

CS513: Theory & Practice of Data Cleaning Final Project

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Abstract: This report describes a data cleaning workflow using the New York Public Library Rare Books Division historical menus dataset as an example to demonstrate various cleaning techniques. This project will use the following software and tools to clean and organize the dataset: OpenRefine, SQLite, and YesWorkflow.

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1. Dataset Overview and Initial Assessment

For the project, we use tools introduced in CS513 to clean and prepare a sample dirty dataset. Along the way we will document the steps from dirty to clean. The sections that follow describe this process in detail: (2.) Data cleaning with OpenRefine, (4.) Develop Rational Database Schema, and (5.) Create a Workflow Model.

An initial assessment of the New York Public Library dataset (referred to now forward as ‘NY menus’ dataset) is over 45,000 historical menus. The majority of these were organized by Frank E. Buttolph ([Ref1](#)) around 1900-1921. The dates on the menus range from the 1850s to 2010s. The data contains information on restaurant menu, but also other organizations like railroad or shipping companies. The dataset was digitized in 2011 via the “What’s on the Menu?” project ([Ref2](#)). So far 17,500 the libraries’ historical menus have been digitized. We are using the June 17, 2017 version for this project.

The data is in four files: Menu, MenuPage, MenuItem, and Dish. The ‘Menu.csv’ file has a unique id number, location information, venue, currency used, and other description-based information. The ‘MenuPage.csv’ file contains the id, plus an additional unique menu_id, image_id, height, width, and another with other image related information. The ‘MenuItem.csv’ file contains the id, plus an additional_page_id, dish_id, and other price related information for each dish. The ‘Dish.csv’ file contains the id, name of the dish, description, first/last appearance, and various price information.

A detailed description of each file’s columns follows:

Menu.csv

id: unique id for this menu

name: name on menu, name of the restaurant, or blank

sponsor: sponsor, often the name of the restaurant

event: name of the meal or the event the menu was created for
venue: location where the food is served
place: often includes city, state, country, address, or name of venue
physical description: paper stock, dimensions, colors, design, etc. of menu
occasion: special occasion, holiday, daily, or blank
notes: additional details about the menu
call number: number within the NYPL collection
keywords: keywords on menu
language: language the menu is printed in
date: date the menu was collected, formatted as a string as YYYY-MM-DD
location: where the menu was used
location type: type of the location value
currency: money type charged for items on this menu
currency symbol: symbol for the currency
status: the digitization status of this menu – complete or under review
page count: number of pages on the menu
dish count: number of dishes on the menu

MenuPage.csv

id: unique designator for this menu item
menu id: specific id for menu
page number: page number in the menu
image id: a unique id for the scanned image of this menu, accessible on the NYPL site
full height: height of menu
full width: width of menu
uuid: another unique id for this page/image

MenuItem.csv

id: unique designator for this menu item
menu page id: id of the menu page that this item appears
price: the cost of the smallest portion of this item
high price: cost of the largest portion of this item
dish id: designator id of the dish that this menu item refers
created at: date/time that this database entry was created
updated at: the most recent date the database entry was updated
xpos: x-axis position of the item on the scanned image
ypos: y-axis position of the item on the scanned image

Dish.csv

id: a unique designator for this dish
name: the name of this dish
description: a description of this dish, always blank
menus appeared: number of menus this dish appears on
times appeared: number of times this dish appears (including additional sections)
first appeared: year this dish first appeared (also can be: 0, 1, or NA)
last appeared: year this dish last appeared (also can be: 0, 1, 2928, or NA)

lowest price: lowest price that this item was sold for
highest price: highest price that this item was sold for

Some hypothetical use cases for a dataset like this could be – How has the composition of restaurants changed over time? The density, clusters, or price changes? Can a model be made to predict food prices in certain areas? How have consumer food preferences changed over time? Can a model be made to estimate food prices based on ingredients/description?

The problem with answering all these questions is - the dataset is quite messy and need to be organized. For example, the date columns seem full of repeat or missing dates. However, some files are cleaner than others; we are not choosing to clean MenuPage.csv, as it is clean enough.

How clean does the dataset need to be? You can sort the columns and get some sense of the composition of the data, but there will need to be some prep work to answer practical questions. Having the data broken into multiple files makes it hard to compare across sheets. However, this format should be a straight forward to import into the SQL database.

Progress throughout his project can be tracked at our github repository ([Ref3](#)) and this associated webpage ([Ref4](#)). This platform was mostly used to aid in our team collaboration, but also provides a way to share our data cleaning techniques with a wider audience outside of this class.

2. Data cleaning with OpenRefine

OpenRefine, formally called Google Refine, is an open source desktop application the has many helpful features for data cleaning. It behaves like a database with rows and cells under columns which are similar to relational database tables. An OpenRefine project itself consists of one table. I plan to clean each of the four data file separately, some more than others as needed.

The major OpenRefine feature that will be helpful in cleaning our dataset is the clustering feature. The option allows the user to cluster similar text and replace it with a more standardized description. The common problem this solves the many variants of spelling but reference the same object.

The following subsections will describe the step-by-step process from input file to output file. We will use UTF-8 encoding.

2.1 Menu.csv Cleaning

Input File: Menu.csv

For column: sponsor

- (1) Trim leading and trailing white spaces
- (2) Collapse consecutive white spaces
- (3) Convert all column values to upper case
- (4) Remove special characters using GREL (`%`, `#`, `!`, `/`, `(`, `)`, `[`, `]`, `?`)
- (5) Replace “,” with a space instead and then trim leading/trailing white spaces

- (6) Make a facet and perform the cluster operation using the key-collision method and fingerprint function. Next merge the selected clusters.
- (7) Repeat the previous step with n-gram, fingerprint, meta-phone3, and cologne-phonetic methods.
- (8) Create a new facet. Next, use the cluster operation nearest neighbor method and levstein distance function. Then, merge the selected clusters.
- (9) Create a new facet. Next, use the cluster operation nearest neighbor method and PPM distance function. Then, merge the selected clusters.

Cluster & Edit column "sponsor"

This feature helps you find groups of different cell values that might be alternative representations of the same thing. For example, the two strings "New York" and "new york" are very likely to refer to the same concept and just have capitalization differences, and "Gödel" and "Godel" probably refer to the same person. [Find out more ...](#)

Method **key collision** Keying Function **fingerprint** **223 clusters found**

Cluster Size	Row Count	Values in Cluster	Merge?	New Cell Value
8	24	<ul style="list-style-type: none"> RED STAR LINE - ANTWERPEN - NY (7 rows) RED STAR LINE - ANTWERPEN NY (6 rows) RED STAR LINE - ANTWERPEN -NY (5 rows) RED STAR LINE -ANTWERPEN NY (2 rows) RED STAR LINE -ANTWERPEN - NY (1 rows) RED STAR LINE -ANTWERPEN -NY (1 rows) RED STAR LINE- ANTWERPEN -NY (1 rows) RED STAR LINE- ANTWERPEN NY (1 rows) 	<input checked="" type="checkbox"/>	RED STAR LINE - ANTWERPEN -
6	667	<ul style="list-style-type: none"> NORDDEUTSCHER LLOYD BREMEN (630 rows) 	<input checked="" type="checkbox"/>	NORDDEUTSCHER LLOYD BREM

Choices in Cluster: 2 — 8

Rows in Cluster: 0 — 700

Average Length of Choices

Cluster & Edit column "event"

This feature helps you find groups of different cell values that might be alternative representations of the same thing. For example, the two strings "New York" and "new york" are very likely to refer to the same concept and just have capitalization differences, and "Gödel" and "Godel" probably refer to the same person. [Find out more ...](#)

Method **key collision** Keying Function **ngram-fingerprint** Ngram Size **2** **30 clusters found**

2	3	<ul style="list-style-type: none"> DINNER A LA CARTE (2 rows) DINNER-A LA CARTE (1 rows) 	<input checked="" type="checkbox"/>	DINNER A LA CARTE
2	2	<ul style="list-style-type: none"> ST. VALENTINE'S DAY DINNER (1 rows) ST. VALENTINES DAY DINNER (1 rows) 	<input checked="" type="checkbox"/>	ST. VALENTINE'S DAY DINNER
2	12	<ul style="list-style-type: none"> FRUHSTUCK-BREAKFAST (7 rows) FRUHSTUCK/BREAKFAST (5 rows) 	<input checked="" type="checkbox"/>	FRUHSTUCK-BREAKFAST

Choices in Cluster: 2 — 4

Rows in Cluster

For column: physical_description

- (1) Slit the columns using ‘;’
- (2) Then rename the first column: physical_description_type
- (3) Use GREL to join ‘physical_description 2’, ‘physical_description 3’, and ‘physical_description 4’ into one column named: physical_description_additional.
- (4) Use ‘ - ’ to separate the values from the different columns (Remember the space before and after the dash). Note: if the cell in the column is empty, leave that value as a blank space. For example, if a column is blank, make the new column in ‘physical_description_additional’ blank also.

Preview

History

Starred

Help

```
row value    if(isBlank(cells["physical_description 2"].value), "", cells["physical_description
2"].value + " - " + if(isBlank(cells["physical_description 3"].value),
"",cells["physical_description 3"].value)+ " - " +
if(isBlank(cells["physical_description 4"].value), "",cells["physical_description
4"].value))
```

For column: date

(1) Convert date format to YYYY-MM-DD

(2) Remove date outliers, where the year is either less than 1851 or greater than 2012. Make these flagged cells blank.

For column: call number

(1) Trim leading/trailing white spaces

(2) Collapse consecutive white spaces

Unchanged columns: id, name, keywords, language, status, page_count, dish_count

> Output File: CMenu.csv

2.2 MenuPage.csv Cleaning

Input File: MenuPage.csv

File not cleaned in OpenRefine

Unchanged columns: id, menu_id, page_number, image_id, full_height, full_width, uuid

> Output File: CMenuPage.csv

2.2 MenuItem.csv Cleaning

Input File: MenuItem.csv

For column: created at

(1) Convert date format to YYYY-MM-DD

(2) Remove date outliers, where the year is either less than 1851 or greater than 2012. Make these flagged cells blank.

For column: updated at

(1) Convert date format to YYYY-MM-DD

(2) Remove date outliers, where the year is either less than 1851 or greater than 2012. Make these flagged cells blank.

> Output File: CMenuItem.csv

2.2 Dish.csv Cleaning

Input File: Dish.csv

For column: name

(1) Use key-collision to cluster values. Note: cannot do nearest_neighbours cluster method because the time required to do this too computationally expensive

> Output File: CDish.csv

3. (Optional) Clean data further with an alternative tool

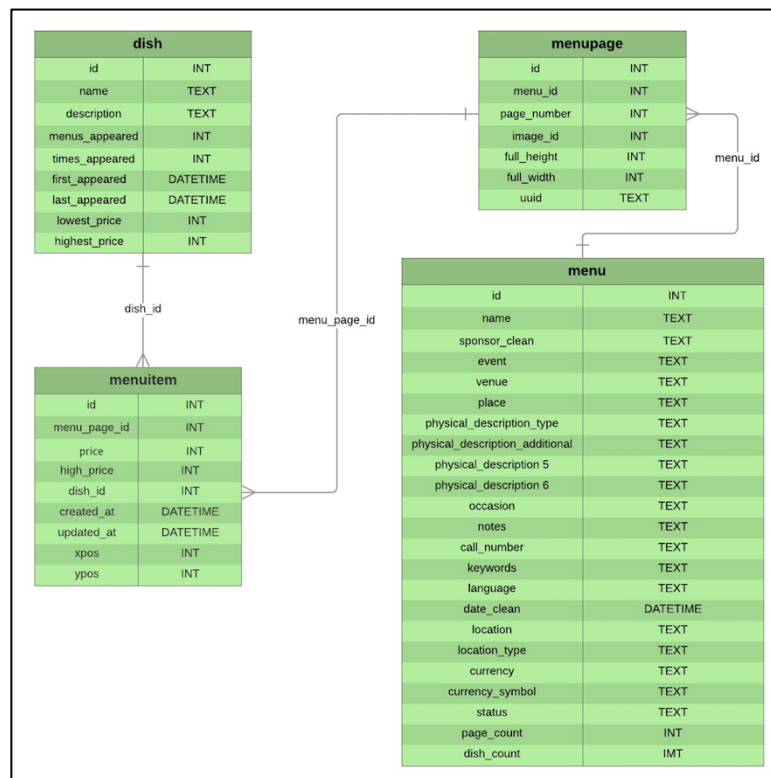
We choose not to do this optional part.

4. Develop Rational Database Schema

The next step in our data cleaning workflow is to import the cleaned data into a database. We are choosing to use SQLite as it is open source, simple, and straightforward to work with. When first designing a database, we must think about integrity constraints and the relational schema.

4.1 Schema

Below, is the schema in which there are four tables (one for each input file): dish, menuitem, menupage, and menu.



4.2 Table creation and Data load

SQL to create Database as per the Schema defined above.

```
*****Creating Database per the Schema*****;  
  
CREATE TABLE dish(  
  "id" INTEGER,  
  "name" TEXT,  
  "description" TEXT,  
  "menus_appeared" INTEGER,  
  "times_appeared" INTEGER,  
  "first_appeared" DATETIME,  
  "last_appeared" DATETIME,  
  "lowest_price" INTEGER,  
  "highest_price" INTEGER  
);  
  
CREATE TABLE menuitem(  
  "id" INTEGER,  
  "menu_page_id" INTEGER,  
  "price" REAL,  
  "high_price" REAL,  
  "dish_id" REAL,  
  "created_at" DATETIME,  
  "updated_at" DATETIME,  
  "xpos" INTEGER,  
  "ypos" INTEGER  
);  
  
CREATE TABLE menupage(  
  "id" INTEGER,  
  "menu_id" INTEGER,  
  "page_number" INTEGER,  
  "image_id" INTEGER,  
  "full_height" INTEGER,  
  "full_width" INTEGER,  
  "uuid" TEXT  
);
```

```
CREATE TABLE menu(
  "id" INTEGER,
  "name" TEXT,
  "sponsor" TEXT,
  "event" TEXT,
  "venue" TEXT,
  "place" TEXT,
  "physical_description_type" TEXT,
  "physical_description_additional" TEXT,
  "physical_description 5" TEXT,
  "physical_description 6" TEXT,
  "occasion" TEXT,
  "notes" TEXT,
  "call_number" TEXT,
  "keywords" TEXT,
  "language" TEXT,
  "date_clean" DATETIME,
  "location" TEXT,
  "location_type" TEXT,
  "currency" TEXT,
  "currency_symbol" TEXT,
  "status" TEXT,
  "page_count" INTEGER,
  "dish_count" INTEGER011.3
);
```

Importing .CSV data into the tables

```
sqlite3 ../dish.db

*****Importing Data*****;

.mode csv
.import final_project/CDish.csv dish
.import final_project/CMenu.csv menu
.import final_project/CMenuItem.csv menuitem
.import final_project/CMenuPage.csv menupage
```

4.3 Integrity Constraints

The following are the integrity constraints:

Menu (menu) Table

- Id cannot be Null
- Identify rows where sponsor is NULL. Sponsor cannot be NULL so deleted these rows as they are violating the Integrity Constraint.

- Page count should not be NULL
- Deleted physical_description 7 as it had all the NULL values

Dish (dish) Table

- Id should not be Null
- menus_appeared or times_appeared cannot be NULL
- Lowest price of the dish should be less than the highest price
- Identify number of rows of data where last_appeared is "0". These rows will not be deleted as these dishes may be part of the other data.

Menu Page (menupage) Table

- Id cannot be Null
- Page number should not be NULL or "0". No such rows were identified
- created_at date should be always greater than updated_at. Few rows were identified with this constraint
-

Menu Item (menuitem) Table

- Id cannot be Null
- created_at date should be always greater than updated_at. No such rows were violating this IC check.
- Xpos and ypos values should always be between 0 and 1.

```

-- IC Check for dish table

select * from dish where id is NULL;

select * from dish
where menus_appeared is NULL or times_appeared is NULL;

select * from dish
where cast(first_appeared as year) > cast(last_appeared as year) and last_appeared <> '0';

select * from dish where lowest_price > highest_price;

-- IC Check for menu table

select * from menu where id is NULL;

select * from menu where sponsor_clean is 'NULL' or '';

select * from menu where page_count is 'NULL' or '';

-- IC Check for menupage table

select * from menupage where id is NULL;

select * from menupage where page_number = '0';

select * from menupage where page_number is NULL;

select * from menupage where created_at > updated_at;

-- IC Check for menuitem table

select * from menuitem where id is NULL;

select * from menuitem where updated_at < created_at;

select * from menuitem where xpos < 0 and xpos > 1;

select * from menuitem where ypos < 0 and ypos > 1;

```

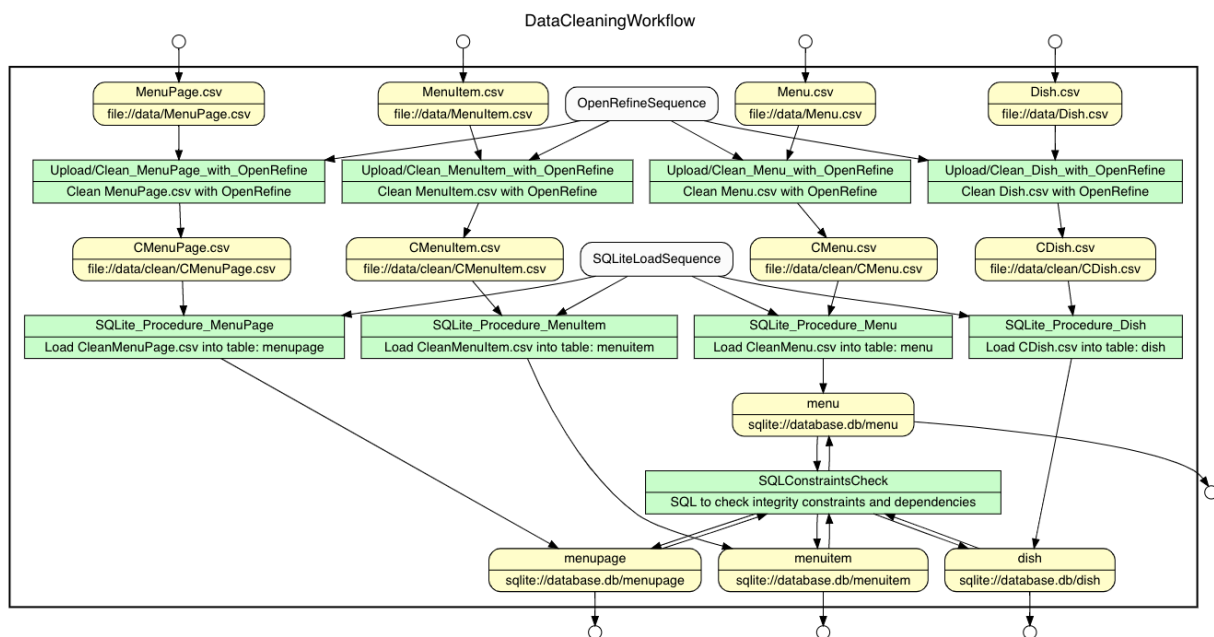
5. Create a Workflow Model

YesWorkflow is a solution to annotating your data workflow. It's easy to script and doesn't require you to re-write any of your existing code. Simply add a special (YW) comments to your existing script. Later, these comments are used to declare how the data was transformed step-by-step.

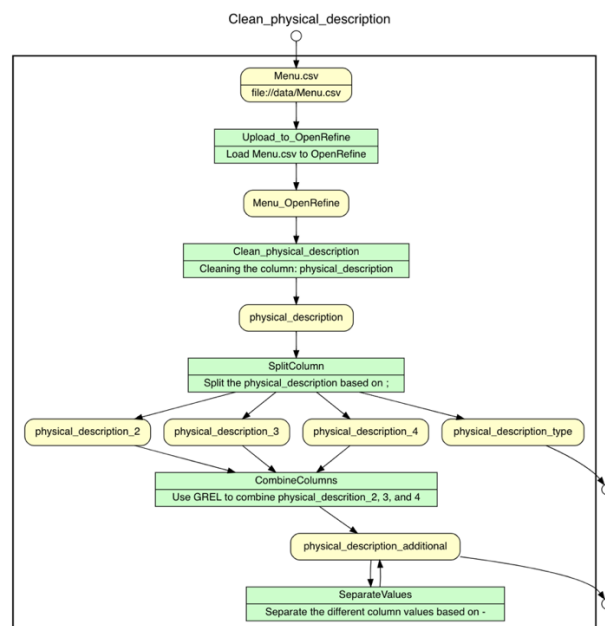
We used the online editor [[Ref5](#)] to generate various workflow diagrams shown below. The first diagram is the complete YW graph including the data and operations steps.

The second diagram down is a more detailed example of how the data was cleaned using OpenRefine. In order to provide a detailed example of how the data was cleaned, we selected a single column from the Menu.csv file, `physical_description`, and visualized how we prepared the data.

Below, is the overall workflow for cleaning the dataset as a whole. The code can be seen in Appendix 1.



Below, is the workflow for cleaning the 'physical_description' column for the Menu.csv dataset. The code can be seen in Appendix 2.



6. (Optional) Develop provenance queries

We choose not to do this optional part.

7. Conclusion

Any scientist, engineer, or researcher spends a substantial amount of time cleaning data for their research. Further, at conferences or when publishing research papers, often detailing steps documenting where you got the data from and how it was cleaned are required. These steps are required in order to potentially replicate your research/models later. Tools described in this paper aim to help document these cleaning steps in a simple and easy way.

In this project we used OpenRefine and SQLite for the cleaning steps. The challenges we faced generally is handling all the duplicate names or invalid/NA entries. Without much information about how to fill in the gaps, we often had to delete these entries. One tries to avoid deleting data if possible, but in our case, we felt it an appropriate solution.

Due to the size of the datasets in this project, it is hard to verify integrity of each clustering step. In some cases, we were not able to see all the clusters that were suggested by OpenRefine and had to rely on its decision on those.

Another problem is the slow run time and manual man hours - imputing GREL commands, reviewing cluster groups, documenting steps – data cleaning still requires a lot of time even given tools like these. OpenRefine, like excel and some other tools, has limitations in the size of datasets it can work with. This is an example of where other open source programming languages help, such as Python or R. There is no ‘silver bullet’ in data cleaning. It remains a piecewise blend of various tool as the data moves through a line of steps.

8. Appendix

Appendix 1: DataCleaningWorkflow

```
1 # @begin DataCleaningWorkflow @desc The overall workflow for cleaning the NYPL Menus Dataset
2 # @in Menu.csv @uri file://data/Menu.csv
3 # @in MenuPage.csv @uri file://data/MenuPage.csv
4 # @in MenuItem.csv @uri file://data/MenuItem.csv
5 # @in Dish.csv @uri file://data/Dish.csv
6
7 # @begin Upload/Clean_Menu_with_OpenRefine @desc Clean Menu.csv with OpenRefine
8 # @in Menu.csv @uri file://data/Menu.csv
9 # @param OpenRefineSequence
10 # @out CMenu.csv @uri file://data/clean/CMenu.csv
11 # @end Upload/Clean_Menu_with_OpenRefine
12
13 # @begin Upload/Clean_MenuPage_with_OpenRefine @desc Clean MenuPage.csv with OpenRefine
14 # @in MenuPage.csv @uri file://data/MenuPage.csv
15 # @param OpenRefineSequence
16 # @out CMenuPage.csv @uri file://data/clean/CMenuPage.csv
17 # @end Upload/Clean_MenuPage_with_OpenRefine
18
19 # @begin Upload/Clean_MenuItem_with_OpenRefine @desc Clean MenuItem.csv with OpenRefine
20 # @in MenuItem.csv @uri file://data/MenuItem.csv
21 # @param OpenRefineSequence
22 # @out CMenuItem.csv @uri file://data/clean/CMenuItem.csv
23 # @end Upload/Clean_MenuItem_with_OpenRefine
24
25 # @begin Upload/Clean_Dish_with_OpenRefine @desc Clean Dish.csv with OpenRefine
26 # @in Dish.csv @uri file://data/Dish.csv
27 # @param OpenRefineSequence
28 # @out CDish.csv @uri file://data/clean/CDish.csv
29 # @end Upload/Clean_Dish_with_OpenRefine
30
31 # @begin SQLite_Procedure_Menu @desc Load CleanMenu.csv into table: menu
32 # @in CMenu.csv @uri file://data/clean/CMenu.csv
33 # @param SQLiteLoadSequence
34 # @out menu @uri sqlite://database.db/menu
35 # @end SQLite_Procedure_Menu
36
37 # @begin SQLite_Procedure_MenuPage @desc Load CleanMenuPage.csv into table: menupage
38 # @in CMenuPage.csv @uri file://data/clean/CMenuPage.csv
39 # @param SQLiteLoadSequence
40 # @out menupage @uri sqlite://database.db/menupage
41 # @end SQLite_Procedure_MenuPage
42
43 # @begin SQLite_Procedure_MenuItem @desc Load CleanMenuItem.csv into table: menuitem
44 # @in CMenuItem.csv @uri file://data/clean/CMenuItem.csv
45 # @param SQLiteLoadSequence
46 # @out menuitem @uri sqlite://database.db/menuitem
47 # @end SQLite_Procedure_MenuItem
```

```

48
49 # @begin SQLite_Procedure_Dish @desc Load CDish.csv into table: dish
50 # @in CDish.csv @uri file://data/clean/CDish.csv
51 # @param SQLiteLoadSequence
52 # @out dish @uri sqlite://database.db/dish
53 # @end SQLite_Procedure_Dish
54
55 # @begin SQLConstraintsCheck @desc SQL to check integrity constraints and dependencies
56 # @in menu @uri sqlite://database.db/menu
57 # @in menupage @uri sqlite://database.db/menupage
58 # @in menuitem @uri sqlite://database.db/menuitem
59 # @in dish @uri sqlite://database.db/dish
60
61 # @out menu @uri sqlite://database.db/menu
62 # @out menupage @uri sqlite://database.db/menupage
63 # @out menuitem @uri sqlite://database.db/menuitem
64 # @out dish @uri sqlite://database.db/dish
65 # @end SQLConstraintsCheck
66
67 # @out menu @uri sqlite://database.db/menu
68 # @out menupage @uri sqlite://database.db/menupage
69 # @out menuitem @uri sqlite://database.db/menuitem
70 # @out dish @uri sqlite://database.db/dish
71 # @end DataCleaningWorkflow

```

Appendix 2: Clean_physical_description

```

1 # @begin Clean_physical_description @desc Workflow for cleaning physical_description in Menu.csv
2 # @in Menu.csv @uri file://data/Menu.csv
3
4 # @begin Upload_to_OpenRefine @desc Load Menu.csv to OpenRefine
5 # @in Menu.csv
6 # @out Menu_OpenRefine
7 # @end Upload_to_OpenRefine
8
9 # @begin Clean_physical_description @desc Cleaning the column: physical_description
10 # @in Menu_OpenRefine
11 # @out physical_description
12 # @end Clean_physical_description
13
14 # @begin SplitColumn @desc Split the physical_description based on ;
15 # @in physical_description
16 # @out physical_description_type
17 # @out physical_description_2
18 # @out physical_description_3
19 # @out physical_description_4
20 # @end SplitColumn
21
22 # @begin CombineColumns @desc Use GREL to combine physical_description_2, 3, and 4
23 # @in physical_description_2
24 # @in physical_description_3
25 # @in physical_description_4
26 # @out physical_description_additional
27 # @end CombineColumns
28
29 # @begin SeparateValues @desc Separate the different column values based on -
30 # @in physical_description_additional
31 # @out physical_description_additional
32 # @end SeparateValues
33
34 # @out physical_description_type
35 # @out physical_description_additional
36 # @end Clean_physical_description

```

References

[Ref1] https://en.wikipedia.org/wiki/Frank_E._Buttolph

[Ref2] <http://menus.nypl.org>

[Ref3] <https://github.com/bradballard/dc-workflow>

[Ref4] <https://bradballard.github.io/dc-workflow>

[Ref5] <https://try.yesworkflow.org>