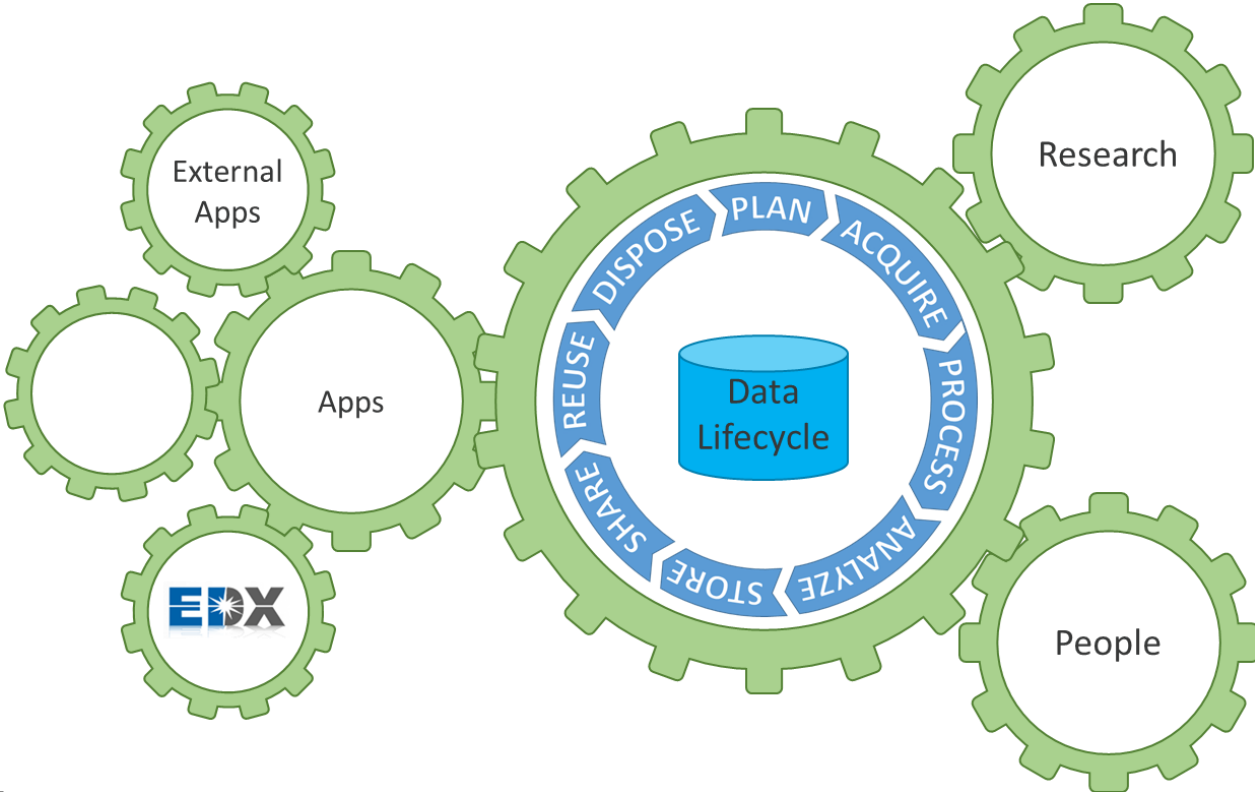


Using SmartParse NLP Tools to Develop a Living Database for Carbon Storage Data



Michael Sabbatino and
Paige Morkner
NETL Support Contractor
Research Innovation Center



NETL Carbon Storage Virtual Meeting
August 5, 2021

Disclaimer



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Author Information



Michael Sabbatino^{1,2}, Paige Morkner^{1,2}, Jennifer Bauer¹, Kelly Rose¹

¹ National Energy Technology Laboratory, 1450 Queen Avenue SW, Albany, OR, 97321 USA

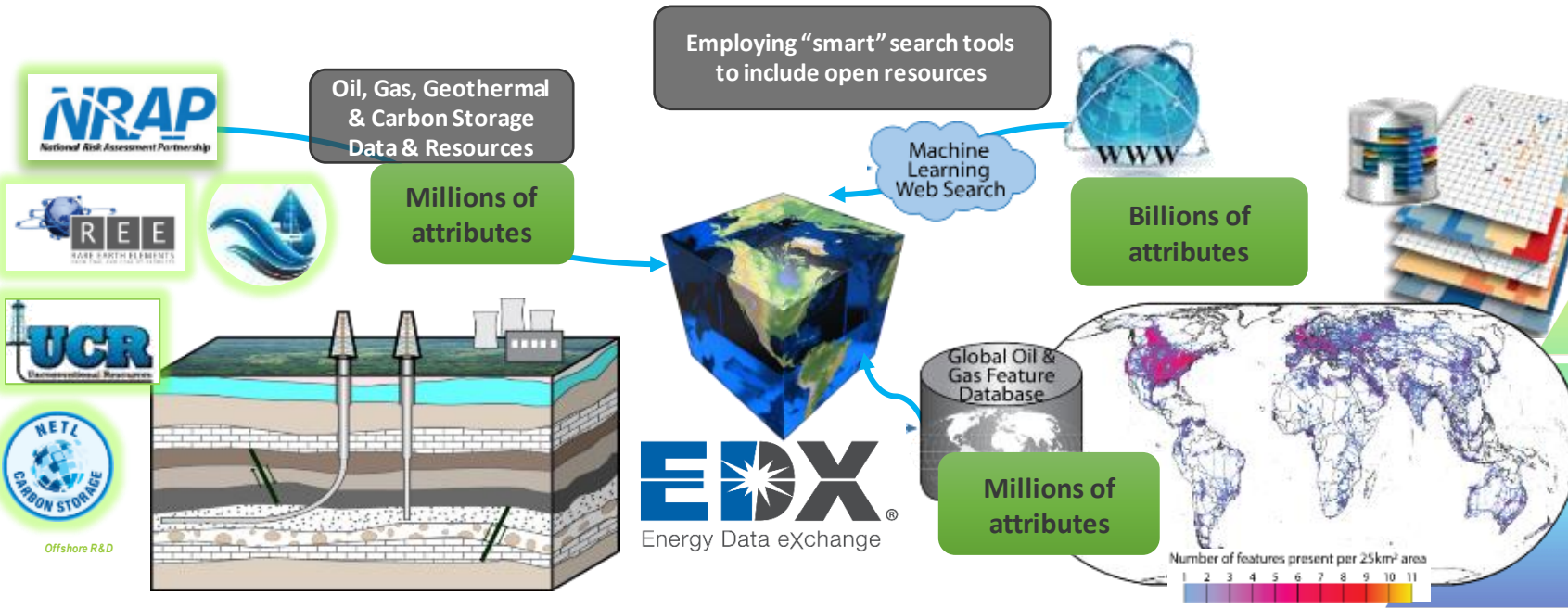
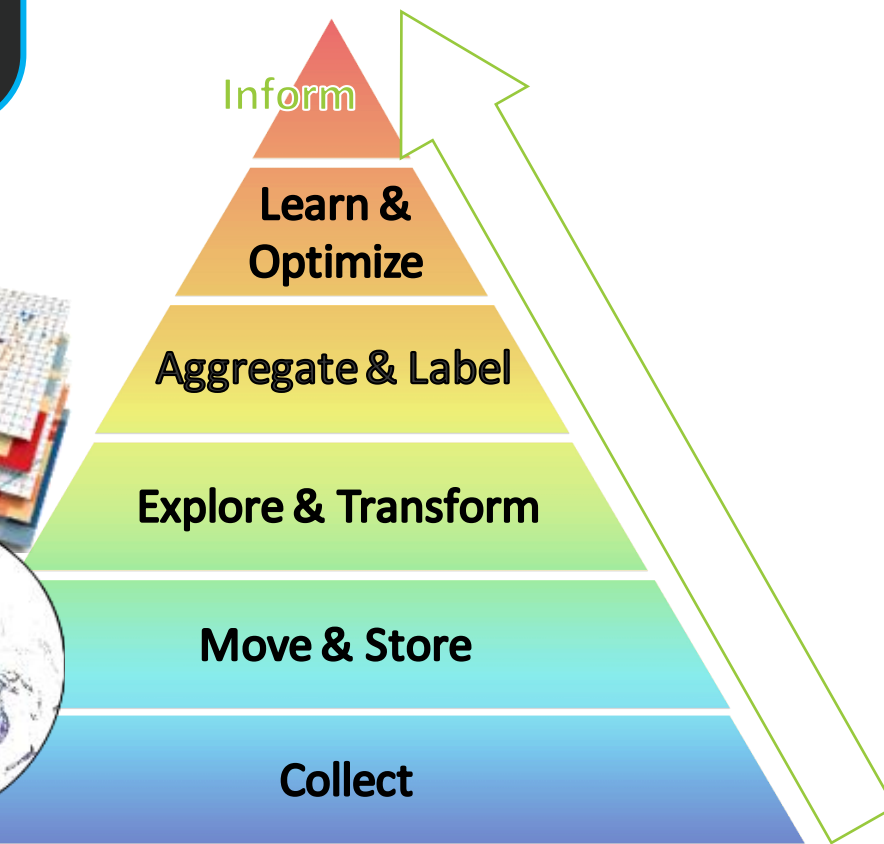
² NETL Support Contractor, 1450 Queen Avenue SW, Albany, OR, 97321, USA

³ NETL Support Contractor, 3610 Collins Ferry Rd., Morgantown, WV, 26505, USA

Research is data-driven

- Millions of dollars of research and data are available from carbon storage efforts
- How can we **preserve** and **efficiently access** those resources **to drive the next generation** of R&D?

Address the needs of the community through AI/ML enhanced methods via DOE's virtual data library and laboratory, EDX



Supporting the whole life cycle of carbon storage data



Collection

- SmartSearch
- Expert-driven research
- EDX submissions

Metadata development and capture

- Cataloging
- ReadMe file development
- Natural language processing for keywords, topic modeling, geographic association

Quality Assessment

- Data ranking
- Data assessment method scoring

Data Organization and publishing

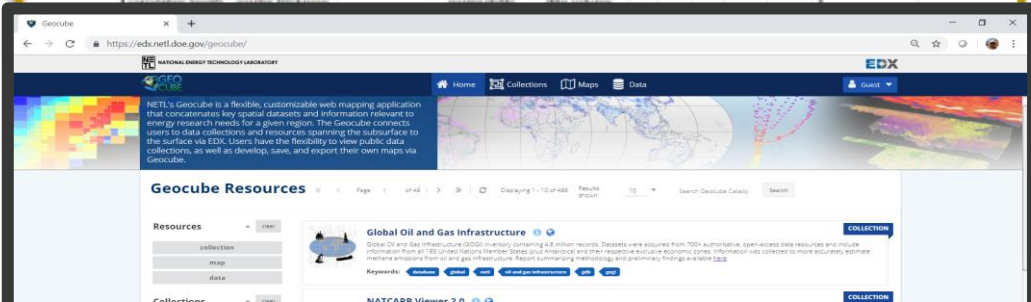
- Private workspaces
- Groups
- Submission packaging
- GeoCube data integration

Community Datasets CCS Site Catalog

File Edit View Insert Format Data Tools Address Help

Tool input per data category for each specific tool

Data Category	AIM							DREAM	
	Aquifer Characteristics Confined	Aquifer Characteristics Unconfined	Time	Porosity or Permeability	Geochemistry	CO2	Brine properties	Location (other)	Reservoir Characteristics
Date Subcategory	sand fraction []	correlation length [m]	injection time [yr]	permeability sand [log10(mD)]	calcite volume fraction	CO2 flow [kg/d]	brine flow [kg/d]	A, J, Z (within a leakage plane)	flow simulation output parameter value* (one or several) []
	correlation length A [m]	Kelty	Brine and CO2 leak time [yr]	porosity sand []	gastite volume fraction	CO2 mass [log10 (kg)]	brine mass [log10 (kg)]		



Carbon Storage

Data information

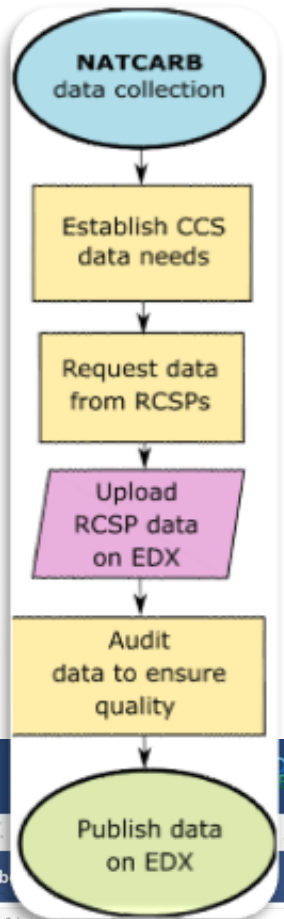
Agricultural Processing CO2 Sources BSCSP
Created by: null on 2020-1-03

Metadata:

- category: CO2_Sources
- layerDescription: Big Sky carbon storage partnership agricultural processing point sources for CO2 production. These point sources span across Washington, northern Oregon, Idaho, Montana, Wyoming, North Dakota and South Dakota.
- licensing: Open Data Commons Attribution License
- hyperlink: https://mapping.bigskyco2.org/gis/rest/services/Public/Services/CO2Emissions_2015/MacServer

View Selected


Name	Category	i	Q	+	-
MRCSP Project L...	Boundaries				
Agricultural Proce...	CO2 Sources				
Cement Plant CO...	CO2 Sources				
Fertilizer Facility ...	CO2 Sources				

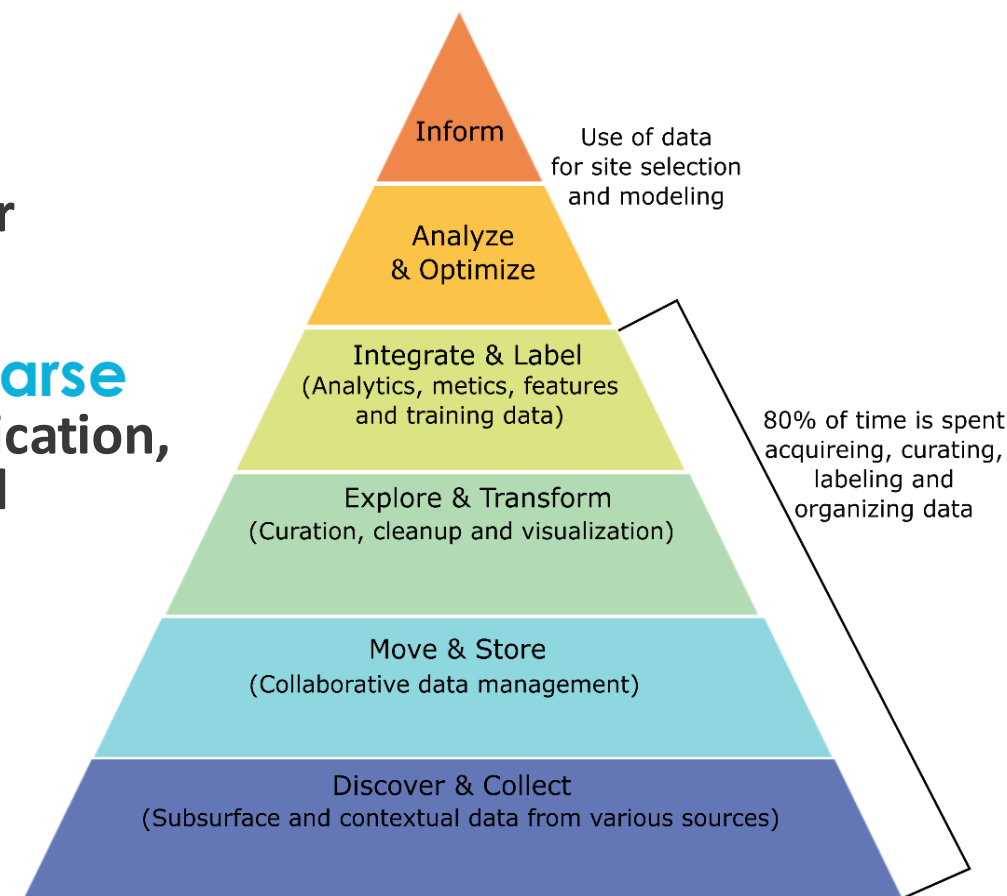


Using AI/ML Tools for CS Data Curation

Challenge: Making available data discoverable, searchable, and easy to reuse

Solutions:

- Open-source **data scraping** efforts  **NETL SmartSearch**
- **Cataloging for metadata extraction** and preservation
- Geographic database development to make searches easier (**GeoCube**)
- **Natural language processing** for text-based resource classification, organization, keyword identification (metadata building) and geographic association (for searchability)
- SmartParse NLP has integrations with New API for EDX
- **ML image object recognition** and data extraction



Types of Carbon Storage Data

Spatial data:

- Shapefiles (field, basin, regional scale)
- Datasets
- Models

Text-based Data

- Documents
- Publications
- Power points
- Memos
- Posters

Image Extraction:

- Documents
- Presentations
- Maps
- Posters

Other types of data:

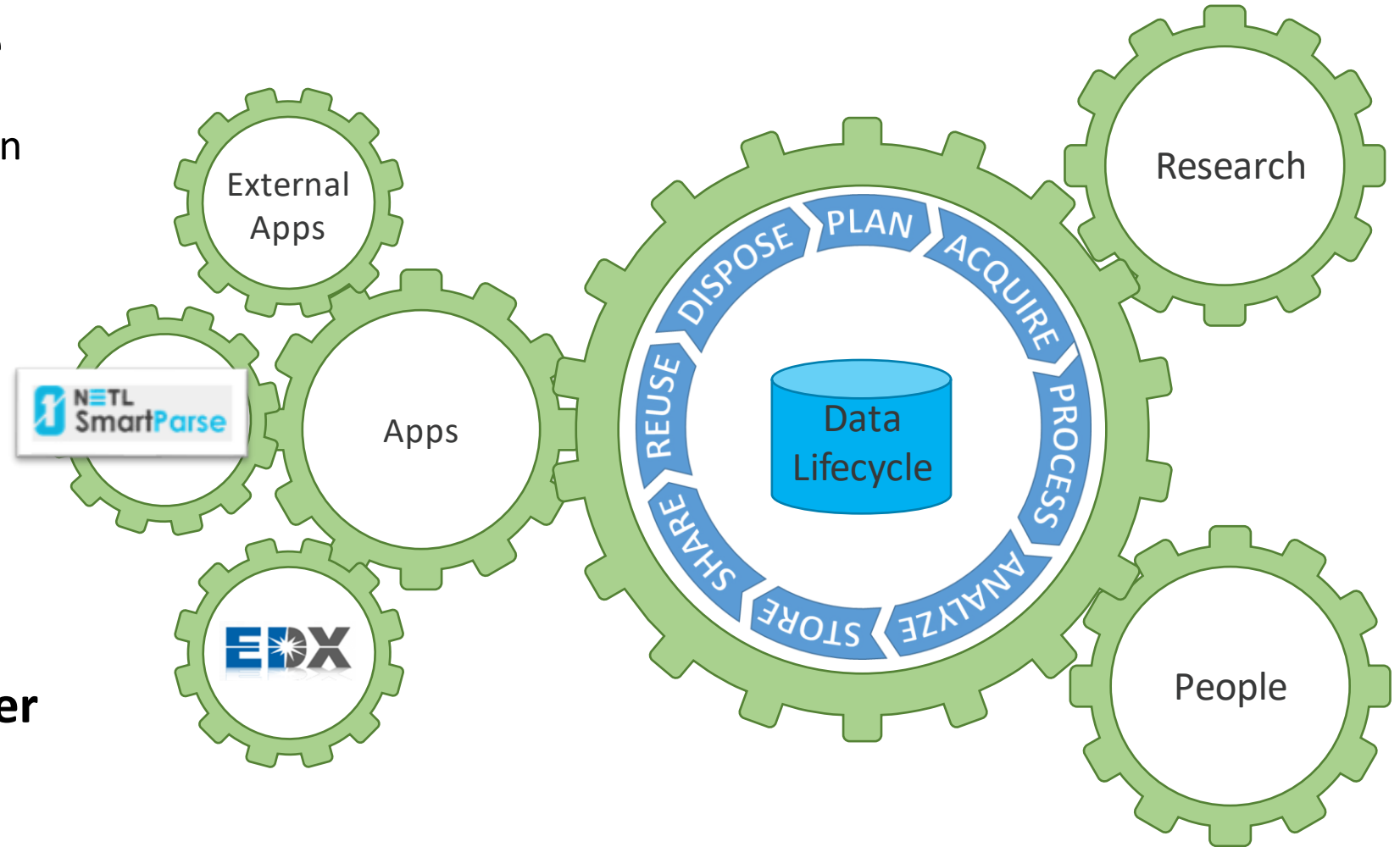
- Tools
- Applications
- APIs
- LivingDatabase



Feeding the data hippo!

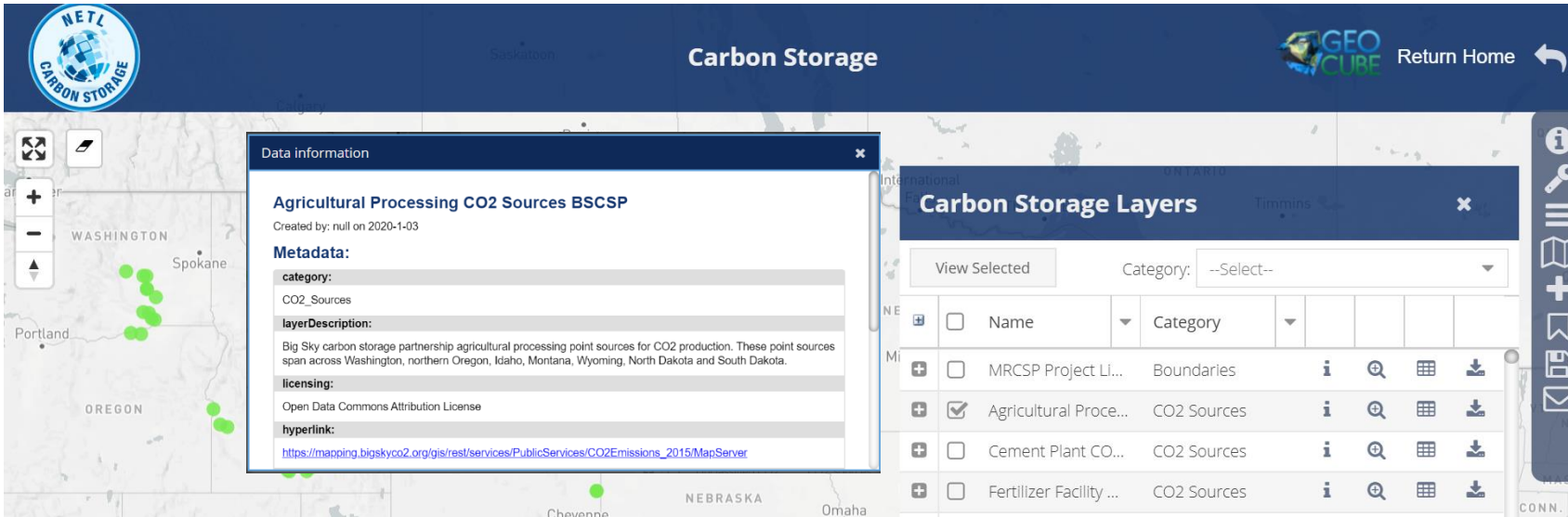
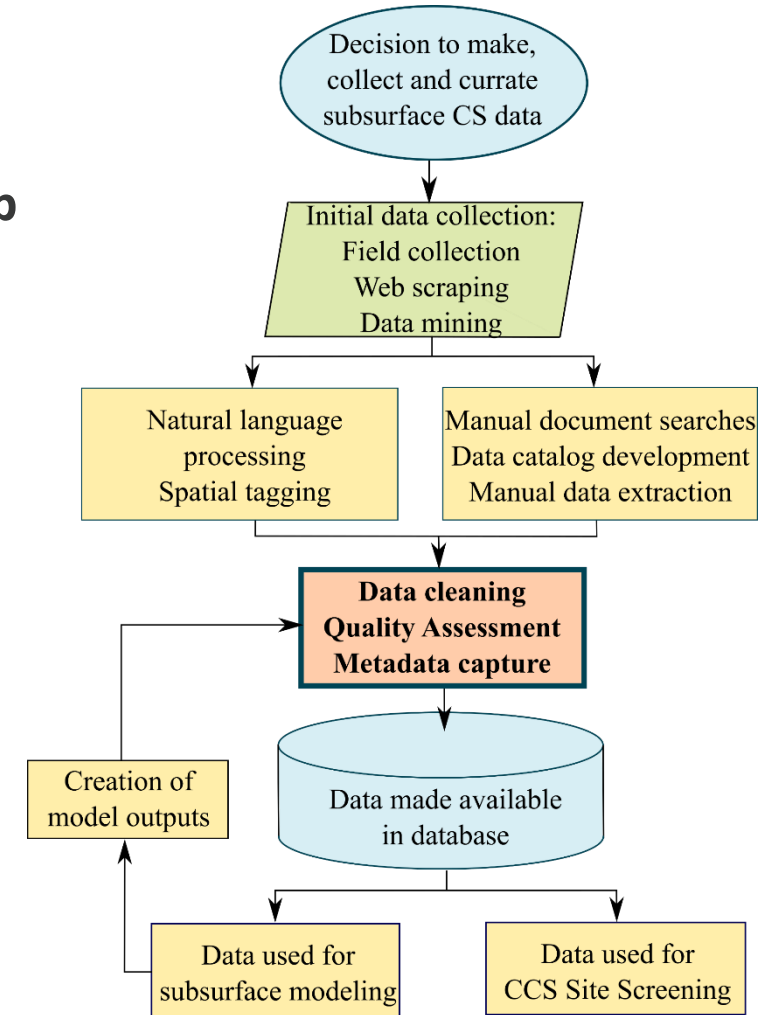
Living Database

- **Store and Share Data in a Structured Secure Database Environment**
 - Reduce Redundant Acquisition
 - Direct Data Access (not file based storage)
 - Consistent Data with Staff Turnover
 - Enhanced Collaboration
- **Curation of data and knowledge**
- **Allows Direct Analysis from Database**
- **Available On Research network and Watt ML Cluster**



Data Cleaning for ML, AI and Spatial Analysis

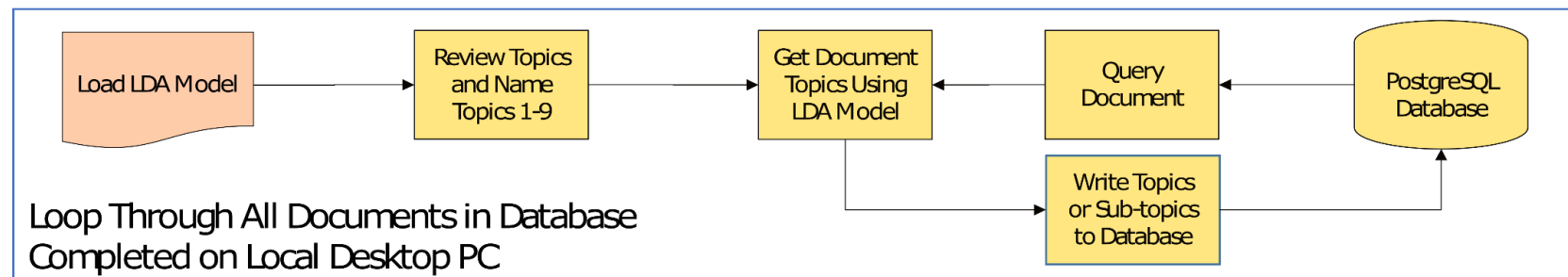
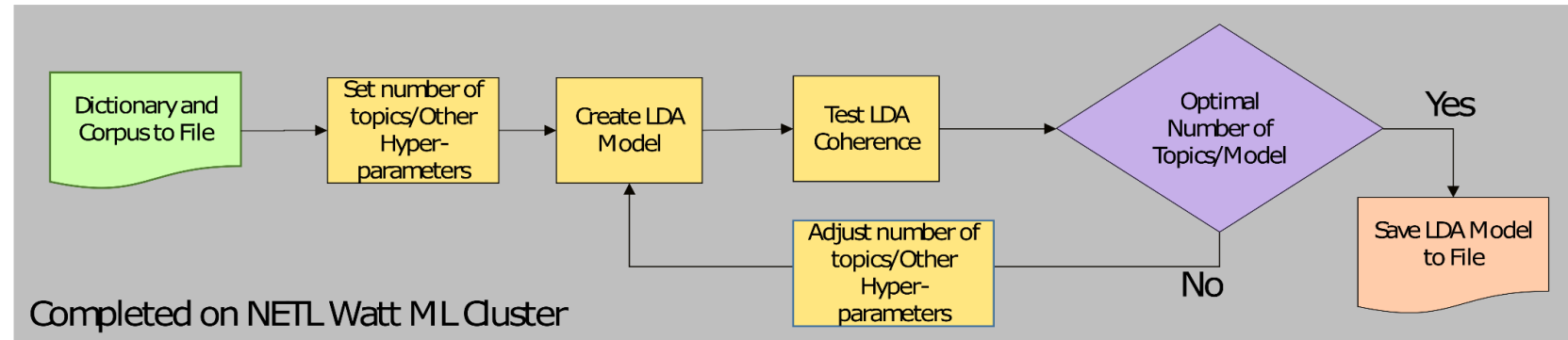
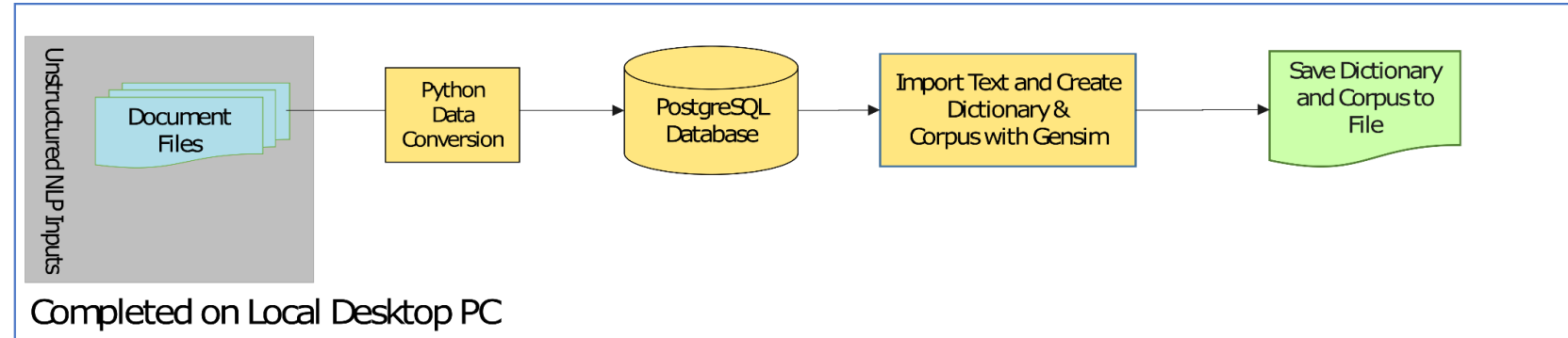
- Use Python scripts to automate data cleaning and help rapidly add structure, labels and metadata for datasets
- Metadata development for open carbon storage database
 - Use of ArcREST data, geographic location, and attribute table to develop metadata for layers in Geocube
- Link to EDX to capture additional metadata for datasets



Natural Language Processing (NLP)

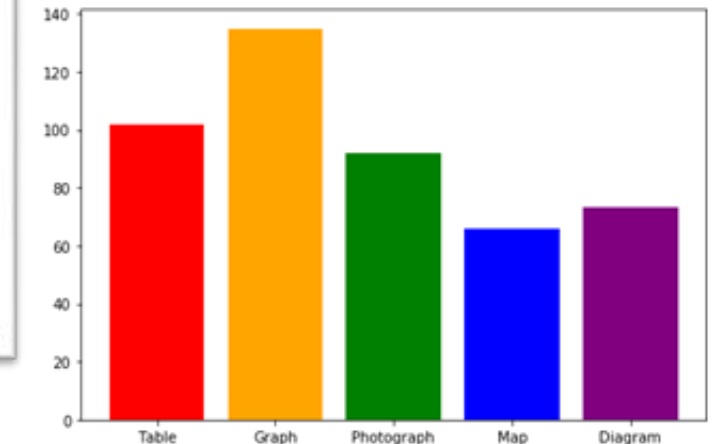
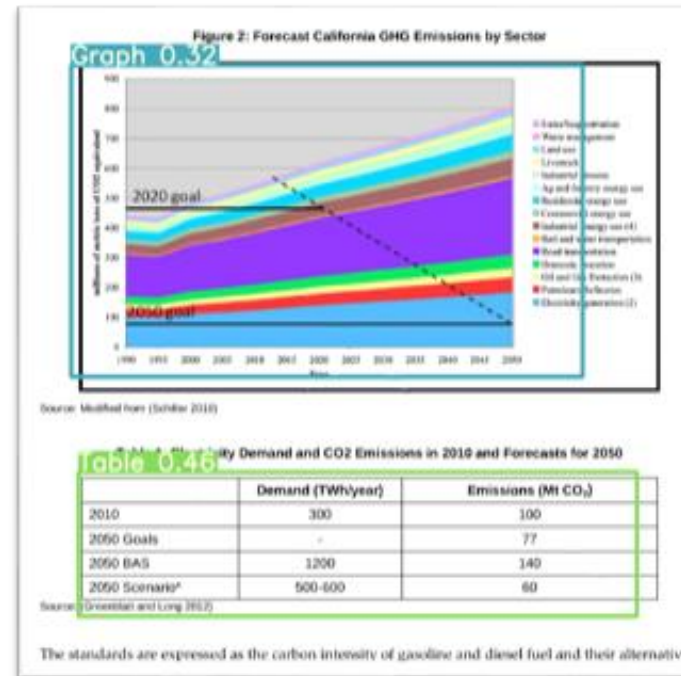
Unsupervised ML for Document Classification

- Latent Dirichlet allocation (**LDA**) **model based on corpus of 2071 text-based documents**
- Topic names assigned by subject-matter experts
- **Each document is classified by % of each topic it's associated with**
- **Each document has 50+ keywords identified and can be associated metadata on EDX**
- **Parse geographic location to associate with each document – when possible**

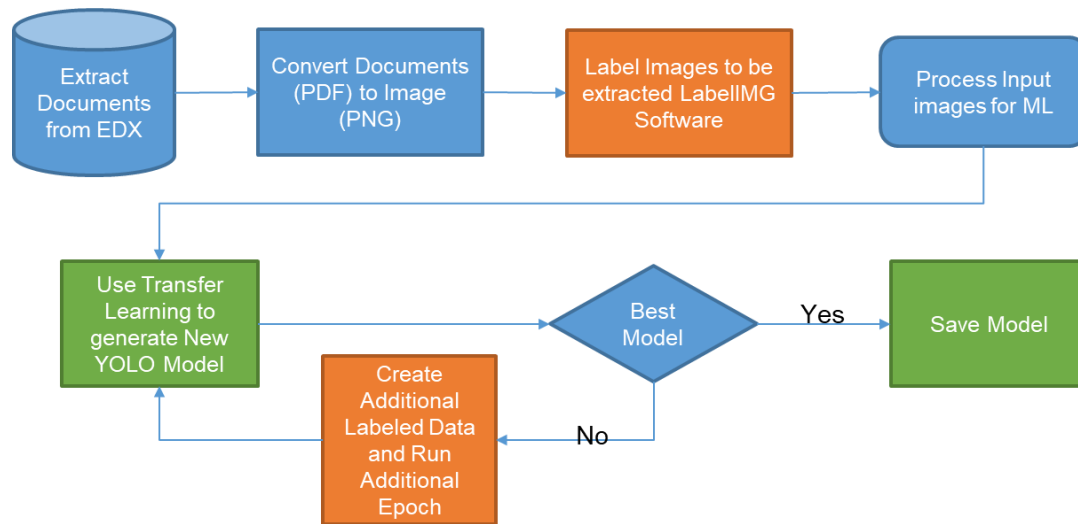


Machine Learning Image Data Extraction

- Object Detection Model Development Process
 - Use transfer learning to train object detection model for specific image and data types
 - Detect Graphs, Diagrams, Photos, Maps, and Tables
 - Image Labeling and process Developed with help from Mickey Leland Energy Fellowship



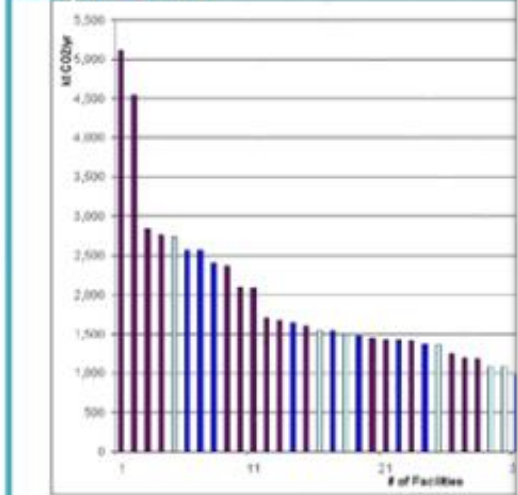
Images and Tables Targeted for Data for Extraction



Machine Learning Data Extraction

Utilize Object Identification ML Models to Extract Additional Data

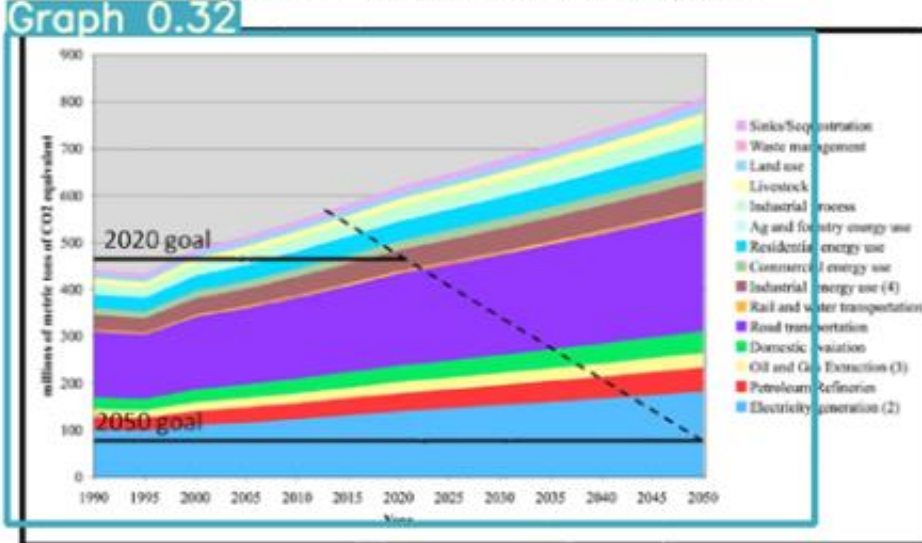
Figure 3: Fifty Largest CO₂ Point Sources
Graph 0.84



Source: (Katzner and Herzog 2006)

Some studies have suggested that application of CCUS to biomass is a valuable option for the state to achieve its 2050 emissions reduction goals (California Air Resources Board 2012). Only about 2 percent of the state's electricity (600 MW) is generated by biomass power plants. Approximately 196 million gallons of biofuels are produced at biodiesel facilities; the demand estimated by the California Energy Commission is 1 billion gallons per year. California's Low Carbon Fuel Standard requires a measure to lower the carbon intensity of fuel stocks. Emissions from biomass are less individually and in aggregate than from coal and NGCC power plants, but these sources are free from cap-and-trade emission constraints. Negative emissions can be achieved if biomass is used for power generation or fuels if allowed by policy. The California 2012 Biomass Action Plan identifies the need to analyze and mitigate potential problems with particle emissions and other challenges facing biofuel development, such as accounting for

Figure 2: Forecast California GHG Emissions by Sector
Graph 0.32



Source: Modified from (Schiller 2010)

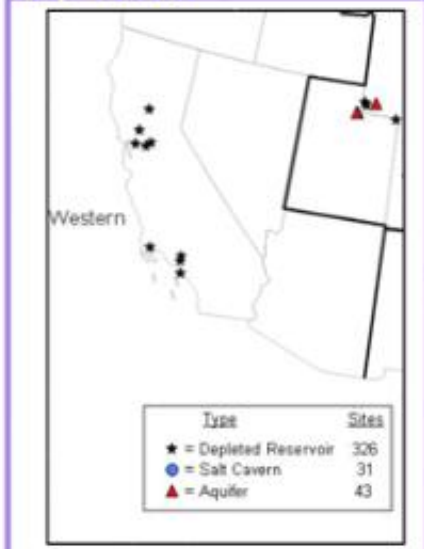
Table 1: Electricity Demand and CO₂ Emissions in 2010 and Forecasts for 2050
Table 0.46

	Demand (TWh/year)	Emissions (Mt CO ₂)
2010	300	100
2050 Goals	-	77
2050 BAS	1200	140
2050 Scenario*	500-600	60

Source: (Greenblatt and Long 2012)

... projects could provide the proof-of-concept needed for commercialization. The potential CO₂ demand for this application probably is not significant relative to the total CO₂ demand.

Figure 8: Map 0.23 of Natural Gas Storage Facilities

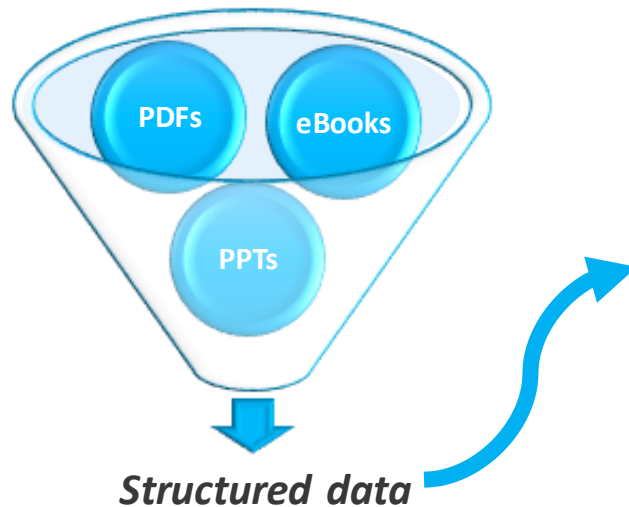
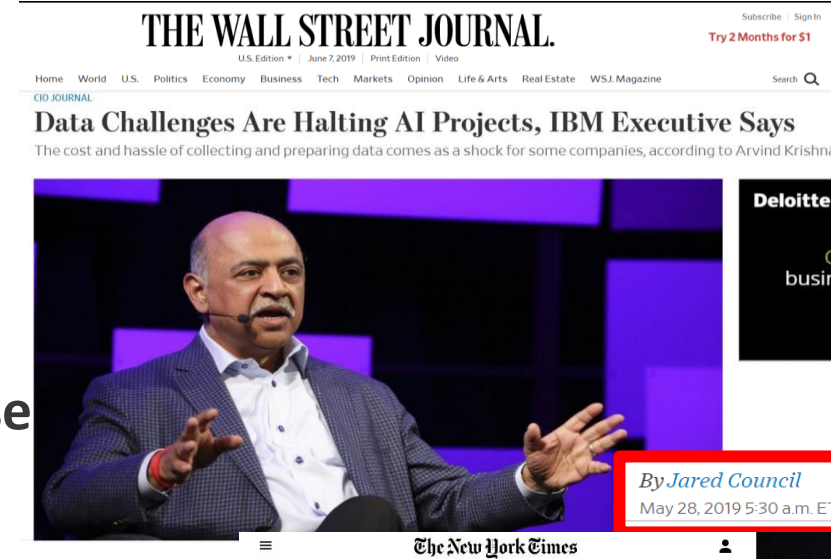


California Department of Conservation, Office of Oil and Gas, Natural Gas Division, Gas Transportation Information system.

... use in use of CO₂ as a cushion gas for natural gas storage. Demand for cushion gas is significant. California has 12 underground natural gas storage sites (Figure 8) with a working capacity of 1.2 billion cubic feet (Bcf) and a daily withdrawal capacity of 6875 million cubic feet (MMcf).

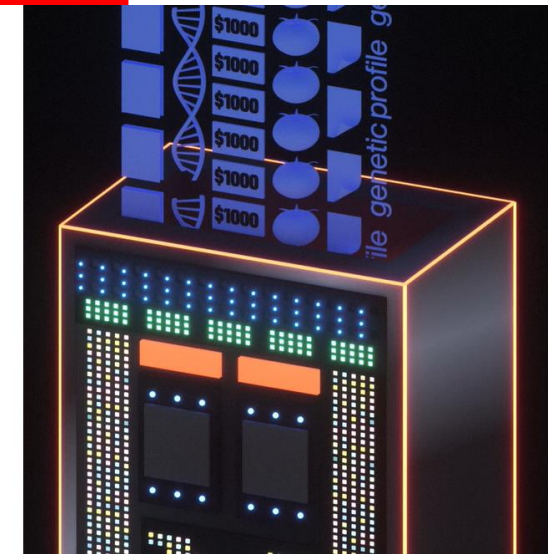
Lessons Learned

- **Machine Learning, Artificial Intelligence and Natural Language processing are Difficult**
 - Whatever happened to Watson?
- **Lack of Labeled Training Data**
 - Training data is time consuming to develop and can be costly
- **Data availability is limited with Living Database**
 - Currently deployed on Research network
 - The database would improve if deployed on a cloud service or other shared environment



What Ever Happened to IBM's Watson?

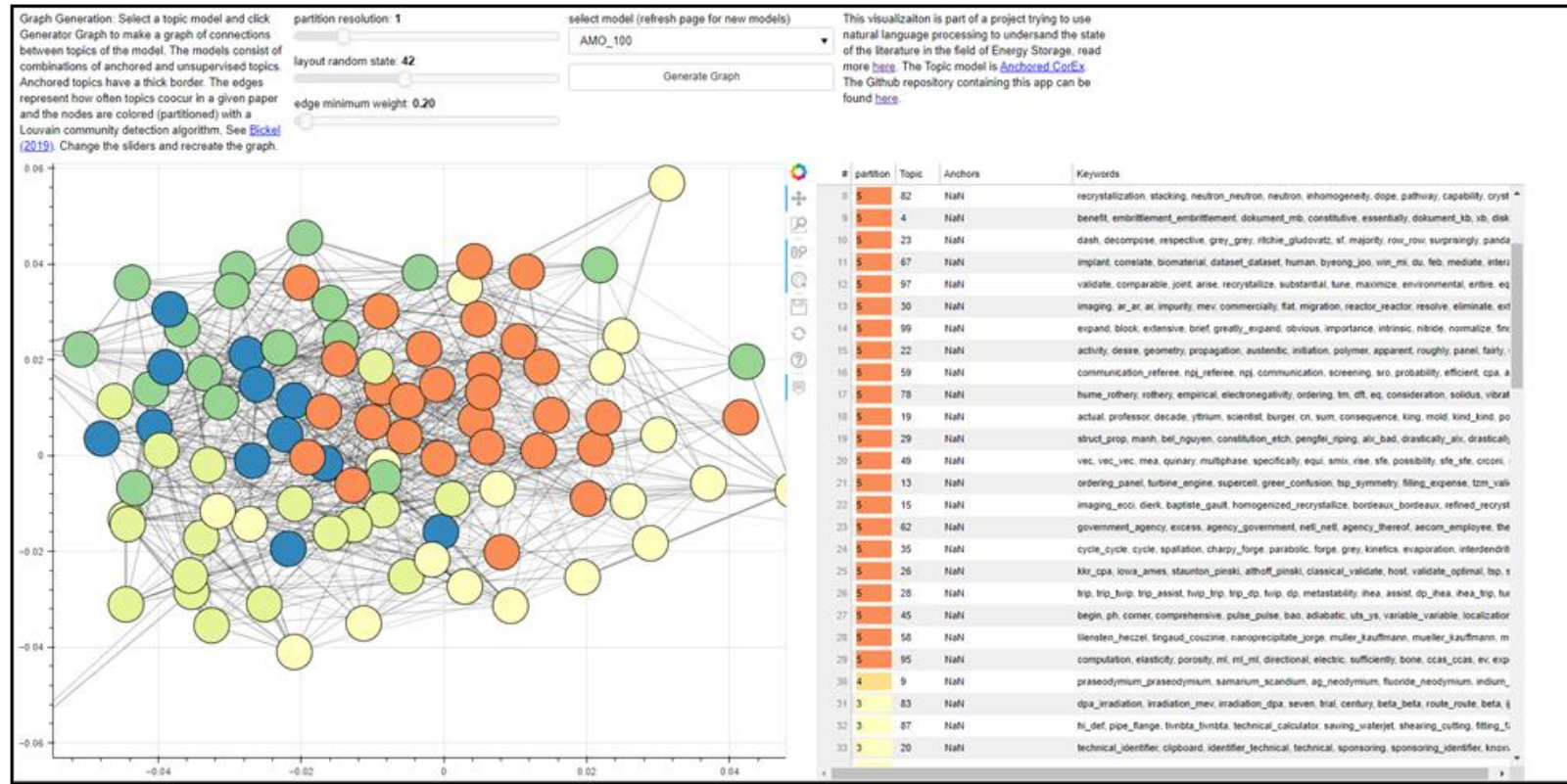
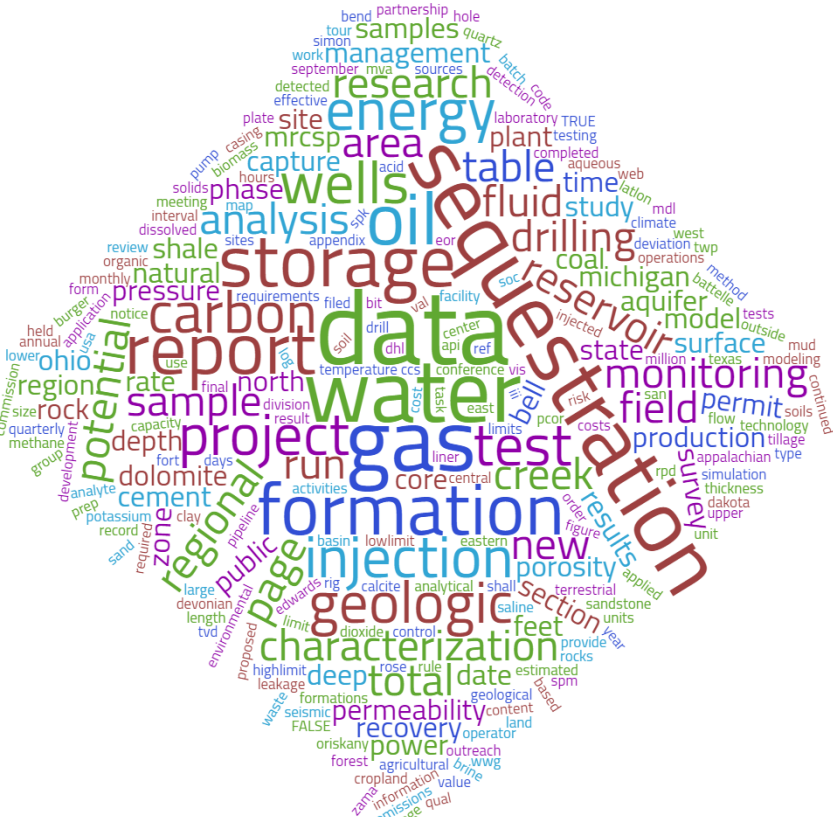
IBM's artificial intelligence was supposed to transform industries and generate riches for the company. Neither has panned out. Now, IBM has settled on a humbler vision for Watson.



<https://www.nytimes.com/2021/07/16/technology/what-happened-ibm-watson.html>

Synergy Opportunities

- Collaborative cross project technology
 - Use material same NLP tech
 - Using other NLP Models Louvian Community Detection

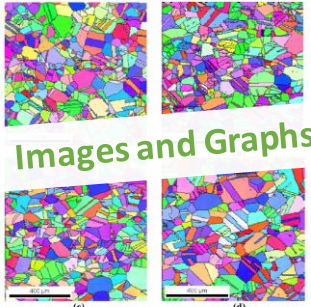


Supporting Data Collection, Curation & Analysis in Other Areas

Data mining, including...

Alloy (wt%)	N	C	Mn	Cr	Mo	Ni	Si
316LNSS-7N	0.00	0.027	1.7	17.53	2.49	12.2	0.22
316LNSS-11N	0.01	0.025	1.78	17.62	2.51	12.27	0.21
316LNSS-14N	0.14	0.025	1.57	17.57	2.53	12.15	0.2
316LNSS-22N	0.22	0.028	1.7	17.57	2.54	12.36	0.2

Structured Data



Images and Graphs

CT C	CS (MPa)	RT, hrs
593	310.3	1.45
593	275.8	5.5
593	275.8	6.33
593	206.8	55
593	171.7	357
593	144.8	1446
704		0.37
704	172.4	1.5
704	137.9	9.5
704	103.4	50.5
704	75.8	337
704	62.1	1227
816	103.4	0.75
816	89.6	1.87
816	68.9	12.75
816	48.06	84.3
816	36.5	331.8
816	29.0	1153

Measurements

Move & Convert...



...& use in predictive analytics for alloy behavior

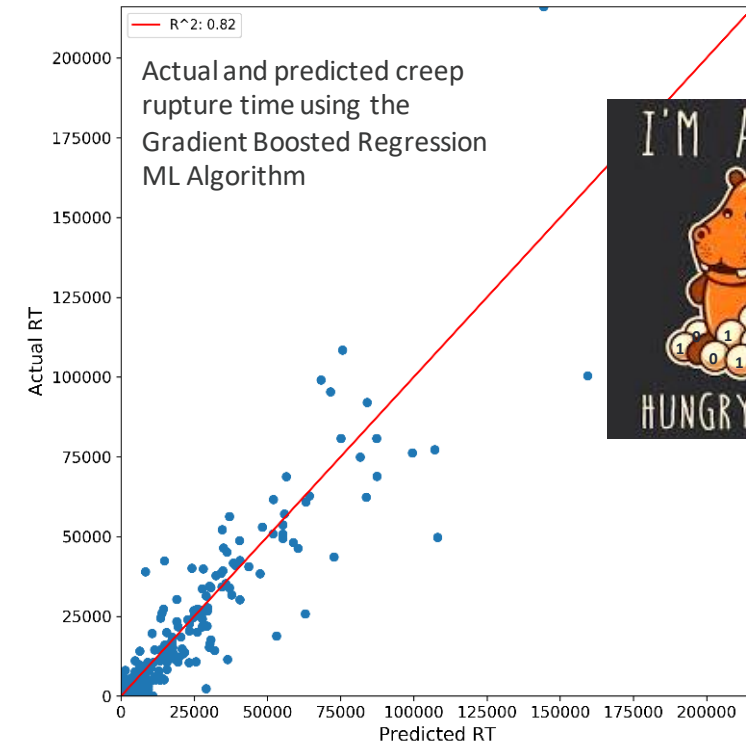


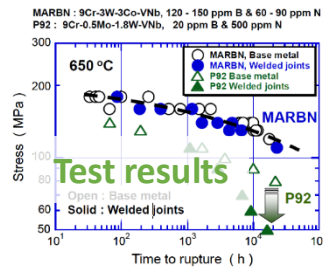
Fig. 4. Orientation mapping micrographs of solution annealed 316LN SS containing nitrogen (wt%) of 0.00, 0.01, 0.14, 0.22 and 0.22N. Newly revealed grain and annealing twins have been observed.

Materials data analytics for 9% Cr family steel

Vyacheslav N. Romanov, Narayanan Krishnamurthy, Amit K. Verma, Laura S. Bruckman, Roger H. French, Jennifer L.W. Carter, Jeffrey A. Hawk
 First published: 15 February 2019 | <https://doi.org/10.1002/sum.11406>
 U.S. Department of Energy, DE-FE0026685.

Read the full text >

Abstract
 A materials data analytics (MDA) method is used in this study to evaluate publicly available information on the mechanical behavior of 9% Cr family steels. The goal is to accelerate the design process by identifying key features and expense associated with performance in nuclear reactor applications. Data entries in the literature include alloy compositions, several processing parameters, and mechanical tests selected for this study were arranged in 34 classes. While detailed microstructural information was not available, it is assumed that the compositional space for the 9 to 12% Cr steels is limited such that all steel grades have a tempered martensitic microstructure during service. Establishing a hierarchy of first-order trends in the publicly available data requires the MDA to filter out the biases. Complexity of the phase transformations and microstructure evolution in the multicomponent alloys (using 21 chemical elements) with major influence on mechanical



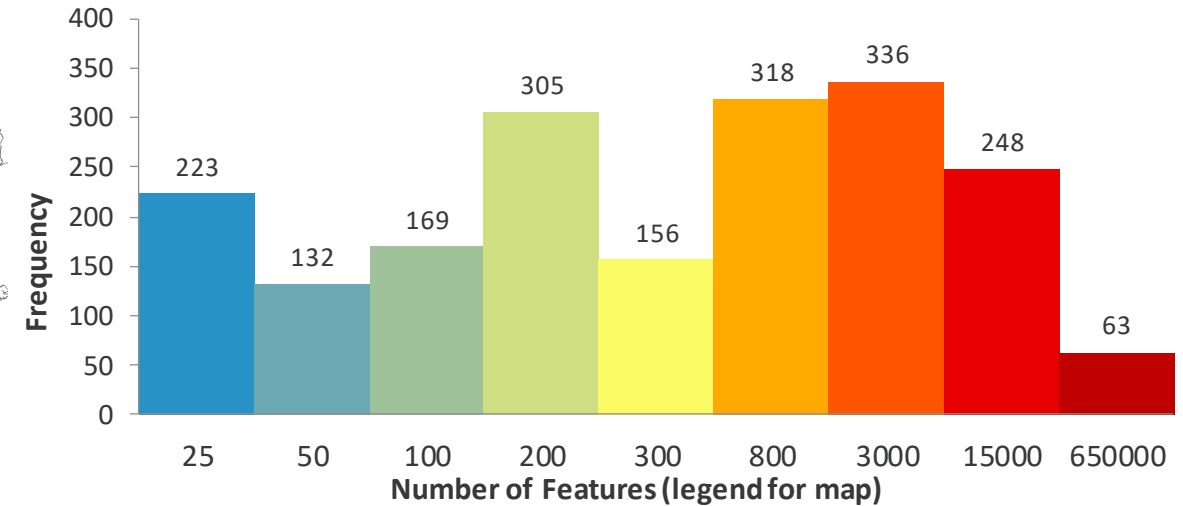
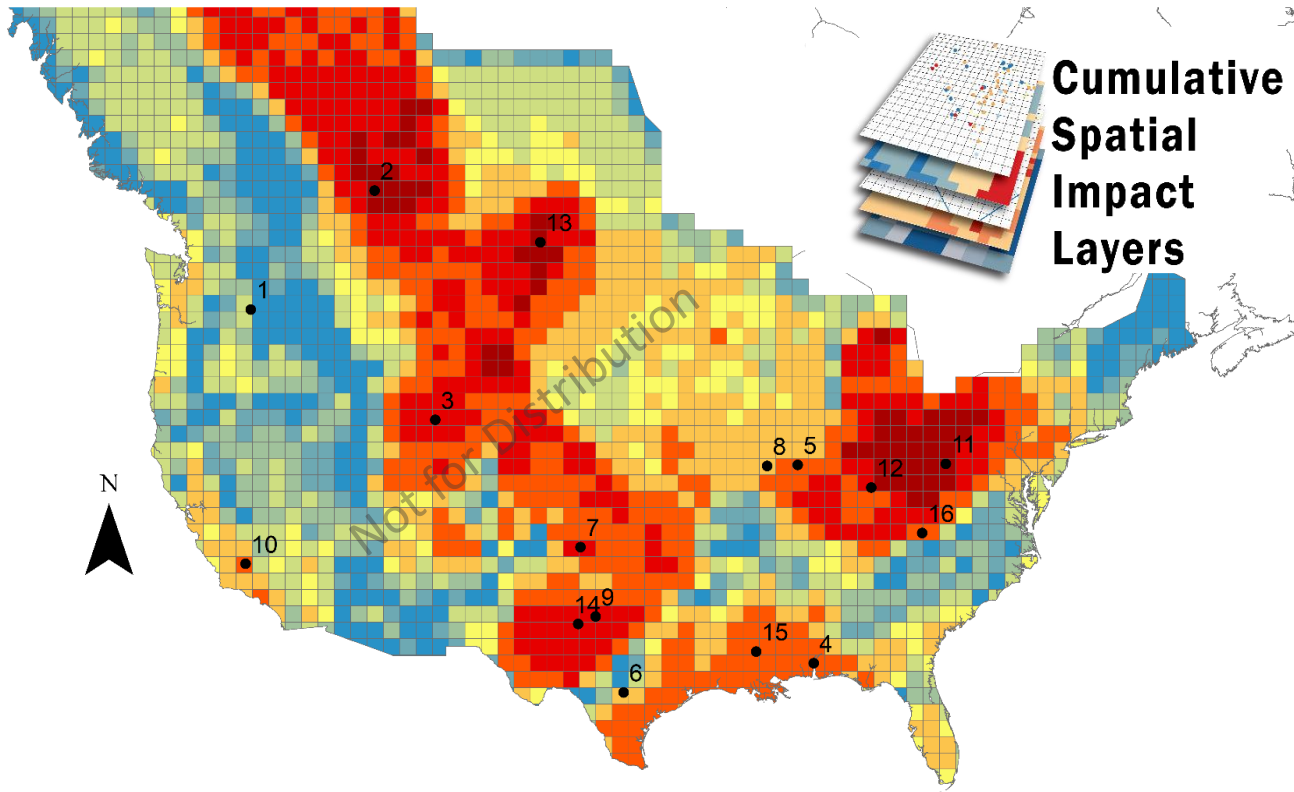
Test results

Evaluating machine learning models to:

- address data gaps
- identify key features in lifetime behavior of the alloy

Results: Spatio-temporal trends in CS data

Bringing together NatCarb, NRAP catalog and the Carbon Storage Open Database



CCS Projects Datasets Cataloged

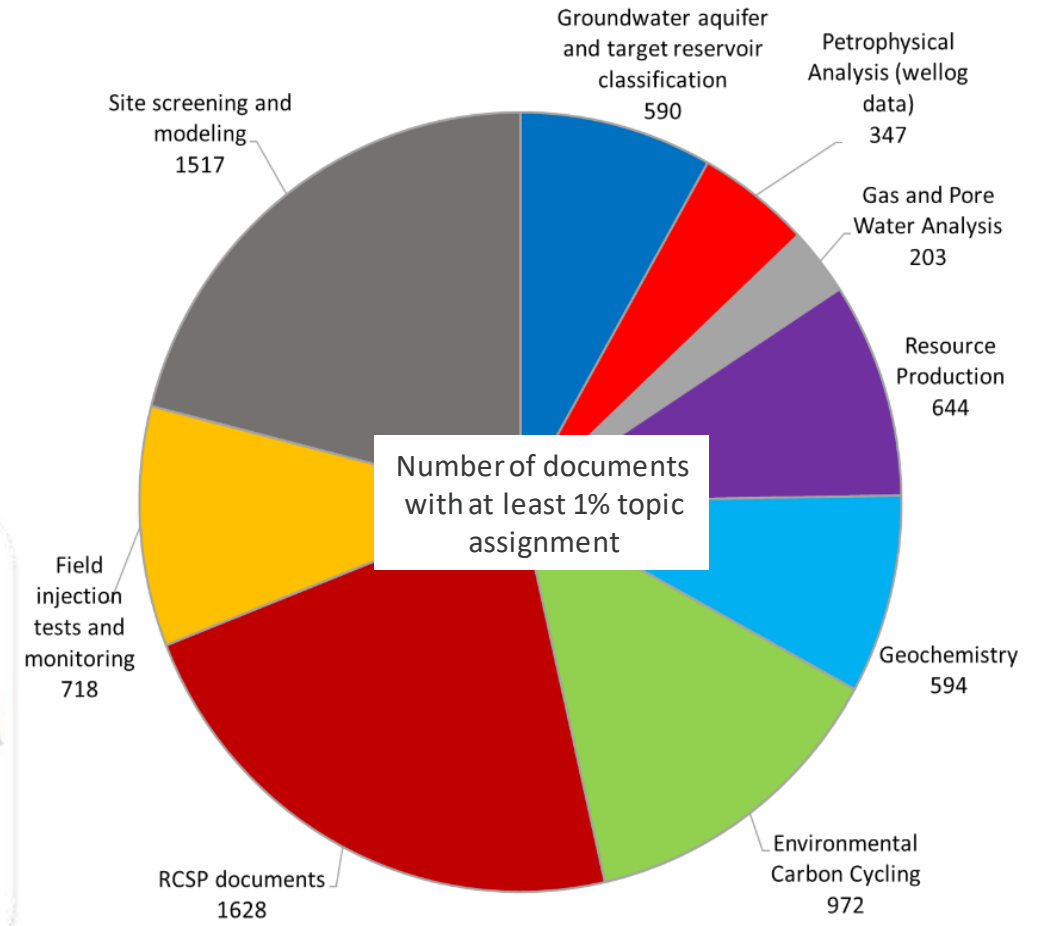
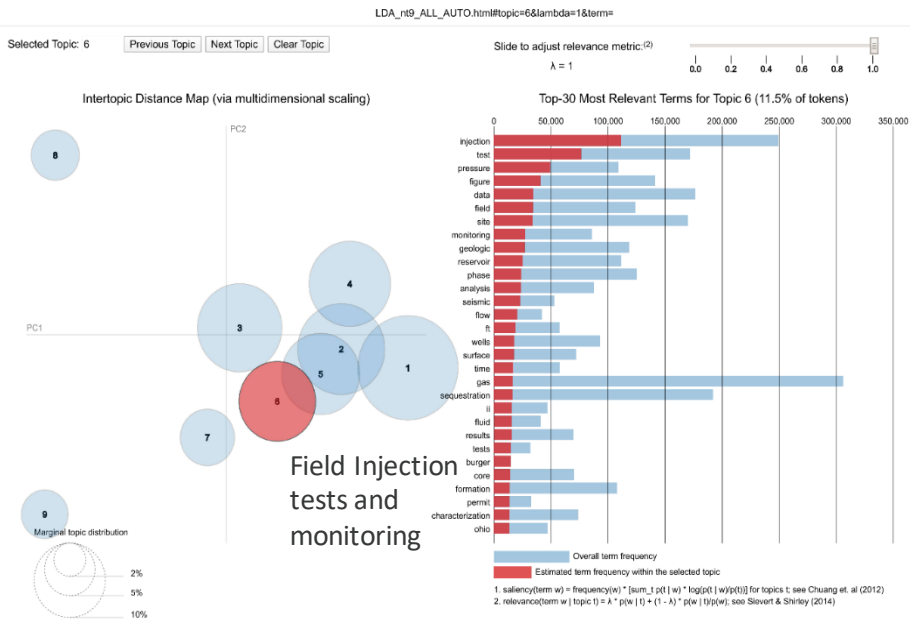
- | | |
|--|---|
| 1. Big Sky Validation Phase - Wallula Basalt Pilot Project | 9. High Plains Aquifer |
| 2. CAMi - Field Research Station | 10. Kimberlina (WESTCARB) |
| 3. CarbonSAFE - Wyoming | 11. Appalachian Basin Test (MRCSP) |
| 4. Citronelle (SECARB) | 12. Cincinnati Arch Test (MRCSP) |
| 5. Decatur | 13. Williston Basin Oil Field Test (PCOR) |
| 6. Edwards Aquifer | 14. Scurry Area Canyon Reef Operations |
| 7. Farnsworth - Anadarko Basin | 15. Cranfield Site (SECARB) |
| 8. FutureGen | 16. Central Appalachian Basin Test (SECARB) |

Morkner, P., Bauer, J., Creason, C., Sabbatino, M., Wingo, P., Greenburg, R., Walker, S., Yeates, B., and Rose, K., **in review**, Distilling Data to Drive Carbon Storage Insights, journal: *Computers & Geoscience*

Results: Natural Language processing

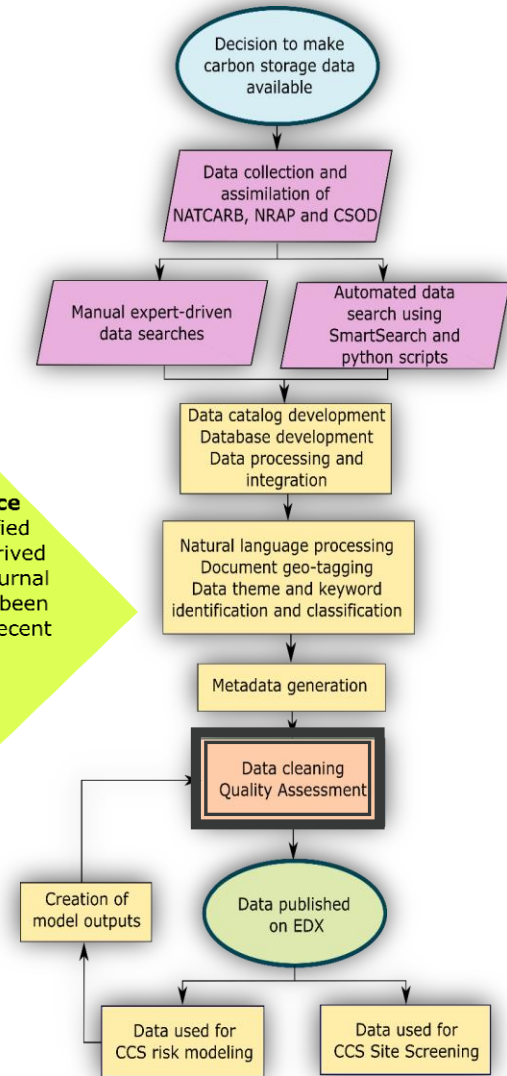
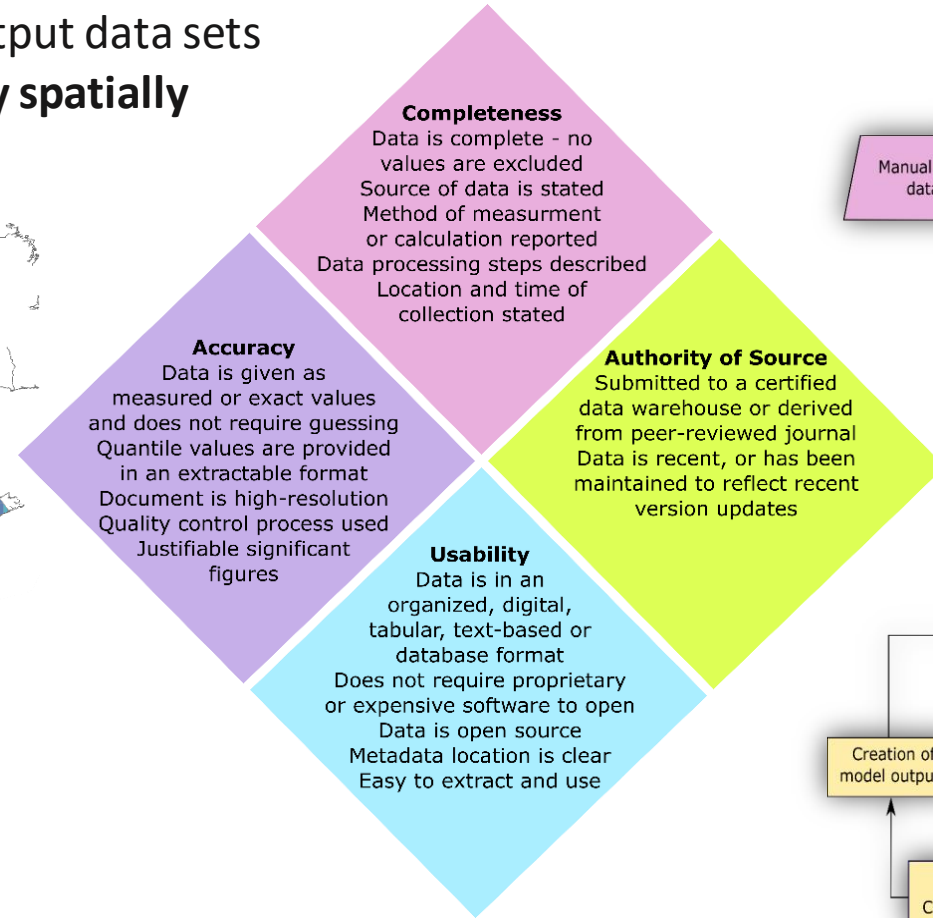
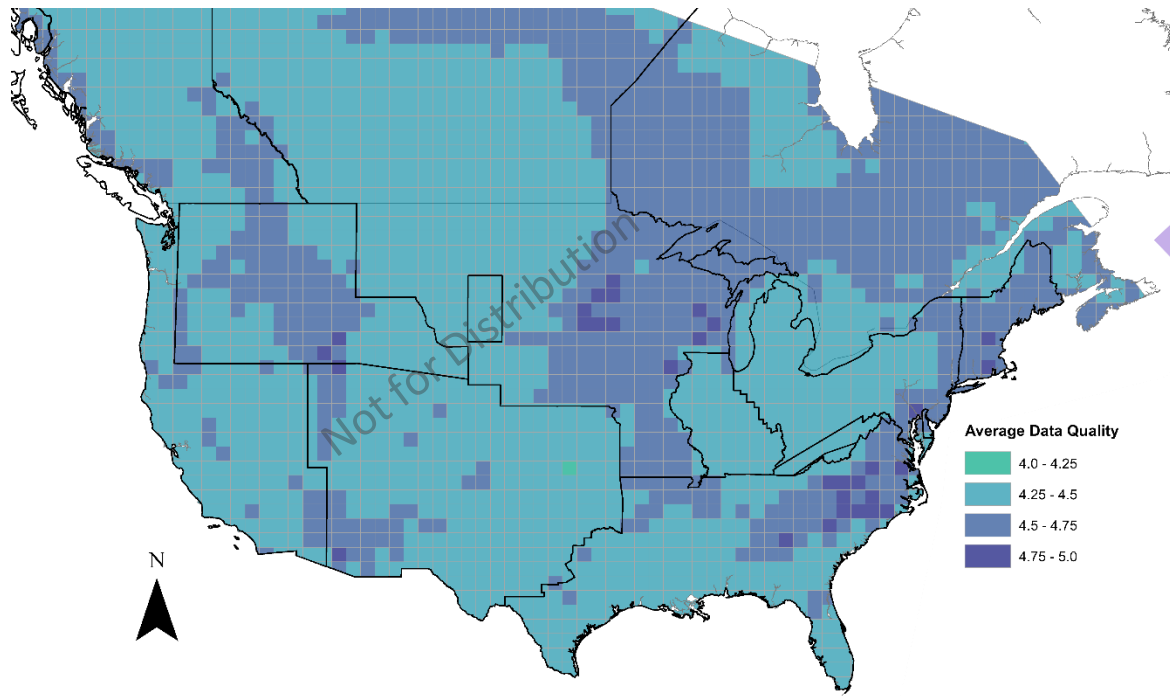
Keywords and geographic associations

- Produced a **9 topic LDA model** – grouping similar papers
- Produced **keywords** associated with resources
- Geographic location recognition
- Integration into EDX through



Results: Data Quality assessment method development and spatial trends in CS data quality

- 5-point data quality assessment method developed
- Quality based on **completeness, accuracy, usability, and authority of source**
- **Applicable to many subsurface data sets** and model output data sets
- Combined with CSIL can be **used to analyze data quality spatially**
- **Manuscript outlining method in prep**



Summary

FE and Carbon Storage program investments into data curation and management has led to the development of AI/ML tools and the preservation of millions of dollars of research products which benefits ongoing and future research. This has led to:

- A better understanding of CS relevant open- **data density** and **data quality** throughout US and Canada
- Improved access through the integration of CS data resources on EDX into **GeoCube**, **SmartSearch** and **SmartParse** (EDX version of NLP tools presented here) for further searchability with spatial searches and keyword searches
 - Updates to GeoCube for enhanced spatial searchability and integration of modeling tools to come
- EDX AI/ML data discovery, labeling, integration tool developments trained to support Carbon Storage, SMART-CS, and NRAP
 - Deployment of AI/ML algorithms to allow on-demand data discovery and integration, ready-made for each end-user needs



Next Steps

Carbon Storage program investments into data curation and management has led to the development of AI/ML tools and the preservation of millions of dollars of research products which benefits ongoing and future research. This has led to:

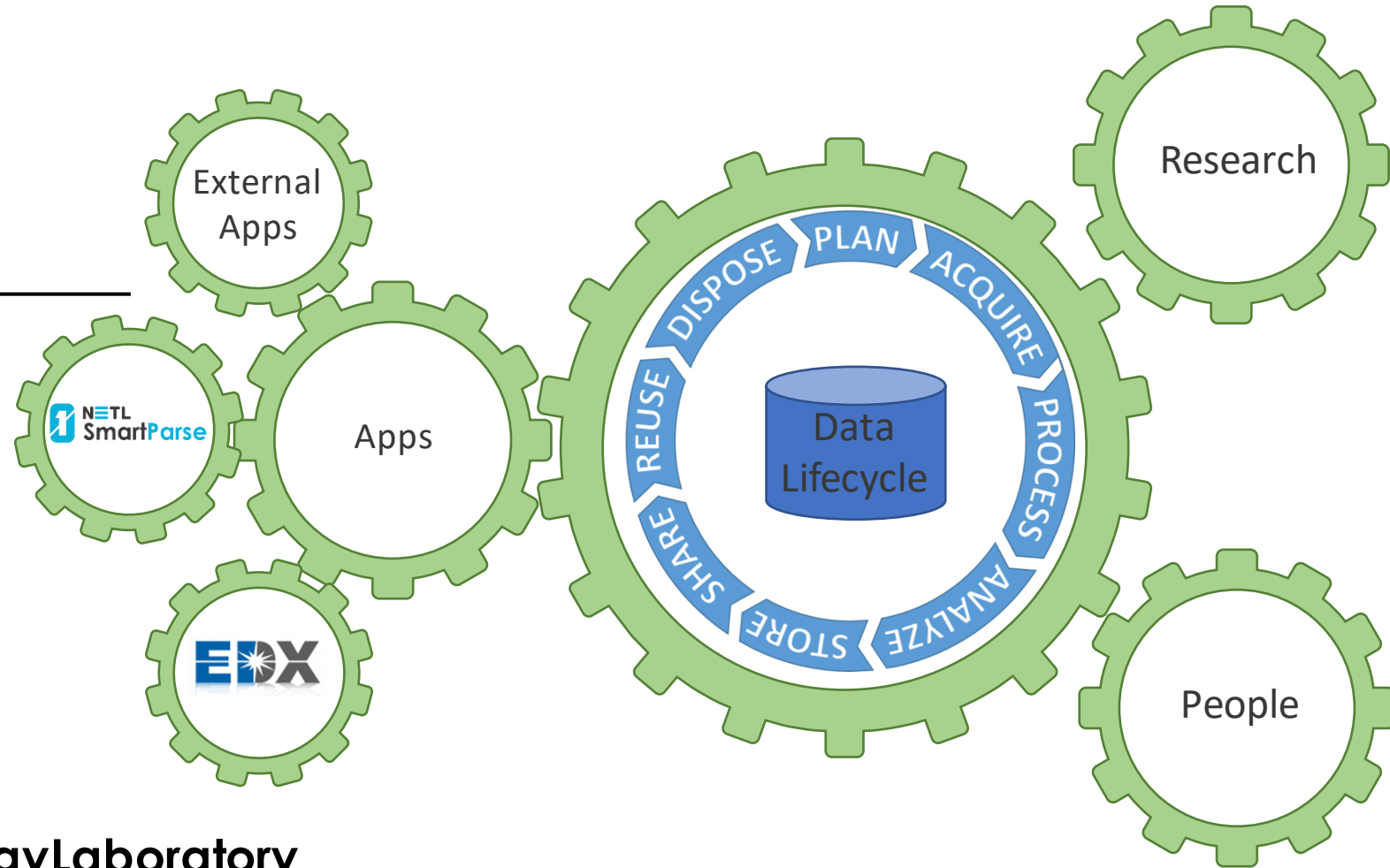
- Continue collecting and adding data to EDX, Geocube, and LivingDatabase
- Develop additional integrations between SmartSearch, SmartParse, and EDX
- Improve ML models and NLP analysis utilizing additional libraries, developing more training data, and applications
- Share and expand technology and data resources across NETL projects to improve and expand data curation



Thank you!

NETL RESOURCES

VISIT US AT: www.NETL.DOE.gov



CONTACT:

Michael Sabbatino and Paige Morkner

Michael.Sabbatino@netl.doe.gov, Paige.Morkner@netl.doe.gov

Appendix

- These slides will not be discussed during the presentation, **but are mandatory.**

Benefit to the Program

- Task 27 supports the development of data, materials, maps, analyses, and figures for the Carbon Storage Atlas, Natcarb Viewer, and Natcarb database. This includes release of new data insights to the GCS community, through the sixth edition of the Carbon Storage Atlas, and through bi-annual updates to the Natcarb Viewer and Natcarb database.
- Task 28 focuses on addressing CS R&D data curation challenges associated with ingesting, describing, and curating data products from DOE FE to [ensure enduring access and more efficient utilization of those resources using AI/ML enhanced approaches to support future CS R&D](#). Ultimately, this effort will result in tools, data resources, and virtual capabilities for the CSP and community to facilitate efficient CS data discovery, integration, and curation using NETL's EDX
- Use of EDX and development of tools to support the collection, curation, organization, labeling, and publishing large quantities of data for carbon storage. Whether laboratory, field, or computational, CS R&D is both a producer and consumer of data resources (datasets, tools, models, etc.). However, while the volume of open, online data is increasing exponentially, scientists struggle to find, access, and make operable data products from previous R&D projects due to insufficient and/or burdensome online data curation tools and outdated techniques.

Project Overview

Goals and Objectives

- Funded by DOE as part of Carbon Storage DE FE-1022465, Tasks 27 and 28
- RSS Contract and ITSS contract researchers
- Ongoing performance dates 2018-2022
- Project Participants
 - PI: Kelly Rose
 - LRST: Paige Morkner, Michael Sabbatino, Andrew Bean, Lucy Romeo, Patrick Wingo
 - ITSS: Chad Rowan, TJ Jones, Aaron Barkhurst, Vic Baker

Organization Chart

Carbon Storage Data

Project Partners

DOE
NETL
RCSPs – Big Sky Carbon Sequestration Partnership, Southwest Partnership, Southeast Regional Carbon Sequestration Partnership, Midwest Regional Carbon Sequestration Partnership, Midwest Geological Sequestration Consortium, Plains CO2 Reduction Partnership.

Lead Organization

NETL

Principal Investigators

Kelly Rose, Jennifer Bauer

Task 27.0

Next Generation Development, Deployment, and Modernization of Database, Tools, Online Viewer, and Atlas

Lead: Jennifer Bauer

Contractors: **Paige Morkner**, Michael Sabbatino, Patrick Wingo, Andrew Bean, TJ Jones, Aaron Barkhurst, other Matric Software Engineers and Developers

Task 28

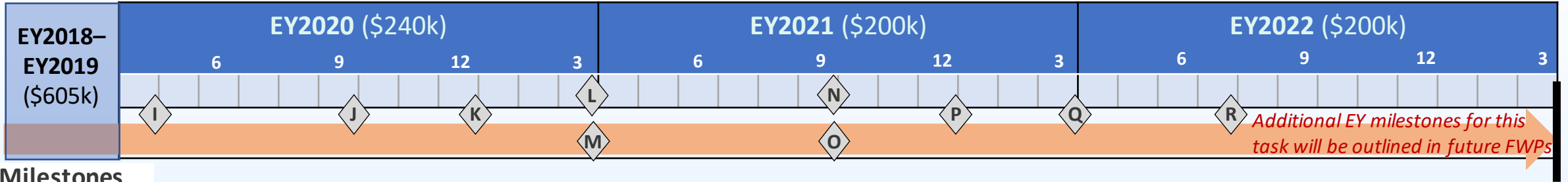
Curation of Carbon Storage R&D Products Through Advanced Data Computing Solutions

Lead: Jennifer Bauer

Contractors: **Chad Rowan**, **Michael Sabbatino**, Paige Morkner, Andrew Bean, Lucy Romeo, TJ Jones, Aaron Barkhurst, Vic Baker, Other Matric Software Engineers and Developers

Task 28.0: Project Timeline Overview

Curation of Carbon Storage R&D Products Through Advanced Data Computing Solutions
(PIs: Michael Sabbatino, Jennifer Bauer)



Milestones

Number	Expected Completion Date	Milestone Description
EY20.28.I	04/30/2020	Push to public on EDX appropriate MGSC Partnership data products.
EY20.28.J	09/30/2020	Deploy LivingDatabase beta version capability in EDX, private side, for CS teams (e.g., RCSPs) use and testing.
EY20.28.K	12/31/2020	Integration of CSP data products that are spatially related through enhanced EDX spatial search and discovery tool on GeoCube.
EY20.28.L	03/31/2021	Deploy NETL SmartSearch version 2 algorithm in EDX to support automated gathering of open, CS relevant data.
EY20.28.M	03/31/2021	Deploy LivingDatabase version 1 capability in EDX, private side, for CS teams (e.g., RCSPs) use and testing.
EY21.28.N	09/30/2021	Develop and test SmartSearch and SmartParse beta integration.
EY21.28.O	09/30/2021	Complete testing of Living Database dashboard tools.
EY21.28.P	12/31/2021	Create additional training data for SmartParse image, graph, and table extraction model improvement.
EY21.28.Q	03/31/2022	Develop beta Living Database user interface and dashboard.
EY22.28.R	07/29/2022	Ingestion and push to public on EDX appropriate SW Regional Partnership data products.

Chart Key

- ◆ Milestone
- █ Project Completion
- █ Go/No-Go Timeframe

Key Accomplishments/Deliverables

- 2018–Present, Addition of **Big Sky**, **PCOR**, Midwest CS Partnership, SECARB, and MGSC data and resources on EDX, for a combined total of 3,037 and 1.64 TB of data
- 2018–2020, Big data computing cluster, Watt, set up and work to directly link EDX with these computing capabilities
- 2019–2021, Test and validate SmartSearch for use with commercial cloud & EDX to evaluate capabilities to assimilate relevant CS data; including work as part of an NDA with Google and collaboration with DOE-HQ OCIO
- 2020–2021, Develop Living Database logic to host and store large volumes of CS data
- 2021–2022, Deploy beta instance of Living Database front end and dashboard tools
- 2022, Addition of any final RCSP and other CS resources to EDX

Value Delivered

- Collecting, curating, and cataloging** data from all regional CS partnerships and open-sources.
- Developing capabilities** to query curated data.
- Delivering** EDX's public-private capabilities, including growing access to its **big data computing cluster** and **Amazon Web Services (AWS) cloud services**, seek to facilitate more effective research for **DOE-FE subsurface scientists**.
- Pairing EDX hosted CS data resources and products with other online capabilities**, data, custom ML algorithms and capabilities to enhance user experience and provide research teams with the resources needed to make subsurface energy research more efficient, reduce redundancy, and drive innovation.

* Task 28.0 is integrating data into an existing tool with no development of a technology. Therefore, no TRL is assigned.

Bibliography

- List peer reviewed publications generated from the project per the format of the examples below.
- Morkner, P., Bauer, J., Creason, C., Bean, A., and Rose, K., “A Data Quality Assessment Method to Support Carbon Storage,” in preparation . Target journal: *Nature Scientific Data*. (Tasks 27.0, 28.0)
- Morkner, P., Creason, C., Sabbatino, M., Wingo, P., DiGiulio, J., Jones, K., Greenburg, R., Bauer, J., and Rose, K., “Distilling Data to Drive Carbon Storage Insights,” accepted pending final revisions, *Computers and Geosciences*. (Tasks 27.0, 28.0)
- Barkhurst, A., Morkner, P., Bauer, J., Rose, K. GeoCube, TRS report, in prep, target completion Fall 2021.