



### Overview

- Progress on Enterprise Metadata Inventory
- Review of Past Topics
- Data Management Workgroup Goals/Strategy
- More Immediate Goal Agency Data Sharing
- Record Linkage
- Next Topics



## Progress on Enterprise Metadata Inventory

- Aggregation of ingress and egress technologies
- Multiple lines for ingress and egress
- High level overview of dataset/application function use
- Key entities represented in dataset/concepts in reports for instance
- Any questions and/or suggestions?

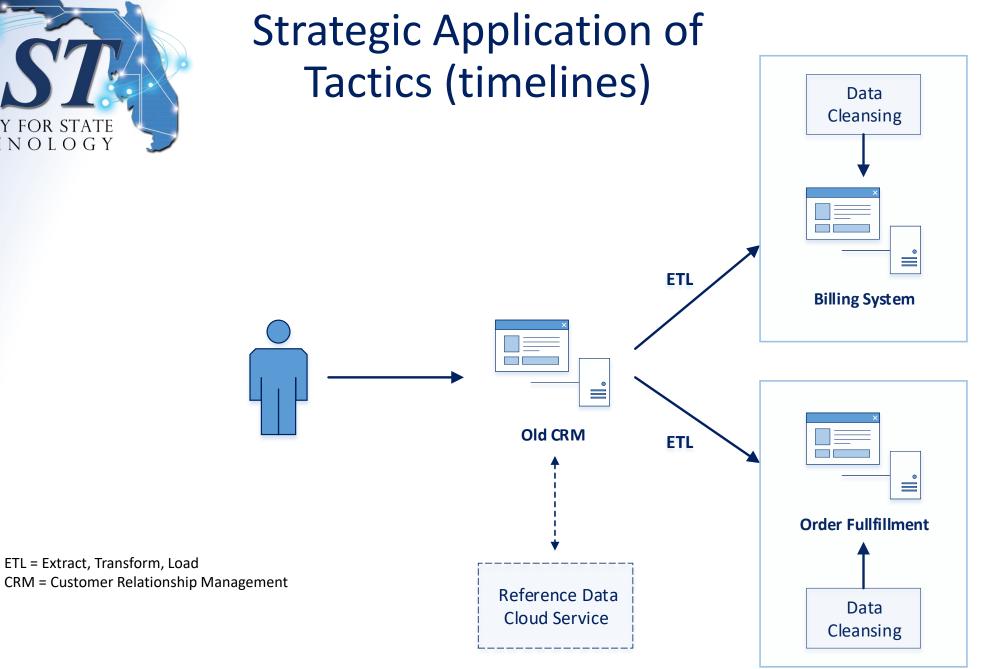


## **Review of Past Topics**

- Key Dataset Identification/Key Reports
- Data Quality and Metrics
  - Do you have a quality process in place?
  - Is it quantitative or qualitative, or both?
  - Is quality monitored?
  - Is there a remediation strategy?



ETL = Extract, Transform, Load





## **Review of Past Topics**

- Variety of Tools (Open Source/Commercial/Cloud Based)
  - Do you have data quality tools?
  - Did you have an opportunity to use any of the demonstrated tools?
  - Are you planning on acquiring tools?
  - How can we help?
- Would a survey (and report) of existing tools used at agencies be valuable?



## **Review of Past Topics**

- Data Lineage
  - Do you know the source of the data?
  - How many steps back?
- Memorandum on Understanding (MOU) / Data Use License (DUL)



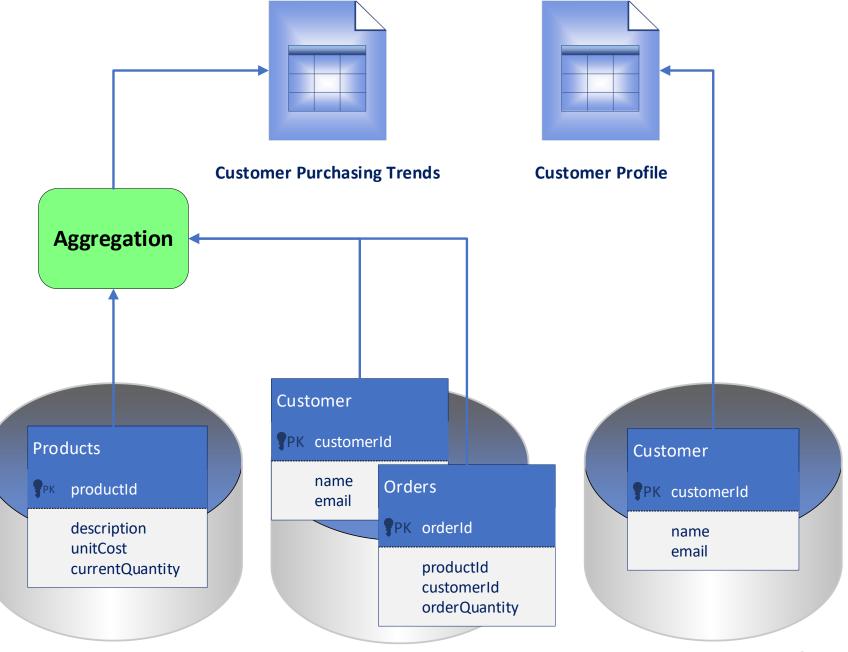
## **Review of Past Topics**

### Performance Measure/Risk Management

- How do we know we are doing well?
  - (Key Performance Indicators)
- What things should be on our problem radar?
  - (Key Risk Indicators)
- Is this data conveyed to management mostly by reports?



# Data Lineage for Reporting





## Data Lineage Mapping

Report	Field (Concept)	Data Source Type	Source Field	Description
Customer Retention	Years Retained	Aggregate (SQL)	DB.Table.field	Number of years person retained as a customer
Customer Retention	Expenditures by Year	Aggregate	DB Stored Procedure Name	Expenditures (USD) per year for each year the person is retained as a customer
Customer Retention	Geographic Region Map	GIS	CRM	Geospatial data store



### **Review of Past Topics**

Report Data Source Mapping

- Is report data quality important?
- Can you guarantee quality if asked?
- Do you have control of the quality? Where is the true source?
- Is it important to map sources to report entities?
- We can help with any mapping!



## Data Management Workgroup Goal

Establish and promote data management standards to ensure the responsible use and full power of the state's data so it can be used to serve the citizens of Florida.



#### **Data Governance**

"Data Governance is a quality control discipline for managing, using, improving and protecting organizational information. Effective data governance enhances the quality, availability, integrity, and protection of a company's data by fostering cross-organizational collaboration and structured policymaking."

- IBM





## Data Management Workgroup Strategy

- Discuss data management topics and generic best practices
- Assess the current maturity level
- Understand each agency's particular needs
- Develop improvement plans
- Serve agencies in the plan execution/governance
- Memorialize shared consensus on best practices as standards



## What is Currently Ahead of Us

- Enterprise Data Inventory (living document)
- Convenience of dataset discovery
- Convenience of data sharing between state agencies
- Context for data and improved quality
- Tools, tools, tools
- Serving the citizens of Florida!



## **Agencies Leveraging State Data**

### **Data Catalog**



### **MOUs**

Data Use Agreements (Data Use Licenses)

### Searchable Metadata

(for agencies only)

Data Quality
Record Linkage
& Privacy-Protected
Record Linkage

Techniques & Tools









# **Data Quality**

If data has value in a certain context, then it may be an indication that more rigorous data quality rules are required.

#### **Data Quality Problems**

- Data entry errors
- Missing integrity constraints (e.g., age = 345)
- Multiple conventions for data input
- Multiple entries for the same object
- Data tables not normalized
- Systematic conflicts between Database
   Management Systems (DBMS)

### **Implications of Data Quality Problems**

- Data integration efforts compromised
- Data migration efforts stalled
- Disjointed & fragmented reporting sources
- Inefficient / ineffective business processes
- Impact to delivery of services and benefits
- Missed information → missed opportunities



## Deduplication/Record Linkage

- What are the key entities/concepts that drive business?
- What constitutes a duplicate (key fields)?
- Are the fields the same as the measured data quality fields?
- Do you meet the same expectations of quality over multiple data sets?
- Are certain fields more important?
- Does the entity (concept) span tables or data stores?
- How do we "measure" similarity?

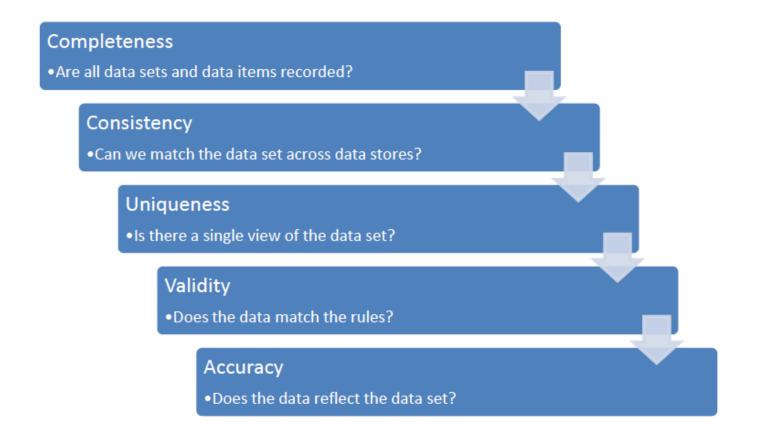


# **Data Quality**

### Dimensions & Measurements for Data Quality Assessment

#### **Data Quality Dimensions**

Describe a feature (characteristic, attribute or facet) of data that can be measured or assessed against defined standards in order to determine the quality of data.





# Data Quality Assessment Dimensions & Measurements

**Source:** Askham, N., Cook, D., Doyle, M., Fereday, H., Gibson, M., Landbeck, U., ... & Schwarzenbach, J. (2013). The six primary dimensions for data quality assessment. DAMA UK Working Group, 432-435.

Title	Uniqueness
Definition	No thing will be recorded more than once based upon how that thing is
	identified.
Reference	Data item measured against itself or its counterpart in another data set or
	database.
Measure	Analysis of the number of things as assessed in the 'real world' compared to
	the number of records of things in the data set. The real world number of
	things could be either determined from a different and perhaps more reliable
	data set or a relevant external comparator.
Scope	Measured against all records within a single data set
Unit of Measure	Percentage
Type of Measure:	Discrete
<ul> <li>Assessment</li> </ul>	
<ul> <li>Continuous</li> </ul>	
<ul> <li>Discrete</li> </ul>	
Related dimension	Consistency
Optionality	Dependent on circumstances
Example(s)	A school has 120 current students and 380 former students (i.e. 500 in total)
	however; the Student database shows 520 different student records. This
	could include Fred Smith and Freddy Smith as separate records, despite there
	only being one student at the school named Fred Smith.
	This indicates a uniqueness of 500/520 x 100 = 96.2%
Pseudo code	(Number of things in real world)/(Number of records describing different
	things)
External Validation	IAM Asset Information Quality Handbook
	Principles of Data Management, Keith Gordon



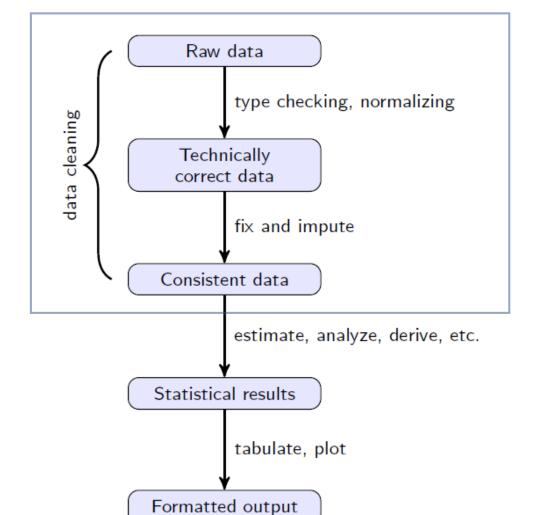
# Data Quality Assessment Dimensions & Measurements (example dataset)



Age Entry Errors

rowID	firstName	lastName	age	si:reet	apt	city	state	zip	ssn
					арс	•			
R01	John	Willams	38	643 Gulf Ln		Half Moon Bay	CA	94013	A2B-4C-678D
R02	Richard	Alpert	151	15 Black Rock St		Cannon Beach	OR	97110	A3B-5C-78D1
R03	Ana Lucia	Cortez	39	48 Ocean Park Ave		Santa Monica	CA	90405	A4B-6C-891D
R04	Joh	Williams	42	642 Gulf Lane		Halfmoon Bay	CA	94013	A2B-4C678D
R05	Daniel	Faraday	48	23 Martin St		Essex	MA	01929	A5B-7C-9123
R06	Jonathan	Williams	42*	643 Gulf Lane		Half Moon Bay	CA	94013	A2B4C-678D
R07	Penny	Widmore	43	1623 Hawthorne Road		Palos Verdes	CA	90275	A6B-8C-123D
R08	Austen	Kate	38	1516 Ontario Street		Ames	IA	50014	A78-9B-234D
R09	John	William	47	403 Stadium Dr	B-005	Tallahassee	FL	32304	A2B4C678D
R10	Benjamin	Linus	63	815 Oceanic Ave		Portland	OR	97205	A8B-C2-345D







# Data Preprocessing & Cleaning with R

Figure 1: Statistical analysis value chain



# Data Quality Assessment Dimensions & Measurements (data cleaning with R)



### (1) From Raw Data to "Technically Correct" Data

Table 1: Steps to take when converting lines in a raw text file to a data. frame with correctly typed columns.

	Step	result
1	Read the data with readLines	character
2	Select lines containing data	character
3	Split lines into separate fields	list of character vectors
4	Standardize rows	list of equivalent vectors
5	Transform to data.frame	data.frame
6	Normalize and coerce to correct type	data.frame

```
(M <- matrix(
   unlist(standardFields)
   , nrow=length(standardFields)
   , byrow=TRUE))
## [,1] [,2] [,3]
## [1,] "Gratt" "1861" "1892"
## [2,] "Bob" NA "1892"
## [3,] "Emmet" "1871" "1937"
colnames(M) <- c("name","birth","death")
(daltons <- as.data.frame(M, stringsAsFactors=FALSE))
## name birth death</pre>
```

#### (2) Consistent Data

Missing values, special values, (obvious) errors, and outliers are either removed, corrected, or imputed (replaced with substitute values).

```
# numerical rules
age >= 0
height > 0
age <= 150
age > yearsmarried

* categorical rules
status %in% c("married","single","widowed")
agegroup %in% c("child","adult","elderly")
if ( status == "married" ) agegroup %in% c("adult","elderly")

# mixed rules
if ( status %in% c("married","widowed")) age - yearsmarried >= 17
if ( age < 18 ) agegroup == "child"
if ( age >= 18 && age <65 ) agegroup == "adult"
if ( age >= 65 ) agegroup == "elderly"
```



# Data Quality Assessment Dimensions & Measurements (data cleaning with R)



**Correct Age Errors** 

Normalize SSN Values (remove dashes)

rowID	firstName	lastName	age	street	apt	city	state	zip	ssn
R01	John	Willams	38	643 Gulf Ln		Half Moon Bay	CA	94013	A2B-4C-678D
R02	Richard	Alpert	151	15 Black Rock St		Cannon Beach	OR	97110	A3B-5C-78D1
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R07	Penny	Widmore	43	1623 Hawthorne Road	i	Palos Verdes	CA	90275	A6B-8C-123D
R08	Austen	Kate	38	1516 Ontario Street		Ames	IA	50014	A78-9B-234D
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# Data Quality Assessment Dimensions & Measurements (data deduplication with R)



Soundex codes and algorithms can be used to detect similarity.

soundex('Ann') == soundex('Anne') == 'A500'

rowID	firstName	lastName	age	street	apt	city	state	zip	ssn
R01	John	Willams	38	643 Gulf Ln		Half Moon Bay	CA	94013	A2B-4C-678D
R02	Richard	Alpert	151	15 Black Rock St		Cannon Beach	OR	97110	A3B-5C-78D1
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R08	Austen	Kate	38	1516 Ontario Street		Ames	IA	50014	A78-9B-234D
R09	John	William	47	403 Stadium Dr	B-005	Tallahassee	FL	32304	A2B4C678D
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The Soundex code for "John" is J500 ... for "Jonathan," J535... for "Joh," it's J000... for "ohn," it's O500\*.

<sup>\*</sup> The first letter of the code is simply the first letter of the word; otherwise, the Soundex algorithm will disregard vowels.



# Data Quality Assessment Dimensions & Measurements (data deduplication with R)



#### Soundex Codes and Algorithms

Wild Guess: M. D. Avila, male, born

Driver's License Analyzer: Florida Results	
Input	
Florida Driver's License Number: A	
Output	
First Name: M.  Middle Initial: D.  Last Name: Starts with a A, followed by a labial (B, F, P, or V), followed by a long liquid (L). Perhaps it sounds like "Aebele"  Last Name Guesses: Avila, Abel, Abel, Apple, Appel, Able, Apel, Avilla, Appell, Auvil, Abila, Abele, Abella, Avella, Apfel, Apolo, Avolio, Appello Avello, Abuhl, Ablao, Avola  Gender: male  Date of Birth:	Apollo, Abilay,

#### What is a Soundex code? - High Programmer

www.highprogrammer.com → Alan De Smet → Unique ID ▼
Soundex is a hashing system for english words. ... You might be interested in a history of various different versions of the Soundex coding system. ... So Pfizer becomes Pizer, Sack becomes Sac, Czar becomes Car, Collins becomes Colins, and Mroczak becomes Mrocak.



# Data Quality Assessment Dimensions & Measurements (data deduplication with R)



There are a number of other metrics that can be used to measure data closeness or similarity.

e.g., the Levenshtein Distance Algorithm (1965)

```
LevDistance <- function (str1, str2)
  if (typeof(str1) != "character" && class(str1) != "factor")
    stop(sprintf("Illegal data type: %s", typeof(str1)))
  if (class(str1) == "factor")
    str = as.character(str1)
  if (typeof(str2) != "character" && class(str2) != "factor")
    stop(sprintf("Illegal data type: %s", typeof(str2)))
  if (class(str2) == "factor")
    str = as.character(str2)
  if ((is.array(str1) || is.array(str2)) && dim(str1) != dim(str2))
    stop("non-conformable arrays")
  if (length(str1) == 0 || length(str2) == 0)
    return(integer(0))
  l1 <- length(str1)</pre>
  12 <- length(str2)
  out <- .C("levenshtein", as.character(str1), as.character(str2),
            11, 12, ans = integer(max(11, 12)), PACKAGE = "RecordLinkage")
  if (any(is.na(str1), is.na(str2)))
    out$ans[is.na(str1) | is.na(str2)] = NA
  if (is.array(str1))
    return(array(out$ans, dim(str1)))
  if (is.array(str2))
    return(array(out$ans, dim(str2)))
  return(out$ans)
LevDistance("John", "Jon")
```



# Data Quality Assessment Dimensions & Measurements (data deduplication with Python)



Temporal / Transient Data (addresses can change over time)

rowID	firstName	lastName	age	street	pt	city	state	zip	ssn
R01	John	Willams	38	643 Gulf Ln		Half Moon Bay	CA	94013	A2B-4C-678D
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# Data Quality Assessment Dimensions & Measurements (data deduplication with Python)



**Emphasis of Business Rules** 

rowID	firstName	lastName	age	street	apt	city	state	zip	ssn
R01	John	Willams	38	643 Gulf Ln		Half Moon Bay	CA	94013	A2B-4C-678D
R02	Richard	Alpert	151	15 Black Rock St		Cannon Beach	OR	97110	A3B-5C-78D1
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Business rules tell us that SSN represents the strongest indicator of similarity (duplication).



# Data Quality Assessment Dimensions & Measurements (data deduplication with Python)



Soundex functions

Temporal Data

**Business Rules Emphasis** 

rowID	firstName	lastName	age	street	apt	city	state	zip	ssn
R01	John	Willams	38	643 Gulf Ln		Half Moon Bay	CA	94013	A2B-4C-678D
R02	Richard	Alpert	151	15 Black Rock St		Cannon Beach	OR	97110	A3B-5C-78D1
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Putting it all together—with an understanding of the primary business rules—increases the confidence level for finding duplicate records in the database.



# Data Cleaning & Deduplication



### RecordLinkage Python Package

```
# pandas is used for data manipulation.
# jellyfiish is needed for approximate string comparison and string encoding.
# numexpr is used to speed up numeric comparisons.
import pandas
import numpy
import scipy
import sklearn
import jellyfish
import numexpr
# Load the dataset
import recordlinkage
from recordlinkage.datasets import load_febrl4
dfA, dfB = load_febrl4()
dfA
indexer = recordlinkage.FullIndex()
pairs = indexer.index(dfA, dfB)
print (len(dfA), len(dfB), len(pairs))
```



# Data Cleaning & Deduplication



### RecordLinkage Python Package

```
# full code
import recordlinkage
from recordlinkage.datasets import load febrl4
dfA, dfB = load febrl4()
# Indexation step
indexer = recordlinkage.BlockIndex(on='given name')
pairs = indexer.index(dfA, dfB)
# Comparison step
compare cl = recordlinkage.Compare()
compare cl.exact('given name', 'given name', label='given name')
compare cl.string('surname', 'surname', method='jarowinkler', threshold=0.85, label='surname')
compare cl.exact('date of birth', 'date of birth', label='date of birth')
compare_cl.exact('suburb', 'suburb', label='suburb')
compare cl.exact('state', 'state', label='state')
compare cl.string('address 1', 'address 1', threshold=0.85, label='address 1')
features = compare cl.compute(pairs, dfA, dfB)
# Classification step
matches = features[features.sum(axis=1) > 3]
print(len(matches))
```



# Data Cleaning & Deduplication



### RecordLinkage Python Package

....

The comparing of record pairs starts when the compute method is called. All attribute comparisons are stored in a DataFrame with horizontally the features and vertically the record pairs. The first 10 comparison vectors are:

.....

features

		given_name	surname	date_of_birth	suburb	state	address_1
rec_id	rec_id						
rec-1070-org	rec-3024-dup-0	1	0.0	0	0	1	0.0
	rec-2371-dup-0	1	0.0	0	0	0	0.0
	rec-4652-dup-0	1	0.0	0	0	0	0.0
	rec-4795-dup-0	1	0.0	0	0	1	0.0
	rec-1314-dup-0	1	0.0	0	0	1	0.0
rec-2371-org	rec-3024-dup-0	1	0.0	0	0	0	0.0
	rec-2371-dup-0	1	1.0	1	1	1	1.0
	rec-4652-dup-0	1	0.0	0	0	1	0.0
	rec-4795-dup-0	1	0.0	0	0	0	0.0
	rec-1314-dup-0	1	0.0	0	0	0	0.0

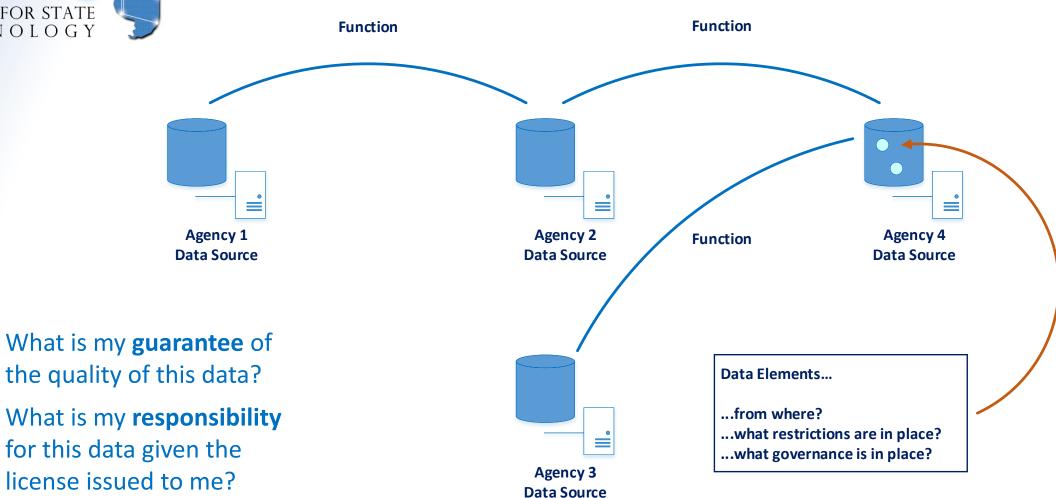


## Data Sharing Concerns (start for next meeting)

- Do you know the lineage of your data?
- Do you know the quality of every key data element? Even data from other sources?
- Should there be an expectation of quality for the data being received?
  - Is there a definition of quality?
  - Is the data fit for purpose?
  - Does the data include metadata for context?
- Who should be responsible for data misuse?



### Why Share Data





## **Data Sharing Agreements**

- Should the process to create these be formalized?
- What are you licensing?
  - Behavior
  - Responsibility (in both directions)
- Are you making an assessment of the data sharing party?
  - Is this context driven?
  - Are there certain licensed attributes of the party?



### **Data Sharing Agreements**

- Purpose for using the data
- Justification (rationale) for issuance of license
- Licensing entity / certifications
- Audit and disclosure requirements
- Indemnification
- Limitation of liability
- Requirements for data provider (e.g., data quality, data formats, timeliness)



### **Next Topics**

- Inter-agency approaches to data sharing
- Sunshine law Chapter 119, Florida Statutes
- Enabling Act: Florida Statutes, Sections 163.61-.64 (2017) permitting governmental agencies within Florida to participate in "collaborative client information systems" like the IDS
- Privacy Rules and Regulations (HIPPA, FERPA, DPPA, GDPR)
- Privacy Preserving Record Linkage
- What should the structure of an MOU/DUA/DUL be and can we streamline the process?



## References

Elmagarmid, A. K., Ipeirotis, P. G., & Verykios, V. S. (2007). Duplicate record detection: A survey. IEEE Transactions on knowledge and data engineering, 19(1), 1-16. Retrieved April 27, 2018 from the Purdue University, Department of Computer Science website, <a href="https://www.cs.purdue.edu/homes/ake/pub/TKDE-0240-0605-1.pdf">https://www.cs.purdue.edu/homes/ake/pub/TKDE-0240-0605-1.pdf</a>

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Florida Department of State. (2012). Address Confidentiality Exemption Request Form Revised 08-2012 (2), Public Records Exemption Request to the Florida Department of State. Retrieved May 2, 2018 from the Florida Department of State website, <a href="http://dos.myflorida.com/media/696331/dos119-public-records-exemption-form.pdf">http://dos.myflorida.com/media/696331/dos119-public-records-exemption-form.pdf</a>

