CS 513 Final Project Phase II Report (Team 210 Wizards of Illinois Place)

Team Members

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I. Description of Data Cleaning Performed

A description of the actual data cleaning workflow W that was performed, and a comparison with the original Phase-I plan: e.g., were you able to execute the steps as planned, and if not, what did you have to change and why?

1) Convert To Titlecase. Many of the fields below were all capital, which didn't make sense of what they were representing. For example, name of "ANSHUL GOSWAMI" should be titlecase.

- Name, Sponser, Event, Venue, Place, Physical Description, Easter, etc

3) Convert notes to lowercase. There are long description of notes in menu.csv. It would make sense to have those notes lowercase since they are representing full paragraphs of notes. Titlecase would not make sense in this case.

4) Cluster Events, since many different variations for the same word, such as Dinner having 10 different variations. Combining them gives much more clarity. For example, Dinnr, D!nner, diner, were all combined into "Dinner". We don't want mispelling of words because the user will not be able to clearly filter by one keyword such as "Dinner"

5) Converted Date String to Date Type so that analysis software can correctly recognize that the columns are indeed dates. OpenRefine wasn't able to automatically convert to date format so used string transformatio to convert dates prevent into a format that Open Refine was able to recognize. This is a neccessary step so that analysis software can filter by date if neccessary.

6) Most values in Dish.csv were numbers. Convert appropriate columns to number type so that software can be treated as numbers. Import as fields need to be numeric data in order to be used for quantative analysis.

7) Repeated same step as 5 for other sheets

8) Removed Menu Items whose price is greater than $100,000, as a menu item greater than 100,000 is not resonable. This was a neccessary step as these outliers should not skew any quantative analysis of data.

9) Used Text Faucet and clustering in Venue. Similar reason to #3, where we don't want variations of text that is representing the same word.

10) Used Date Faucet in First_Appeared_Year and Last_Appeared in Dish.CV to remove years greater than 2025, since it is not possible for menu items to appear in years greater than 2025 (as of the current date). This is neccessary as it is impossible to have current data representing years greater than 2025.

II. Document Data Quality Changes

```python
import pandas as pd
import pandasql as psql
from helpers import read_in_data

dish_df, menu_df, menu_item_df, menu_page_df = read_in_data()

dish_df.head()
```

```
   id                        name  description  menus_appeared  \
0   1  Consomme printaniere royal          NaN               8
1   2               Chicken gumbo          NaN             111
2   3         Tomato aux croutons          NaN              13
3   4             Onion au gratin          NaN              41
4   5                 St. Emilion          NaN              66

   times_appeared  first_appeared  last_appeared  lowest_price
highest_price
0               8            1897           1927          0.20
0.4
1             117            1895           1960          0.10
0.8
2              13            1893           1917          0.25
0.4
3              41            1900           1971          0.25
1.0
4              68            1881           1981          0.00
18.0
```

```python
dish_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 423397 entries, 0 to 423396
Data columns (total 9 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   id              423397 non-null  int64
 1   name            423397 non-null  object
 2   description     0 non-null       float64
 3   menus_appeared  423397 non-null  int64
 4   times_appeared  423397 non-null  int64
 5   first_appeared  423397 non-null  int64
 6   last_appeared   423397 non-null  int64
 7   lowest_price    394297 non-null  float64
 8   highest_price   394297 non-null  float64
```

```
dtypes: float64(3), int64(5), object(1)
memory usage: 29.1+ MB
```

Queries

Query 1: Identifying the count of distinct dish names before/after standardization

```
query = """
select distinct name
  from dish_df
order by 1 asc
"""

result = psql.sqldf(query, globals())

### Code to run this query:

import pandas as pd
import pandasql as psql

cleaned_df = pd.read_csv('Dish_CLEANED.csv')
not_cleaned_df = pd.read_csv('Dish_NOTCleaned.csv')

query = """
select distinct name
  from dish_df
order by 1 asc
"""

dish_df = cleaned_df
distinct_names_cleaned = psql.sqldf(query, globals())

dish_df = not_cleaned_df
distinct_names_not_cleaned = psql.sqldf(query, globals())

print("Number of Distinct Names Before Cleaning:",
distinct_names_not_cleaned['name'].nunique())
print("Number of Distinct Names After Cleaning:",
distinct_names_cleaned['name'].nunique())
```

```
Number of Distinct Names Before Cleaning: 423363
Number of Distinct Names After Cleaning: 390590
```

```
before_cleaning = 423363
after_cleaning = 390590

percentage_difference = ((before_cleaning - after_cleaning) /
before_cleaning) * 100
```

```
print(f"{percentage_difference:.2f}%")
```

```
7.74%
```

Query 2: Analyzing the average price of dishes in the catalog before/after standardization

```
query = """
select distinct name
    , avg(highest_price) as avg_price
 from dish_df
group by 1
order by 2 desc
"""

result = psql.sqldf(query, globals())

### Code to run this query:

cleaned_df = pd.read_csv('Dish_CLEANED.csv')
not_cleaned_df = pd.read_csv('Dish_NOTCleaned.csv')

query = """
select distinct name
    , avg(highest_price) as avg_price
 from dish_df
group by 1
order by 2 desc
"""
dish_df = cleaned_df  #
result_cleaned = psql.sqldf(query, globals())

dish_df = not_cleaned_df
result_not_cleaned = psql.sqldf(query, globals())

print("Average Price of Dishes After Cleaning:")
print(result_cleaned.head())

print("\nAverage Price of Dishes Before Cleaning:")
print(result_not_cleaned.head())
```

```
Average Price of Dishes After Cleaning:
                                 name    avg_price
0             Pommery & Greno. Ex. Dry  2050.000000
1                                 Luso  1100.000000
2         Omelette Aux Foies De Poulet  1035.000000
3               Oysters Baked In Shell  1032.750000
4   Cream Cheese With Bar-le-duc Jelly  1016.933333
```

```
Average Price of Dishes Before Cleaning:
                                 name  avg_price
0  Cream cheese with bar-le-duc jelly     3050.0
1                          Grape fruit     2540.0
2               Oysters Baked in Shell     2065.0
3             Pommery & Greno. Ex. Dry     2050.0
4                                 luso     1100.0

after_cleaning_data = {
    "name": ["Pommery & Greno. Ex. Dry", "Luso", "Omelette Aux Foies
De Poulet",
             "Oysters Baked In Shell", "Cream Cheese With Bar-le-duc
Jelly"],
    "avg_price": [2050.000000, 1100.000000, 1035.000000, 1032.750000,
1016.933333]
}

before_cleaning_data = {
    "name": ["Cream cheese with bar-le-duc jelly", "Grape fruit",
"Oysters Baked in Shell",
             "Pommery & Greno. Ex. Dry", "luso"],
    "avg_price": [3050.0, 2540.0, 2065.0, 2050.0, 1100.0]
}

after_cleaning_df = pd.DataFrame(after_cleaning_data)
before_cleaning_df = pd.DataFrame(before_cleaning_data)

after_cleaning_df['name'] = after_cleaning_df['name'].str.lower()
before_cleaning_df['name'] = before_cleaning_df['name'].str.lower()

merged_df = pd.merge(after_cleaning_df, before_cleaning_df, on='name',
suffixes=('_after', '_before'))

merged_df['percentage_difference'] = ((merged_df['avg_price_before'] -
merged_df['avg_price_after']) / merged_df['avg_price_before']) * 100

merged_df[['name', 'avg_price_before', 'avg_price_after',
'percentage_difference']]

                                 name  avg_price_before
avg_price_after  \
0            pommery & greno. ex. dry            2050.0
2050.000000
1                                luso            1100.0
1100.000000
2              oysters baked in shell            2065.0
1032.750000
3  cream cheese with bar-le-duc jelly            3050.0
1016.933333
```

```
   percentage_difference
0               0.000000
1               0.000000
2              49.987893
3              66.657924
```

The data cleaning process has significantly improved the accuracy of our dataset. By removing inconsistencies and standardizing the data, we ensured that our analysis is based on reliable information. We found a 7% change in the number of distinct names after performing our cleaning as seen by the results above as well as significant changes in our average price. The notable reduction in the average prices of certain dishes, such as "Oysters Baked In Shell" and "Cream Cheese With Bar-le-duc Jelly," highlights how data cleaning has effectively lead to more accurate average price calculations.

Furthermore, ensuring data integrity is crucial for maintaining a reliable database. During the cleaning process, several integrity constraints were applied to ensure the accuracy and validity of the data. Here are some examples of how we enforced and checked for IC violations:

1) Temporal integrity: We verified that a dish did not first appear after the current year (2024). This constraint ensures that no future dates are mistakenly entered into the database. The following snippet shows how this is done:

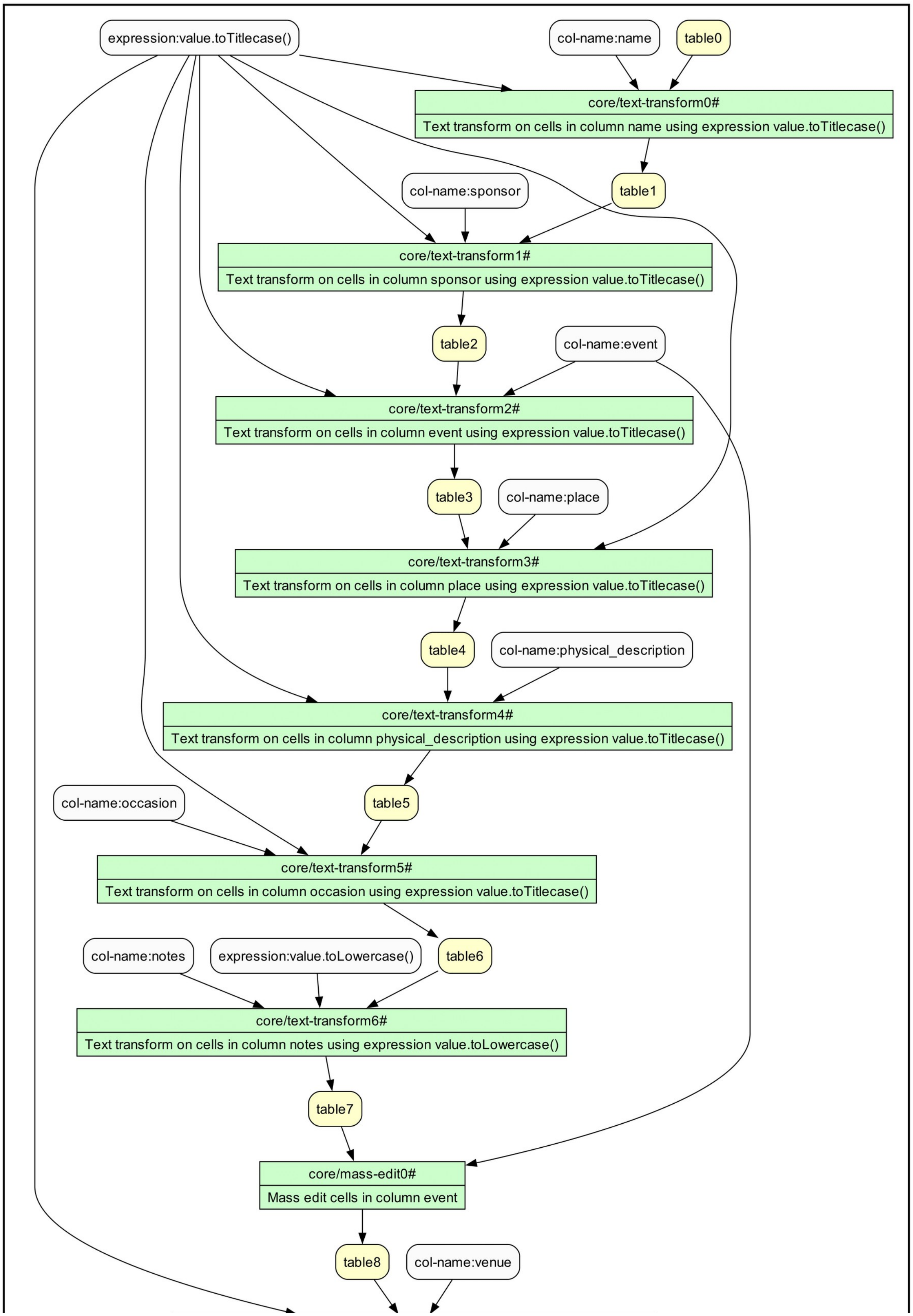
```
violations = df[df['first_appeared'] > 2024]

if not violations.empty:
    print("Temporal integrity violations found:")
    print(violations)
```

2) Non-negative: We ensured that all price entries in the database are non-negative. Negative prices would be illogical and indicate data entry errors. The following snippet shows how this is done:

```
negative_prices = df[df'lowest_price'] < 0]
if not negative_prices empty:
    print("Negative prices found and need to be corrected.")
```

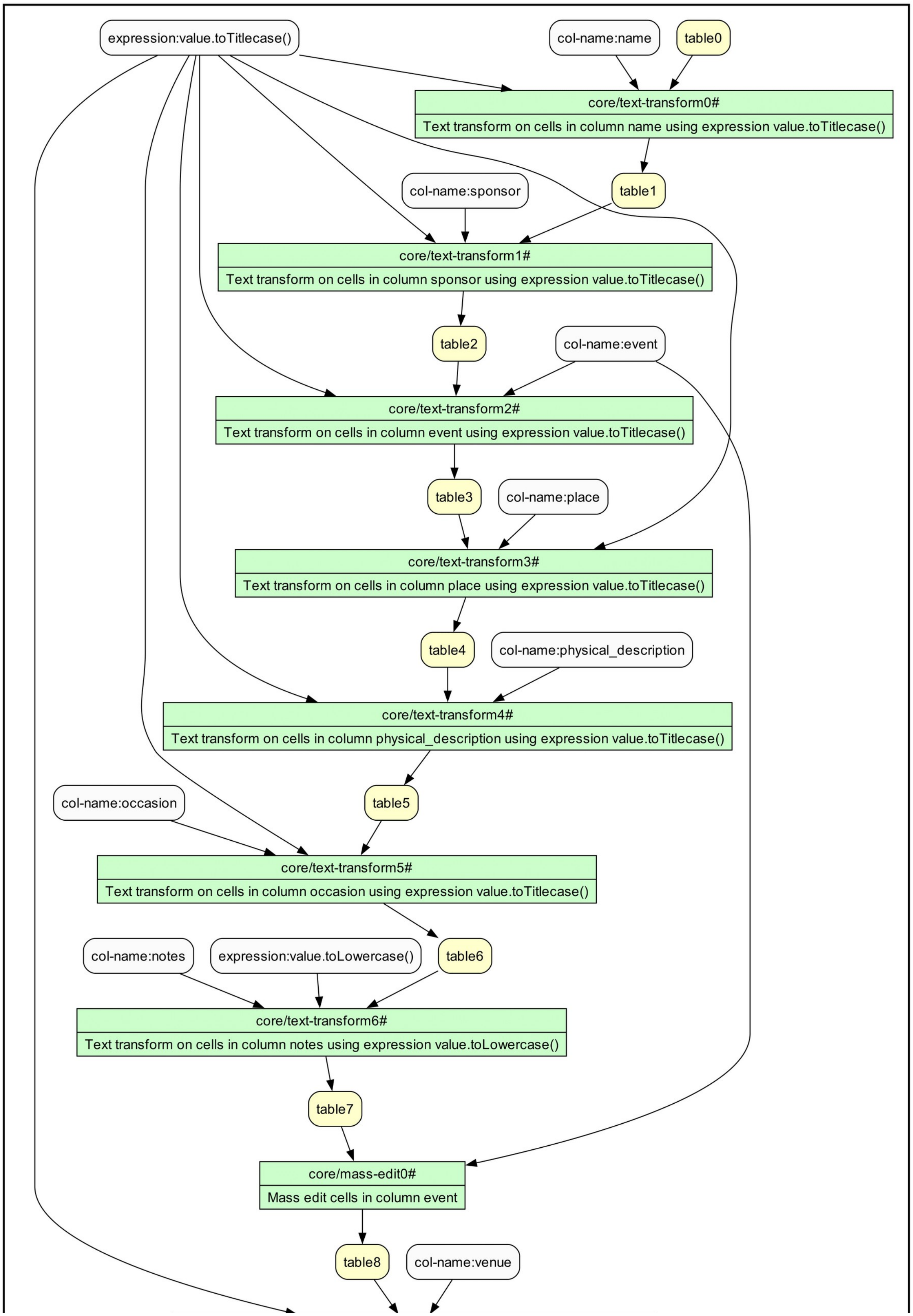
III. Create a Workflow Model

Linear_OR



expression:value.toTitlecase()
col-name:name
table0
core/text-transform0#
Text transform on cells in column name using expression value.toTitlecase()
col-name:sponsor
table1
core/text-transform1#
Text transform on cells in column sponsor using expression value.toTitlecase()
table2
col-name:event
core/text-transform2#
Text transform on cells in column event using expression value.toTitlecase()
table3
col-name:place
core/text-transform3#
Text transform on cells in column place using expression value.toTitlecase()
table4
col-name:physical_description
core/text-transform4#
Text transform on cells in column physical_description using expression value.toTitlecase()
col-name:occasion
table5
core/text-transform5#
Text transform on cells in column occasion using expression value.toTitlecase()
col-name:notes
expression:value.toLowercase()
table6
core/text-transform6#
Text transform on cells in column notes using expression value.toLowercase()
table7
core/mass-edit0#
Mass edit cells in column event
table8
col-name:venue

Linear_OR



expression:value.toTitlecase()
col-name:name
table0
core/text-transform0#
Text transform on cells in column name using expression value.toTitlecase()
col-name:sponsor
table1
core/text-transform1#
Text transform on cells in column sponsor using expression value.toTitlecase()
table2
col-name:event
core/text-transform2#
Text transform on cells in column event using expression value.toTitlecase()
table3
col-name:place
core/text-transform3#
Text transform on cells in column place using expression value.toTitlecase()
table4
col-name:physical_description
core/text-transform4#
Text transform on cells in column physical_description using expression value.toTitlecase()
col-name:occasion
table5
core/text-transform5#
Text transform on cells in column occasion using expression value.toTitlecase()
col-name:notes
expression:value.toLowercase()
table6
core/text-transform6#
Text transform on cells in column notes using expression value.toLowercase()
table7
core/mass-edit0#
Mass edit cells in column event
table8
col-name:venue

IV. Conclusions & Summary

To summarize, in this project we initially set out to address the data quality problem of repeated dish names in the Dish dataset by standardizing dish names. Without standard naming conventions in place, it is impossible to perform accurate analysis on the popularity and pricing trends of dishes. Dishes whose names are mispelled, or use different terminology to refer to the same thing, create erroneous data with separate line items for producsts that should otherwise be examined together as a whole. To promote standardization, we leverage OpenRefine to merge similarly named dishes under the assumption that differences between certain dish names reflect true data quality issues. To analyze and quantify our results, and to determine whether or not we were indeed successful in improving data quality in our approach, we make use of Python; we employ packages in Python such as Pandas, which allows us to read our original and cleaned datasets into DataFrames, and PandaSQL to execute our queries for measuring data quality. We find that...

For the purposes of this project, we divided the work up evenly among our group members based on our respective domain expertise. Anshul, having the most experience and comfort using OpenRefine, took care of the actual merging of dish names and our data cleaning steps within that platform. Blake and Abduhamdan, being more comfortable with analysis in Python, handled the queries and measurement framework to examine and quantify the results.