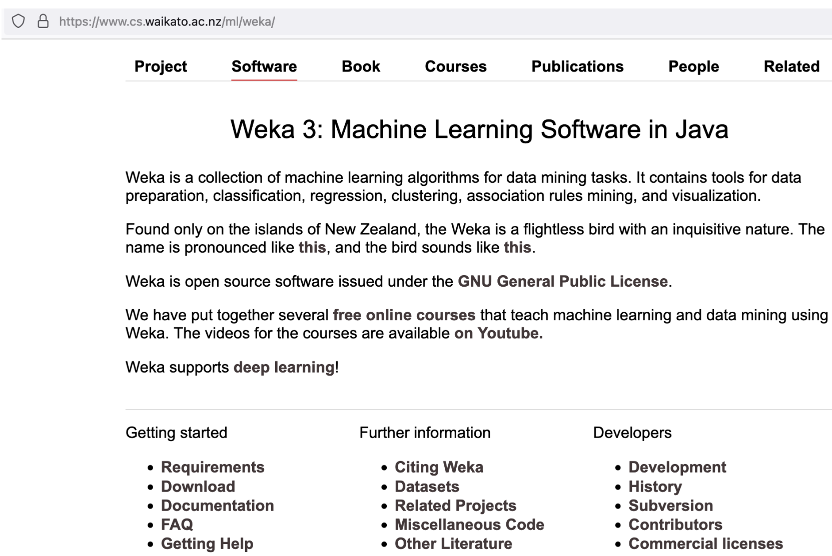


Notebook: https://github.com/biplav-s/course-d2d-ai/blob/main/sample-code/l6-l7-l8-supervised-ml/Supervised-Regression.ipynb

Reference and Demo

- Data: UCI Datasets
  - https://archive.ics.uci.edu/datasets
  - Browse or search





- Tools:
  - Weka - https://www.cs.waikato.ac.nz/ml/weka/
  - Download tool and dataset

- Libraries
  - Scikit - https://scikit-learn.org/stable/

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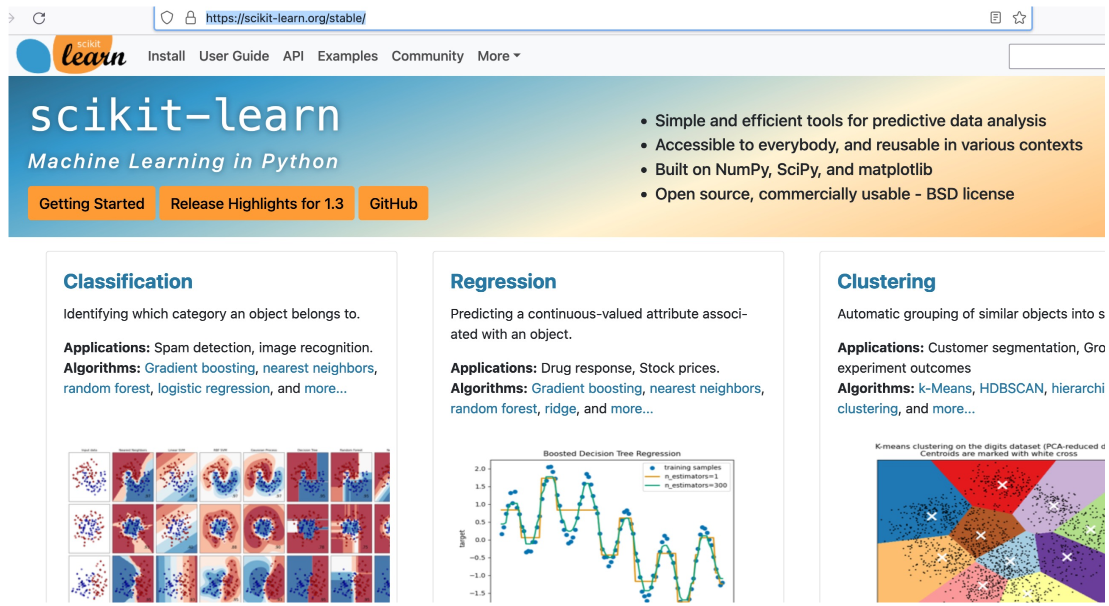

Exercise: German Credit

- Check in UCI
- Look at variants
    - https://archive.ics.uci.edu/dataset/573/south+german+credit+update

Concluding Section

Week 3 (L5 and L6): Concluding Comments

- We looked at
  - Trusted decisions
  - Data and characteristics
  - Common ways to prepare data
  - How to organize content for inferencing / reasoning
- Prepares us for understanding trust issues

About Next Week – Lectures 5, 6

Lectures 7, 8: AI / ML Methods and Trust

- Supervised ML
- Trust issues

1	Jan 14 (Tu)	Introduction, Trusted AI
2	Jan 16 (Th)	Case Studies: Data Analysis for AI, Analysis for Trust [Traffic], Recommendations and Trust [Fairness and ULTRA]
3	Jan 21 (Tu)	Review: Trusted Decisions, Expectations, Course Scope; Data
4	Jan 23 (Th)	AI: Data Prep, Knowledge Graph
5	Jan 28 (Tu)	Common AI methods: ML Landscape
6	Jan 30 (Th)	AI - Structured: Analysis – Supervised ML
7	Feb 4 (Tu)	AI - Structured: Analysis – Supervised ML
8	Feb 6 (Th)	AI - Structured: Analysis – Supervised ML – Trust Issues
9	Feb 11 (Tu)	AI - Structured: Analysis – Supervised ML – Trust Issues
10	Feb 18 (Th)	AI - Structured: Analysis – Supervised ML – Mitigation Methods
11	Feb 18 (Tu)	AI - Supervised ML: Explanation Tools