Project 3: Food Demand

Target Region: Maharashtra, India

Goals:

- Gain understanding of the different factors that may influence food demand
- Estimate a relationship between diet, prices, and budget.
- Test Engel's Law for different food items in our subject

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Import Data Libraries

In [1]:

```
import pandas as pd
!pip install pyarrow

import ipywidgets
from ipywidgets import interactive, fixed, interact, Dropdown
```

```
Collecting pyarrow
  Using cached pyarrow-7.0.0-cp39-cp39-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (2
6.7 MB)
Requirement already satisfied: numpy>=1.16.6 in /opt/conda/lib/python3.9/site-packages
(from pyarrow) (1.21.5)
Installing collected packages: pyarrow
Successfully installed pyarrow-7.0.0
```

In [2]:

```
!pip install -r requirements.txt
import numpy as np
import sys
!pip install eep153-tools
!pip install gspread-pandas

from eep153_tools.sheets import read_sheets
import cfe
```

```
Collecting CFEDemands>=0.4.1
  Using cached CFEDemands-0.4.1-py2.py3-none-any.whl (39 kB)
Collecting ConsumerDemands
  Using cached ConsumerDemands-0.3.dev0-py2.py3-none-any.whl (12 kB)
Requirement already satisfied: gspread>=4.0.1 in /opt/conda/lib/python3.9/site-packages
(from -r requirements.txt (line 10)) (4.0.1)
Requirement already satisfied: matplotlib>=3.3.4 in /opt/conda/lib/python3.9/site-packag
es (from -r requirements.txt (line 13)) (3.4.3)
Requirement already satisfied: numpy>=1.21.5 in /opt/conda/lib/python3.9/site-packages
(from -r requirements.txt (line 17)) (1.21.5)
Collecting oauth2client>=4.1.3
  Using cached oauth2client-4.1.3-py2.py3-none-any.whl (98 kB)
```

```
Requirement already satisfied: pandas>=1.3.5 in /opt/conda/lib/python3.9/site-packages
(from -r requirements.txt (line 25)) (1.3.5)
Requirement already satisfied: plotly>=5.1.0 in /opt/conda/lib/python3.9/site-packages
(from -r requirements.txt (line 28)) (5.2.1)
Collecting eep153_tools>=0.11
  Using cached eep153_tools-0.11-py2.py3-none-any.whl (4.4 kB)
Processing /home/jovyan/.cache/pip/wheels/20/7e/30/7d702acd6a1e89911301cd9dbf9cb9870ca80
c0e64bc2cde23/gnupg-2.3.1-py3-none-any.whl
Requirement already satisfied: google-auth>=1.12.0 in /opt/conda/lib/python3.9/site-pack
ages (from gspread>=4.0.1->-r requirements.txt (line 10)) (2.6.2)
Requirement already satisfied: google-auth-oauthlib>=0.4.1 in /opt/conda/lib/python3.9/s
ite-packages (from gspread>=4.0.1->-r requirements.txt (line 10)) (0.4.5)
Requirement already satisfied: cycler>=0.10 in /opt/conda/lib/python3.9/site-packages (f
rom matplotlib>=3.3.4->-r requirements.txt (line 13)) (0.11.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /opt/conda/lib/python3.9/site-packag
es (from matplotlib>=3.3.4->-r requirements.txt (line 13)) (1.4.2)
Requirement already satisfied: pyparsing>=2.2.1 in /opt/conda/lib/python3.9/site-package
s (from matplotlib>=3.3.4->-r requirements.txt (line 13)) (3.0.7)
Requirement already satisfied: python-dateutil>=2.7 in /opt/conda/lib/python3.9/site-pac
kages (from matplotlib>=3.3.4->-r requirements.txt (line 13)) (2.8.0)
Requirement already satisfied: pillow>=6.2.0 in /opt/conda/lib/python3.9/site-packages
(from matplotlib>=3.3.4->-r requirements.txt (line 13)) (8.3.2)
Requirement already satisfied: pyasn1>=0.1.7 in /opt/conda/lib/python3.9/site-packages
(from oauth2client>=4.1.3->-r requirements.txt (line 20)) (0.4.8)
Requirement already satisfied: httplib2>=0.9.1 in /opt/conda/lib/python3.9/site-packages
(from oauth2client>=4.1.3->-r requirements.txt (line 20)) (0.20.4)
Requirement already satisfied: pyasn1-modules>=0.0.5 in /opt/conda/lib/python3.9/site-pa
ckages (from oauth2client>=4.1.3->-r requirements.txt (line 20)) (0.2.8)
Requirement already satisfied: rsa>=3.1.4 in /opt/conda/lib/python3.9/site-packages (fro
m oauth2client>=4.1.3->-r requirements.txt (line 20)) (4.8)
Requirement already satisfied: six>=1.6.1 in /opt/conda/lib/python3.9/site-packages (fro
m oauth2client>=4.1.3->-r requirements.txt (line 20)) (1.16.0)
Requirement already satisfied: pytz>=2017.3 in /opt/conda/lib/python3.9/site-packages (f
rom pandas>=1.3.5->-r requirements.txt (line 25)) (2021.1)
Requirement already satisfied: tenacity>=6.2.0 in /opt/conda/lib/python3.9/site-packages
(from plotly>=5.1.0->-r requirements.txt (line 28)) (8.0.1)
Requirement already satisfied: psutil>=1.2.1 in /opt/conda/lib/python3.9/site-packages
(from gnupg->-r requirements.txt (line 31)) (5.9.0)
Requirement already satisfied: cachetools<6.0,>=2.0.0 in /opt/conda/lib/python3.9/site-p
ackages (from google-auth>=1.12.0->gspread>=4.0.1->-r requirements.txt (line 10)) (5.0.
0)
Requirement already satisfied: requests-oauthlib>=0.7.0 in /opt/conda/lib/python3.9/site
-packages (from google-auth-oauthlib>=0.4.1->gspread>=4.0.1->-r requirements.txt (line 1
0)) (1.3.1)
Requirement already satisfied: oauthlib>=3.0.0 in /opt/conda/lib/python3.9/site-packages
(from requests-oauthlib>=0.7.0->google-auth-oauthlib>=0.4.1->gspread>=4.0.1->-r requirem
ents.txt (line 10)) (3.2.0)
Requirement already satisfied: requests>=2.0.0 in /opt/conda/lib/python3.9/site-packages
(from requests-oauthlib>=0.7.0->google-auth-oauthlib>=0.4.1->gspread>=4.0.1->-r requirem
ents.txt (line 10)) (2.26.0)
Requirement already satisfied: charset-normalizer~=2.0.0; python_version >= "3" in /opt/
conda/lib/python3.9/site-packages (from requests>=2.0.0->requests-oauthlib>=0.7.0->googl
e-auth-oauthlib>=0.4.1->gspread>=4.0.1->-r requirements.txt (line 10)) (2.0.0)
Requirement already satisfied: certifi>=2017.4.17 in /opt/conda/lib/python3.9/site-packa
ges (from requests>=2.0.0->requests-oauthlib>=0.7.0->google-auth-oauthlib>=0.4.1->gsprea
d>=4.0.1->-r requirements.txt (line 10)) (2019.11.28)
Requirement already satisfied: idna<4,>=2.5; python_version >= "3" in /opt/conda/lib/pyt
hon3.9/site-packages (from requests>=2.0.0->requests-oauthlib>=0.7.0->google-auth-oauthl
ib>=0.4.1->gspread>=4.0.1->-r requirements.txt (line 10)) (2.8)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in /opt/conda/lib/python3.9/site-pa
ckages (from requests>=2.0.0->requests-oauthlib>=0.7.0->google-auth-oauthlib>=0.4.1->gsp
read>=4.0.1->-r requirements.txt (line 10)) (1.25.7)
Installing collected packages: CFEDemands, ConsumerDemands, oauth2client, eep153-tools,
gnupg
Successfully installed CFEDemands-0.4.1 ConsumerDemands-0.3.dev0 eep153-tools-0.11 gnupg
-2.3.1 oauth2client-4.1.3
```

```
Requirement already satisfied: eep153-tools in /opt/conda/lib/python3.9/site-packages
(0.11)
Requirement already satisfied: gspread-pandas in /opt/conda/lib/python3.9/site-packages
(2.3.0)
Requirement already satisfied: pandas>=0.20.0 in /opt/conda/lib/python3.9/site-packages
(from gspread-pandas) (1.3.5)
Requirement already satisfied: gspread>=3.0.0 in /opt/conda/lib/python3.9/site-packages
(from gspread-pandas) (4.0.1)
Requirement already satisfied: decorator in /opt/conda/lib/python3.9/site-packages (from
gspread-pandas) (5.0.9)
Requirement already satisfied: google-auth-oauthlib in /opt/conda/lib/python3.9/site-pac
kages (from gspread-pandas) (0.4.5)
Requirement already satisfied: google-auth in /opt/conda/lib/python3.9/site-packages (fr
om gspread-pandas) (2.6.2)
Requirement already satisfied: six in /opt/conda/lib/python3.9/site-packages (from gspre
ad-pandas) (1.16.0)
Requirement already satisfied: python-dateutil>=2.7.3 in /opt/conda/lib/python3.9/site-p
ackages (from pandas>=0.20.0->gspread-pandas) (2.8.0)
Requirement already satisfied: pytz>=2017.3 in /opt/conda/lib/python3.9/site-packages (f
rom pandas>=0.20.0->gspread-pandas) (2021.1)
Requirement already satisfied: numpy>=1.17.3 in /opt/conda/lib/python3.9/site-packages
(from pandas>=0.20.0->gspread-pandas) (1.21.5)
Requirement already satisfied: requests-oauthlib>=0.7.0 in /opt/conda/lib/python3.9/site
-packages (from google-auth-oauthlib->gspread-pandas) (1.3.1)
Requirement already satisfied: pyasn1-modules>=0.2.1 in /opt/conda/lib/python3.9/site-pa
ckages (from google-auth->gspread-pandas) (0.2.8)
Requirement already satisfied: rsa<5,>=3.1.4; python_version >= "3.6" in /opt/conda/lib/
python3.9/site-packages (from google-auth->gspread-pandas) (4.8)
Requirement already satisfied: cachetools<6.0,>=2.0.0 in /opt/conda/lib/python3.9/site-p
ackages (from google-auth->gspread-pandas) (5.0.0)
Requirement already satisfied: oauthlib>=3.0.0 in /opt/conda/lib/python3.9/site-packages
(from requests-oauthlib>=0.7.0->google-auth-oauthlib->gspread-pandas) (3.2.0)
Requirement already satisfied: requests>=2.0.0 in /opt/conda/lib/python3.9/site-packages
(from requests-oauthlib>=0.7.0->google-auth-oauthlib->gspread-pandas) (2.26.0)
Requirement already satisfied: pyasn1<0.5.0,>=0.4.6 in /opt/conda/lib/python3.9/site-pac
kages (from pyasn1-modules>=0.2.1->google-auth->gspread-pandas) (0.4.8)
Requirement already satisfied: certifi>=2017.4.17 in /opt/conda/lib/python3.9/site-packa
ges (from requests>=2.0.0->requests-oauthlib>=0.7.0->google-auth-oauthlib->gspread-panda
s) (2019.11.28)
Requirement already satisfied: idna<4,>=2.5; python_version >= "3" in /opt/conda/lib/pyt
hon3.9/site-packages (from requests>=2.0.0->requests-oauthlib>=0.7.0->google-auth-oauthl
ib->gspread-pandas) (2.8)
Requirement already satisfied: charset-normalizer~=2.0.0; python_version >= "3" in /opt/
conda/lib/python3.9/site-packages (from requests>=2.0.0->requests-oauthlib>=0.7.0->googl
e-auth-oauthlib->gspread-pandas) (2.0.0)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in /opt/conda/lib/python3.9/site-pa
ckages (from requests>=2.0.0->requests-oauthlib>=0.7.0->google-auth-oauthlib->gspread-pa
ndas) (1.25.7)
Missing dependencies for OracleDemands.
```

[A] Population, and Data Cleaning

Parquet Files Cleaning & DataFrame Establishment

We acquired our data from the Indian National Sample Survey (NSS). These original parque files contain data from a very large pool of households from 35 states; the following parts establish dataframes for our choosen Maharashtra population.

In [3]:
```
#food expenditure in Rupee
food_price = pd.read_parquet('x.parquet', engine = 'pyarrow').unstack('i')
food_price
```

Out[3]:

i		apple	arhar (tur)	baby food	bajra & products	banana	barley & products	beef	beer	berries	besan	...	toddy
j	**Frequency**												
410001101	**Monthly**	20.0	121.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	120.0	...	NaN
410001102	**Monthly**	160.0	60.0	NaN	40.0	60.0	NaN	NaN	NaN	NaN	15.0	...	NaN
410001103	**Monthly**	40.0	195.0	NaN	NaN	50.0	NaN	NaN	NaN	NaN	60.0	...	NaN
410001201	**Monthly**	40.0	130.0	NaN	NaN	20.0	NaN	NaN	NaN	NaN	90.0	...	NaN
410001202	**Monthly**	NaN	65.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	60.0	...	NaN
...	**...**	...	...	...	...	...	...	...	...	...	...	...	...
799981301	**Monthly**	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN
799982101	**Monthly**	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN
799982201	**Monthly**	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN
799982202	**Monthly**	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN
799982301	**Monthly**	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN

101660 rows × 164 columns

In [4]:

```
#food quantity
food_quant = pd.read_parquet('q.parquet', engine = 'pyarrow').unstack('i')
food_quant
```

Out[4]:

	i		apple	arhar (tur)	baby food	bajra & products	banana	barley & products	beef	beer	berries	besan	...
j	**unit**	**Frequency**											
410001101	**Re**	**Monthly**	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
	box	**Monthly**	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
	gm	**Monthly**	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
	kg	**Monthly**	250.0	2000.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	2000.0	...
	litre	**Monthly**	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
...	**...**	**...**	...	...	...	...	...	...	...	...	...	...	...
799982301	**gm**	**Monthly**	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
	kg	**Monthly**	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
	litre	**Monthly**	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
	no.	**Monthly**	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
	std. unit	**Monthly**	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...

708205 rows × 164 columns

In [5]:

```
#nutritional content
nutritient = pd.read_parquet('n.parquet', engine = 'pyarrow')
nutritient
```

Out[5]:

	calories per unit(kcal)	fat per unit(gm)	i	protein per unit(gm)	rural	t	unit
1	3280.000000	13.00	ragi	73.00	NaN	50	kg
4	1100.000000	2.00	other cereal subs.	16.00	NaN	50	kg
5	3420.000000	36.00	maize-other sources	111.00	NaN	50	kg
7	3420.000000	36.00	maize - pds	111.00	NaN	50	kg
8	3360.000000	13.00	barley	115.00	NaN	50	kg
...	...	...	...	...	...	...	...
145	24.700001	0.95	other served processed food	0.70	0.0	68	Re
146	21.100000	0.85	cake, pastry, prepared sweets	0.20	0.0	68	Re
147	28.500000	0.17	biscuits, chocolates	0.35	0.0	68	Re
148	24.700001	0.95	papad, bhujia, namkeen, mixture, chanachur	0.70	0.0	68	Re
149	24.700001	0.95	other packaged processed food	0.70	0.0	68	Re

277 rows × 7 columns

In [6]:

```
# age-sex composition
pop = pd.read_parquet('z.parquet', engine = 'pyarrow')
pop
```

Out[6]:

	k	rural	m	religion	social group	Males 0-1	Males 1-5	Males 5-10	Males 10-15	Males 15-20	Males 20-30	...	Males 60-100	Fema
j														
410001101	Urban	Gujarat	Hinduism	Other backward class	0	0	0	0	0	2	...	0	
410001102	Urban	Gujarat	Christianity	Others	0	0	0	1	0	0	...	0	
410001103	Urban	Gujarat	Hinduism	Others	0	0	0	0	0	3	...	0	
410001201	Urban	Gujarat	Christianity	Others	0	0	0	0	0	1	...	1	
410001202	Urban	Gujarat	Hinduism	Others	0	0	0	0	0	0	...	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	
799981301	Rural	Jammu & Kashmir	Hinduism	Others	0	0	0	1	1	0	...	0	
799982101	Rural	Jammu & Kashmir	Hinduism	Others	0	0	0	1	1	0	...	0	
799982201	Rural	Jammu & Kashmir	Hinduism	Others	0	0	0	1	2	0	...	0	
799982202	Rural	Jammu & Kashmir	Hinduism	Others	0	0	2	1	0	0	...	0	
799982301	Rural	Jammu & Kashmir	Hinduism	Others	0	0	0	0	0	0	...	1	

101662 rows × 22 columns

In [7]:
```
#total household expenditure in Rupee
expenditure = pd.read_parquet('total_expenditures.parquet', engine = 'pyarrow')
expenditure
```

Out[7]:

j	total_value
410001101	7813
410001102	3573
410001103	9359
410001201	5671
410001202	6169
...	...
799981301	3842
799982101	2736
799982201	3378
799982202	3221
799982301	3777

101660 rows × 1 columns

In [8]:
```
pop.info()
pop.religion.value_counts()
#from the output, we can see that Maharashtra has the second most data points (8043 hous
#so, this would further insure the validity of our following estimation
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 101662 entries, 410001101 to 799982301
Data columns (total 22 columns):
 #   Column          Non-Null Count   Dtype 
---  ------          --------------   ----- 
 0   rural           101662 non-null  object
 1   m               101662 non-null  object
 2   religion        101659 non-null  object
 3   social group    101648 non-null  object
 4   Males 0-1       101662 non-null  int64 
 5   Males 1-5       101662 non-null  int64 
 6   Males 5-10      101662 non-null  int64 
 7   Males 10-15     101662 non-null  int64 
 8   Males 15-20     101662 non-null  int64 
 9   Males 20-30     101662 non-null  int64 
 10  Males 30-50     101662 non-null  int64 
 11  Males 50-60     101662 non-null  int64 
 12  Males 60-100    101662 non-null  int64 
 13  Females 0-1     101662 non-null  int64 
 14  Females 1-5     101662 non-null  int64 
 15  Females 5-10    101662 non-null  int64 
 16  Females 10-15   101662 non-null  int64 
 17  Females 15-20   101662 non-null  int64 
 18  Females 20-30   101662 non-null  int64 
 19  Females 30-50   101662 non-null  int64 
 20  Females 50-60   101662 non-null  int64 
 21  Females 60-100  101662 non-null  int64 
dtypes: int64(18), object(4)
memory usage: 17.8+ MB
```

Out[8]:
```
Hinduism         77062
Islam            13136
Christianity      7070
```

```
Sikhism              2016
Buddhism             1094
Others                956
Jainism               322
Zoroastrianism          3
Name: religion, dtype: int64
```

Here are some helper functions to extrapolate data for the chosen population from the larger raw dataframe

The `filter_pop` function takes a raw dataframe and households characteristics as arguments and returns a `DataFrame` for the choosen population segement. The optional arguemnts help if you want to target specific demographic groups in the choosen state

Input Parameters:

- **df**: the name of the raw population df you want to extrapolate from
- **state**: an str (any state name from the 35 states)
- **rural**: optional; an str ('Rural' or 'Urban')
- **religion**: optional; an str ('Hinduism', 'Islam', 'Christianity', 'Sikhism', 'Buddhism', 'Others', 'Jainism', or 'Zoroastrianism')

In [9]:
```
def filter_pop(df, state, rural = None, religion = None):
    new = df.loc[df['m'] == state]
    if rural != None:
        new = new.loc[new['rural'] == rural]
    if religion != None:
        new= new.loc[new['religion'] == religion]
    return new
```

The `get_id` function takes a raw dataframe and households characteristics as arguments, uses the `filter_pop` function, and returns a list of household IDs for the chosen population

Input Parameters:

- **df**: the raw df you want to extrapolate from
- **state**: an str (any state name from the 35 states)
- **rural**: optional; an str ('Rural' or 'Urban')
- **religion**: optional; an str ('Hinduism', 'Islam', 'Christianity', 'Sikhism', 'Buddhism', 'Others', 'Jainism', or 'Zoroastrianism')

In [10]:
```
def get_id(df, state, rural = None, religion = None):
    ids = filter_pop(df = pop, state = state, rural = rural, religion = religion).index
    return ids
```

The `match_info` function takes a raw dataframe and household_ids and returns a sliced df for the particular selected households

Input Parameters:

- **ids**: list of column ids
- **df**: the raw df you want to extrapolate from

In [11]:
```
def match_info(ids, df):
    n = df.reset_index()
```

```python
    new = n[n['j'].isin(ids)]
    return new
```

[A] Estimate Demand System

Establish and format DataFrames for the chosen population: Surveyed Households from the state of Maharashtra, India

In [12]:
```python
maharashtra_id =get_id(df = pop, state = 'Maharashtra')
maharashtra_id
```

Out[12]:
```
Index(['421001201', '421001202', '421001203', '421001204', '421002201',
       '421002202', '421002203', '421002204', '421011101', '421011102',
       ...
       '756982202', '756982301', '756991101', '756991102', '756991201',
       '756991202', '756991203', '756991204', '756991301', '756991302'],
      dtype='object', name='j', length=8043)
```

In [13]:
```python
maha_food_quant = match_info(maharashtra_id, food_quant)

maha_food_quant.drop('Frequency', inplace=True, axis=1) #drop unecessary column & level
maha_food_quant.droplevel(0, axis=1)

# add the time 't' and market 'm' column
#since the data is from one year (2016) and one market (maharashtra), equate all to 1
maha_food_quant['m'] = 1
maha_food_quant['t'] = 1

maha_food_quant.rename(columns = {'unit':'u'}, inplace = True) #rename & format
maha_food_quant = maha_food_quant.set_index(['j','t','m','u'])
maha_food_quant.columns.name = 'i'

maha_food_quant = maha_food_quant.apply(lambda x: pd.to_numeric(x,errors='coerce'))
maha_food_quant = maha_food_quant.replace(0,np.nan)
maha_food_quant = maha_food_quant.droplevel(0, axis=1)
maha_food_quant
```

```
/opt/conda/lib/python3.9/site-packages/pandas/core/generic.py:4150: PerformanceWarning: dropping on a non-lexsorted multi-index without a level parameter may impact performanc
e.
  obj = obj._drop_axis(labels, axis, level=level, errors=errors)
```

Out[13]:

			i	apple	arhar (tur)	baby food	bajra & products	banana	barley & products	beef	beer	berries	besan	...	tod
j	**t**	**m**	**u**												
421001201	**1**	**1**	**Re**	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	Na
			box	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	Na
			gm	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	Na
			kg	NaN	1000.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	500.0	...	Na
			litre	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	Na
...	**...**	**...**	**...**	...	...	...	...	...	...	...	...	...	...	...	
756991302	**1**	**1**	**gm**	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	Na
			kg	NaN	1500.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	Na
			litre	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	Na
			no.	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	Na

std. unit	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	Na

55497 rows × 164 columns

In [14]:
```
maha_tol_exp = match_info(maharashtra_id, expenditure)
maha_tol_exp
```

Out[14]:

	j	total_value
7577	421001201	4857
7578	421001202	5246
7579	421001203	2725
7580	421001204	4750
7581	421002201	5207
...	...	...
78734	756991202	2497
78735	756991203	2028
78736	756991204	2833
78737	756991301	3706
78738	756991302	4566

8043 rows × 2 columns

In [15]:
```
maha_food_exp = match_info(maharashtra_id, food_price)

maha_food_exp.drop('Frequency', inplace=True, axis=1) #drop unecessary columns
maha_food_exp.columns.name = 'i'
maha_food_exp.set_index('j')
maha_food_exp = maha_food_exp.groupby('i',axis=1).sum()
maha_food_exp = maha_food_exp.replace(0,np.nan) # Replace zeros with NaN
maha_food_exp.rename(columns={maha_food_exp.columns[-1] :'j'}, inplace=True)

# add the time 't' and market 'm' column
#since the data is from one year (2016) and one market (maharashtra), equate all to 1
maha_food_exp.insert(loc=165, column='t', value=1)
maha_food_exp.insert(loc=166, column='m', value=1)

# Take logs of expenditures and name the new df 'y'
y = np.log(maha_food_exp.set_index(['j','t','m']))
y
```

```
/opt/conda/lib/python3.9/site-packages/pandas/core/generic.py:4150: PerformanceWarning:
dropping on a non-lexsorted multi-index without a level parameter may impact performanc
e.
  obj = obj._drop_axis(labels, axis, level=level, errors=errors)
```

Out[15]:

		i	apple	arhar (tur)	baby food	bajra & products	banana	barley & products	beef	beer	berries	besan	...	t
j	**t**	**m**												
421001201	**1**	**1**	NaN	4.317488	NaN	NaN	NaN	NaN	NaN	NaN	NaN	3.401197	...	
421001202	**1**	**1**	NaN	4.382027	NaN	NaN	4.248495	NaN	NaN	NaN	NaN	3.401197	...	
421001203	**1**	**1**	NaN	NaN	NaN	NaN	2.890372	NaN	NaN	NaN	NaN	NaN	...	
421001204	**1**	**1**	NaN	NaN	NaN	NaN	3.555348	NaN	NaN	NaN	NaN	3.401197	...	

421002201	**1**	**1**	NaN	4.317488	NaN	NaN	3.555348	NaN	NaN	NaN	NaN	3.401197	...
...	**...**	**...**	...	...	...	...	...	...	...	...	...	...	...
756991202	**1**	**1**	NaN	3.401197	NaN	NaN	3.688879	NaN	NaN	NaN	2.484907	NaN	...
756991203	**1**	**1**	NaN	4.700480	NaN	NaN	NaN	NaN	NaN	NaN	2.564949	NaN	...
756991204	**1**	**1**	NaN	4.828314	NaN	NaN	NaN	NaN	NaN	NaN	2.708050	NaN	...
756991301	**1**	**1**	NaN	4.867534	NaN	NaN	3.091042	NaN	NaN	NaN	2.484907	NaN	...
756991302	**1**	**1**	NaN	4.574711	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...

8043 rows × 164 columns

In [16]:

```
maha_pop = match_info(maharashtra_id, pop)
maha_pop

# add the time 't' and market 'm' column
#since the data is from one year (2016) and one market (maharashtra), equate all to 1
maha_pop['m'] = 1
maha_pop['t'] = 1
maha_pop.columns.name = 'k'
maha_pop.set_index(['j','t','m'],inplace=True)
maha_pop.drop(maha_pop.columns[0:3], inplace=True, axis=1) #drop unecessary columns

# calculate and add new column 'log Hsize'
maha_pop['log Hsize'] = np.log(maha_pop.sum(axis=1).values)
maha_pop
```

Out[16]:

		k	Males 0-1	Males 1-5	Males 5-10	Males 10-15	Males 15-20	Males 20-30	Males 30-50	Males 50-60	Males 60-100	Females 0-1	Females 1-5	Fema 5-
j	**t**	**m**												
421001201	**1**	**1**	0	1	1	0	0	0	1	0	0	0	0	
421001202	**1**	**1**	0	0	0	0	0	0	1	0	0	0	1	
421001203	**1**	**1**	0	0	0	0	0	1	0	0	0	0	0	
421001204	**1**	**1**	0	0	0	0	0	0	1	0	0	0	0	
421002201	**1**	**1**	0	1	0	0	0	0	1	0	0	0	0	
...	**...**	**...**	...	...	...	...	...	...	...	...	...	...	...	
756991202	**1**	**1**	0	0	0	0	0	0	1	0	0	0	0	
756991203	**1**	**1**	0	0	0	0	0	0	0	0	1	0	0	
756991204	**1**	**1**	0	0	0	0	0	0	1	0	0	1	1	
756991301	**1**	**1**	0	0	0	0	0	1	0	1	0	0	0	
756991302	**1**	**1**	0	0	0	0	1	0	1	0	0	0	0	

8043 rows × 19 columns

Estimation

1.First step:

Recall that there are two steps to estimation; the first step involves estimating the “reduced form” linear regression

$$y^j_{it} = a_{it} + \delta_i' z^j_t + \epsilon^j_{it}.$$

In [17]:
```
result = cfe.Result(y=y,z=maha_pop)
```

This creates a complicated “Result” object, with lots of different attributes. Note from below that attributes y and z are now defined.

In [18]:
```
result
```

Out[18]: xarray.Result

▸ Dimensions: (**k**: 19, **j**: 8043, **t**: 1, **m**: 1, **i**: 103)

▾ Coordinates:

j	(j)	object	'421001201' ... '756991302'
t	(t)	int64	1
m	(m)	int64	1
i	(i)	<U50	'apple' ... 'wheat/atta - other ...
k	(k)	<U14	'Males 0-1' ... 'log Hsize'

▸ Data variables: (20)

▸ Attributes: (10)

In [19]:
```
#the Result class has code to estimate the "reduced form" in one line:
result.get_reduced_form()
```

```
/opt/conda/lib/python3.9/site-packages/cfe/estimation.py:425: UserWarning: No variation
in: (1, 1)
  warnings.warn("No variation in: %s" % str(constant))
```

After running this we can examine the estimated coefficients δ:

In [20]:
```
result.delta.to_dataframe().unstack('k')
```

Out[20]:

k	Males 0-1	Males 1-5	Males 5-10	Males 10-15	Males 15-20	Males 20-30	Males 30-50	Males 50-60	Males 60-100
i									
apple	0.116241	-0.010087	-0.016225	0.042034	0.025789	0.072390	0.185028	0.152401	0.118404
arhar (tur)	-0.023166	-0.038610	-0.012056	0.004052	0.023918	0.061794	0.095395	0.091041	0.096935
bajra & products	0.252834	-0.010578	0.042047	0.071540	0.075980	0.164270	0.045495	0.089150	0.175357
banana	-0.025035	-0.032487	-0.016979	0.010445	0.022264	0.067411	0.131955	0.091155	0.082210
besan	-0.073333	-0.018965	0.036798	0.001278	0.024174	0.085924	0.085044	0.100227	0.111893
...	...	...	...	...	...	...	...	...	...
urd	0.093142	0.039835	0.003065	0.024844	0.053146	0.083538	0.066379	0.026303	0.099115
vanaspati, margarine	0.166406	0.025756	0.048454	0.023660	-0.034821	0.101674	0.074322	0.152296	0.219197
watermelon	0.109513	0.093756	0.096730	0.033754	0.091002	0.080101	0.006049	0.032390	0.097625
wheat/atta -	-0.053065	-0.129640	-0.060660	-0.009596	0.041966	-0.045329	-0.067712	-0.085848	-0.069854

P.D.S.										
wheat/atta - other sources	-0.091201	-0.073899	-0.066786	0.006375	-0.028890	0.013290	0.096776	0.101193	0.056519	-

103 rows × 19 columns

Also the good-time constants a_{it} (this captures the effects of prices):

However, in our data, we only have data from 1 year, so the time factor is mostly irrelevant; this won't create a problem in our estimation because although we only have 1 year, the data is from a large pool of households (8043 j values)

In [21]:

```
result.a.to_dataframe().unstack('i')
```

Out[21]:

i		**apple**	**arhar (tur)**	**bajra & products**	**banana**	**besan**	**biscuits, chocolates**	**black pepper**	**bread (bakery)**	**brinjal**	**cabbage**	**...**
t	**m**											
1	**1**	4.337676	3.689784	3.436197	3.184263	2.69299	3.432596	1.979749	3.462497	2.353381	2.359734	...

1 rows × 103 columns

2. Second step:

The second step involves using Singular Value Decomposition to find the rank one matrix that best approximates the residuals e^j_{it}. This can be interpreted as

$$-\beta_i \log \lambda^j_t,$$

where the $\log \lambda^j_t$ is the log of the marginal utility of expenditures (MUE) for household j at time t, and where β_i are the corresponding “Frisch elasticities” that tell us how much demand changes as the MUE falls.

Estimates can also be computed as a one-liner:

In [22]:

```
result.get_beta(as_df=True)
```

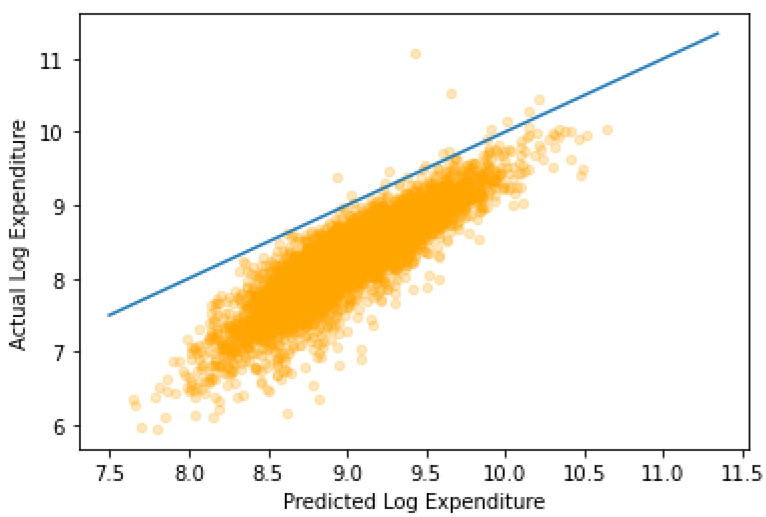
Out[22]:

```
i
apple                           0.451570
arhar (tur)                     0.177062
bajra & products               -0.085787
banana                          0.329504
besan                           0.171622
                                  ...
urd                             0.155062
vanaspati, margarine            0.243740
watermelon                      0.256393
wheat/atta - P.D.S.             0.057134
wheat/atta - other sources      0.116349
Name: beta, Length: 103, dtype: float64
```

3. Assessment of Fit

In [24]:
```python
%matplotlib inline
import matplotlib.pyplot as plt
import matplotlib.cm as cm

xbar = np.exp(result.y).sum(['m','i']).to_dataframe('xbar').replace(0,np.nan).squeeze()
xhat = result.get_predicted_expenditures().sum(['m','i']).to_dataframe('xhat').replace(0

# Make dataframe of actual & predicted
df = pd.DataFrame({'Actual Log Expenditure':np.log(xbar),'Predicted Log Expenditure':np.

df.plot.scatter(x='Predicted Log Expenditure',y='Actual Log Expenditure', c = "orange",

# Add 45 degree line
v = plt.axis()
vmin = np.max([v[0],v[2]])
vmax = np.max([v[1],v[3]])
plt.plot([vmin,vmax],[vmin,vmax])
```

Out[24]:
```
[<matplotlib.lines.Line2D at 0x7fd8c6bd45b0>]
```



In [24]:
```python
#save estimate result in datahub
result.to_dataset('maharashtra.ds')
```

Out[24]: xarray.Dataset

▸ Dimensions: (**j**: 8043, **i**: 103, **k**: 19, **t**: 1, **m**: 1, **kp**: 19)

▾ Coordinates:

j	(j)	object	'421001201' ... '756991302'
t	(t)	int64	1
m	(m)	int64	1
i	(i)	object	'apple' ... 'wheat/atta - other ...
k	(k)	<U14	'Males 0-1' ... 'log Hsize'
kp	(kp)	<U14	'Males 0-1' ... 'log Hsize'

▸ Data variables: (20)

▸ Attributes: (0)

4. Infer Prices

In [25]:
```python
# Estimates most things (not counting std errors for betas).
xhat = result.get_predicted_expenditures(as_df = True)
```

```
result.get_beta(as_df=True).sort_values(ascending=False).tail(30) # Check sanity & incom
```

Out[25]:

```
i
groundnut                                              0.138778
chillis (green)                                        0.135773
chira                                                  0.129129
refined oil [sunflower, soyabean, saffola, etc.]       0.123606
ingredients for pan                                    0.121903
oilseeds                                               0.121774
turmeric                                               0.116570
wheat/atta - other sources                             0.116349
suji, rawa                                             0.113621
jeera                                                  0.112667
other pulses                                           0.109483
garlic                                                 0.108950
cereal substitutes  (tapioca, jackfruit seed etc.)     0.106252
lpg                                                    0.103953
kerosene-pds                                           0.092297
jowar & products                                       0.089634
groundnut oil                                          0.087579
candle                                                 0.080314
salt                                                   0.066118
wheat/atta - P.D.S.                                    0.057134
sugar - other sources                                  0.053577
gram (split)                                           0.030520
peas-pulses                                            0.023732
gram (whole)                                           0.020225
other tobacco products                                 0.018432
other pulse products                                   0.009157
firewood & chips                                      -0.037526
bajra & products                                      -0.085787
dry chillies                                          -0.088085
matches                                               -0.160492
Name: beta, dtype: float64
```

In [26]:

```
phat = xhat/maha_food_quant
# Keep kgs; g
phat = phat.xs('kg',level='u').groupby(['t','m']).median().T.dropna(how='all')
result['prices'] = phat.stack().to_xarray().to_array()
# Make this persistent...
result.to_dataset('./foo.ds')
```

Out[26]:

xarray.Dataset

▸ Dimensions: (**i**: 103, **j**: 8043, **k**: 19, **variable**: 1, **m**: 1, **t**: 1, **kp**: 19)

▾ Coordinates:

i	(i)	object	'apple' ... 'wheat/atta - other ...
j	(j)	object	'421001201' ... '756991302'
t	(t)	int64	1
m	(m)	int64	1
k	(k)	<U14	'Males 0-1' ... 'log Hsize'
kp	(kp)	<U14	'Males 0-1' ... 'log Hsize'
variable	(variable)	int64	1

▸ Data variables: (20)

▸ Attributes: (0)

5. Predicting Positive Consumption

An issue with our assessment of fit is that we *predicted* that every household would consume positive quantitites of every good, and in making our assessment we ignored the (many) cases in which in fact the household had zero expenditures on that good.

Here we're going to go back and use similar framework to try and estimate the probability with which we'll observe zero expenditures as a function of λ, prices, and household characteristics.

In [30]:

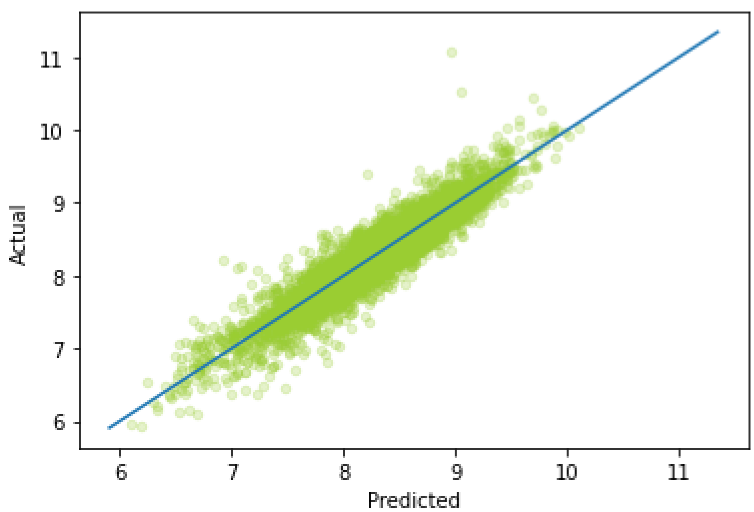
```
zeros_r = cfe.Result(y=(0.+(np.exp(result.y)>0)),z=result.z)
weights = zeros_r.get_predicted_log_expenditures()

# Truncate to make weights live in [0,1]
weights = weights.where((weights<1) + np.isnan(weights),1).where((weights>0) + np.isnan(

xbar = np.exp(result.y).sum(['m','i']).to_dataframe('xbar').replace(0,np.nan).squeeze()

# Calculate *expected* predicted expenditures, to make unconditional on being positive
xhat = (weights*result.get_predicted_expenditures())
xsum = xhat.sum(['m','i']).to_dataframe('xhat').replace(0,np.nan).squeeze()
```

In [32]:

```
# Make dataframe of actual & predicted
df = pd.DataFrame({'Actual':np.log(xbar),'Predicted':np.log(xsum)})

df.plot.scatter(x='Predicted',y='Actual', c = "yellowgreen", alpha = 0.25)

# Add 45 degree line
v = plt.axis()
vmin = np.max([v[0],v[2]])
vmax = np.max([v[1],v[3]])
plt.plot([vmin,vmax],[vmin,vmax])
```

Out[32]:

```
[<matplotlib.lines.Line2D at 0x7fd8b5cce160>]
```



6. Predicting Quantities

Now divide predicted expenditures by predicted prices to get predicted quantities, and put back into a dataframe.

In [33]:

```
xx = result.get_predicted_expenditures()
xhatdf = xx.to_dataset('i').to_dataframe()
xhatdf.columns.name ='i'

qhat = xhatdf.div(phat.T,axis=1)

qhat
```

Out[33]:

t	m	j	apple	arhar (tur)	bajra & products	banana	besan	biscuits, chocolates	black pepper	bread (bakery
1	1	421001201	1279.221862	1840.136729	4524.110669	NaN	644.386451	NaN	NaN	1122.86231
		421001202	1324.586062	1576.557158	4172.857881	NaN	593.310346	NaN	NaN	965.72499
		421001203	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
		421001204	1238.294150	1785.985335	4797.219563	NaN	660.145399	NaN	NaN	1028.26912
		421002201	1272.796247	1758.502814	4685.030580	NaN	641.160273	NaN	NaN	1057.02602
		...	...	...	...	...	...	...	...	.
		756991202	482.729227	867.390844	3519.328137	NaN	342.130511	NaN	NaN	498.41061
		756991203	372.843649	760.291658	4704.241176	NaN	325.509417	NaN	NaN	437.98425
		756991204	245.758148	1001.372565	6172.004967	NaN	347.566563	NaN	NaN	411.64719
		756991301	596.036674	1534.535837	8080.451066	NaN	587.490013	NaN	NaN	663.26236
		756991302	781.672839	1766.669639	6130.609603	NaN	612.833169	NaN	NaN	781.10750

8043 rows × 103 columns

In [34]:
```
qhat.to_csv('qhat.csv')
```

In [ ]:

[B]: Engel's Law

In [35]:
```
original_xhat = result.get_predicted_expenditures(as_df = True)
original_xhat['total_food_exp'] = original_xhat.iloc[:,0:103].sum(axis=1) #calculate tot
pop['total_household'] = pop.sum(axis=1) #calculate total household member

short_maha_pop = filter_pop(df = pop, state= 'Maharashtra')
short_maha_pop = short_maha_pop.drop(columns = ['rural', 'm', 'religion', 'social group'
```

```
/tmp/ipykernel_24/1260386158.py:3: FutureWarning: Dropping of nuisance columns in DataFr
ame reductions (with 'numeric_only=None') is deprecated; in a future version this will r
aise TypeError.  Select only valid columns before calling the reduction.
  pop['total_household'] = pop.sum(axis=1) #calculate total household member
```

In [36]:
```
short_maha_pop.reset_index()
original_xhat.reset_index()
short_maha_food_exp = original_xhat.merge(short_maha_pop, left_on='j', right_on='j') #me
```

In [37]:
```
# get per_capita_food_exp
short_maha_food_exp['per_capita_food_exp'] = short_maha_food_exp['total_food_exp']/short_
```

The `graph_engel` function takes in a food name and generate an Engel's Law graph to demonstrate the relationship between total food expenditure and expenditure on a sigle food

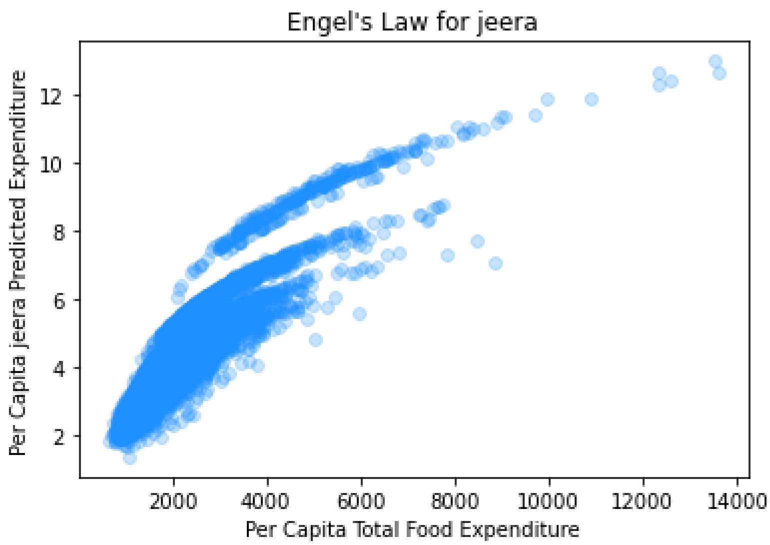
Input Parameters:

- **food**: a string (any food name from the xhat df columns)

In [38]:
```
def graph_engel(food):
```

```
    y = short_maha_food_exp[f"{food}"]/short_maha_food_exp['total_household']
    x = short_maha_food_exp['per_capita_food_exp']
    plt.scatter(x, y, c = "dodgerblue", alpha = 0.25)
    plt.title(f"Engel's Law for {food}")
    plt.xlabel("Per Capita Total Food Expenditure")
    plt.ylabel("Per Capita" + f" {food}" +" Predicted Expenditure")
    plt.show()
```

In [39]:
```
# testing example
graph_engel('jeera')
```



Based on the predicted income elasticities of the food, we chose different food from different elasticity categories:

- dry chillies (negative elasticity, inferior good)
- bajra (negative elasticity, inferior good)
- garlic (likely inferior good)
- peas-pulses (aka dried, likely inferior good)
- peas-vegetable (aka fresh, staple food)
- potato (staple food)
- ice cream (normal good)
- cooked snacks purchased [samosa, puri, paratha,] (normal good)

In [40]:
```
examples = ['dry chillies','bajra & products', 'garlic', 'peas-pulses',
            'peas-vegetables', 'potato', 'ice-cream',
            'cooked snacks purchased [samosa, puri, paratha,']
```

In [41]:
```
#interative plot for each example
interact(graph_engel, food = examples)
```

```
interactive(children=(Dropdown(description='food', options=('dry chillies', 'bajra & pro
ducts', 'garlic', 'pea…
```

Out[41]:
```
<function __main__.graph_engel(food)>
```

[B]: Nutritional Content of Different Foods & Nutritional Adequacy of Diet

Here, we are looking at the nutritional content of the different foods, based on the recommended daily allowances we had access to from the previous project (U.S. recommended daily allowances). We are also comparing the household nutritional intake with the recommended daily intake.

In [42]:
```
DRI_url = "https://docs.google.com/spreadsheets/d/1y95IsQ4HKspPW3HHDtH7QMtlDA66IUsCHJLut

DRIs = read_sheets(DRI_url)

# Define *minimums*
diet_min = DRIs['diet_minimums'].set_index('Nutrition')

# Define *maximums*
diet_max = DRIs['diet_maximums'].set_index('Nutrition')
```

```
Key available for students@eep153.iam.gserviceaccount.com.
```

Now that we have the recommended daily allowances, we want to apply this to our data. The age ranges in our dataframes are slightly different from the age ranges in the diet_min and diet_max dataframes. For example, diet_min has daily allowances for Males from 4-8, but in our household data, we have age ranges such as Males from 1-5 and 5-10. Below, we try to solve this problem by taking averages of certain age ranges where there is varying overlap. In the end, we construct a dataframe that has the estimated recommended daily allowances for all of the age/sex ranges provided in the NSS data that we imported.

In [38]:
```
new_df = pd.DataFrame(index = diet_min.index)
new_df['Males 0-1'] =  diet_min['C 1-3'].to_list()
new_df['Females 0-1'] = diet_min['C 1-3'].to_list()
new_df['Males 1-5'] =  (np.array(diet_min['C 1-3']) + np.array(diet_min['M 4-8'])) / 2
new_df['Females 1-5'] =  (np.array(diet_min['C 1-3']) + np.array(diet_min['F 4-8'])) / 2
new_df['Males 5-10'] =  (np.array(diet_min['M 4-8']) + np.array(diet_min['M 9-13'])) / 2
new_df['Females 5-10'] =  (np.array(diet_min['M 4-8']) + np.array(diet_min['M 9-13'])) /
new_df['Males 10-15'] =  (np.array(diet_min['M 9-13']) + np.array(diet_min['M 14-18']))
new_df['Females 10-15'] =  (np.array(diet_min['F 9-13']) + np.array(diet_min['F 14-18'])
new_df['Males 15-20'] =  np.array(diet_min['M 14-18'])
new_df['Females 15-20'] =  np.array(diet_min['F 14-18'])
new_df['Males 20-30'] =  np.array(diet_min['M 19-30'])
new_df['Females 20-30'] =  np.array(diet_min['F 19-30'])
new_df['Males 31-50'] =  np.array(diet_min['M 31-50'])
new_df['Females 31-50'] =  np.array(diet_min['F 31-50'])
new_df['Males 50-60'] =  np.array(diet_min['M 51+'])
new_df['Males 60-100'] =  np.array(diet_min['M 51+'])
new_df['Females 50-60'] =  np.array(diet_min['F 51+'])
new_df['Females 60-100'] =  np.array(diet_min['F 51+'])
new_df
```

Out[38]:

Nutrition	Males 0-1	Females 0-1	Males 1-5	Females 1-5	Males 5-10	Females 5-10	Males 10-15	Females 10-15	Males 15-20	Females 15-20
Energy	1000.0	1000.0	1200.00	1100.00	1600.00	1600.00	2000.00	1700.00	2200.0	1800.0
Protein	13.0	13.0	16.00	16.00	26.50	26.50	43.00	40.00	52.0	46.0
Fiber, total dietary	14.0	14.0	16.80	15.40	22.40	22.40	28.00	23.80	30.8	25.2
Folate, DFE	150.0	150.0	175.00	175.00	250.00	250.00	350.00	350.00	400.0	400.0
Calcium, Ca	700.0	700.0	850.00	850.00	1150.00	1150.00	1300.00	1300.00	1300.0	1300.0
Carbohydrate, by difference	130.0	130.0	130.00	130.00	130.00	130.00	130.00	130.00	130.0	130.0
Iron, Fe	7.0	7.0	8.50	8.50	9.00	9.00	9.50	11.50	11.0	15.0
Magnesium, Mg	80.0	80.0	105.00	105.00	185.00	185.00	325.00	300.00	410.0	360.0
Niacin	6.0	6.0	7.00	7.00	10.00	10.00	14.00	13.00	16.0	14.0

Phosphorus, P	460.0	460.0	480.00	480.00	875.00	875.00	1250.00	1250.00	1250.0	1250.0	7
Potassium, K	3000.0	3000.0	3400.00	3400.00	4150.00	4150.00	4600.00	4600.00	4700.0	4700.0	47
Riboflavin	0.5	0.5	0.55	0.55	0.75	0.75	1.10	0.95	1.3	1.0	
Thiamin	0.5	0.5	0.55	0.55	0.75	0.75	1.05	0.95	1.2	1.0	
Vitamin A, RAE	300.0	300.0	350.00	350.00	500.00	500.00	750.00	650.00	900.0	700.0	9
Vitamin B-12	0.9	0.9	1.05	1.05	1.50	1.50	2.10	2.10	2.4	2.4	
Vitamin B-6	0.5	0.5	0.55	0.55	0.80	0.80	1.15	1.10	1.3	1.2	
Vitamin C, total ascorbic acid	15.0	15.0	20.00	20.00	35.00	35.00	60.00	55.00	75.0	65.0	
Vitamin E (alpha-tocopherol)	6.0	6.0	6.50	6.50	9.00	9.00	13.00	13.00	15.0	15.0	
Vitamin K (phylloquinone)	30.0	30.0	42.50	42.50	57.50	57.50	67.50	67.50	75.0	75.0	1
Zinc, Zn	3.0	3.0	4.00	4.00	6.50	6.50	9.50	8.50	11.0	9.0	

Now that we have a dataframe detailing the recommended daily intakes with the same age/sex groups as our imported dataset, we want to do a matrix multiplication of this dataframe and z_maha_ages, which tells us how many people are in each age/sex group per household.

In [39]:
```
z_maha_ages = maha_pop.reset_index()
z_maha_ages = z_maha_ages.iloc[:, 3:21]
z_maha_ages.to_numpy()
```

Out[39]:
```
array([[0, 1, 1, ..., 0, 0, 0],
       [0, 0, 0, ..., 1, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       ...,
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 1, 1],
       [0, 0, 0, ..., 1, 0, 0]])
```

In [40]:
```
transposed_new_df = new_df.reset_index().drop(['Nutrition'], axis=1).T
transposed_new_df = transposed_new_df.to_numpy()
```

In [41]:
```
nutrition_by_house = z_maha_ages.dot(transposed_new_df)
nutrition_by_house.columns = diet_min.index
nutrition_by_house['Household'] = maharashtra_id
nutrition_by_house.index = nutrition_by_house['Household']
nutrition_by_house
```

Out[41]:

Nutrition	Energy	Protein	Fiber, total dietary	Folate, DFE	Calcium, Ca	Carbohydrate, by difference	Iron, Fe	Magnesium, Mg	Niacin	Phosphorus, P
Household										
421001201	6200.0	128.0	86.8	1075.0	3850.0	520.0	33.0	930.0	43.0	2890.0
421001202	6400.0	155.0	89.6	1150.0	3300.0	390.0	25.5	1145.0	46.0	2650.0
421001203	1600.0	26.5	22.4	250.0	1150.0	130.0	9.0	185.0	10.0	875.0
421001204	8000.0	191.0	112.0	1550.0	4300.0	520.0	53.5	1365.0	58.0	3350.0
421002201	7000.0	158.0	98.0	1300.0	4000.0	520.0	42.5	1135.0	50.0	3110.0
...	...	...	...	...	...	...	...	...	...	...

756991202	4000.0	99.0	56.0	750.0	2300.0	260.0	17.5	745.0	30.0	1950.0
756991203	3800.0	98.0	53.2	800.0	2500.0	260.0	19.0	730.0	30.0	1950.0
756991204	8200.0	201.0	114.8	1550.0	4600.0	520.0	40.5	1505.0	60.0	3900.0
756991301	8300.0	204.5	116.2	1800.0	5850.0	650.0	54.5	1445.0	65.0	4225.0
756991302	9400.0	227.5	131.6	1800.0	5450.0	650.0	52.5	1670.0	70.0	4225.0

8043 rows × 21 columns

Next, we filtered our nutrient dataset to only look at the most recent round of data collection (t=68, corresponding to 2011-2012 of the NSS data). We then merged a few dataframes we filtered to create new_df, which describes the total_quantity, calorie, fat per unit, and protein per unit intake for each food item in each household.

In [42]:

```
N = nutritient.loc[nutritient.t=='68',:].set_index('i').drop(columns=['rural', 't', 'uni
N = N.reset_index()
N = N.drop_duplicates(subset=['i'])
N
```

Out[42]:

	i	calories per unit(kcal)	fat per unit(gm)	protein per unit(gm)
0	rice - P.D.S.	3460.00	5.00	75.00
1	rice - other sources	3460.00	5.00	75.00
2	chira	3460.00	12.00	66.00
3	khoi, lawa	3250.00	1.00	75.00
4	muri	3250.00	1.00	75.00
...	...	...	...	...
133	ingredients for pan	6.55	0.59	0.21
134	toddy	380.00	3.00	1.00
135	country liquor	380.00	3.00	1.00
136	beer	380.00	3.00	1.00
137	foreign liquor or refined liquor	380.00	3.00	1.00

136 rows × 4 columns

In [43]:

```
q = pd.read_parquet('q.parquet', engine='pyarrow').reset_index()
q_maha = q[q['j'].isin(maharashtra_id)]
#q_maha = q_maha.drop_duplicates(subset=['i'])
q_maha

new_df = q_maha.merge(N, left_on='i', right_on='i')
new_df
```

Out[43]:

	j	i	unit	Frequency	total_quantity	calories per unit(kcal)	fat per unit(gm)	protein per unit(gm)
0	421001201	arhar (tur)	kg	Monthly	1000.0	3350.0	17.0	223.0
1	421001202	arhar (tur)	kg	Monthly	1000.0	3350.0	17.0	223.0
2	421002201	arhar (tur)	kg	Monthly	1000.0	3350.0	17.0	223.0
3	421002202	arhar (tur)	kg	Monthly	1000.0	3350.0	17.0	223.0
4	421002203	arhar (tur)	kg	Monthly	1000.0	3350.0	17.0	223.0

...	...	...	...	...	...	...	...	...
331365	756361201	barley & products	kg	Monthly	2000.0	3360.0	13.0	115.0
331366	756361202	barley & products	kg	Monthly	3000.0	3360.0	13.0	115.0
331367	756361203	barley & products	kg	Monthly	2000.0	3360.0	13.0	115.0
331368	756361204	barley & products	kg	Monthly	4000.0	3360.0	13.0	115.0
331369	756361301	barley & products	kg	Monthly	10000.0	3360.0	13.0	115.0

331370 rows × 8 columns

Here, we imported a csv file that include FDC IDs we found for each of the food items in our dataset.

In [44]:
```
fdc_codes = pd.read_csv('proj_3_fdc_codes.csv').set_index('Item')
fdc_codes = fdc_codes.reset_index()
```

In [45]:
```
#this is the final dataframe
new_df_codes = new_df.merge(fdc_codes, left_on='i', right_on='Item')
new_df_codes['unit'] = ['g'] * len(new_df_codes)
new_df_codes
```

Out[45]:

	j	i	unit	Frequency	total_quantity	calories per unit(kcal)	fat per unit(gm)	protein per unit(gm)	Item	ID
0	421001201	arhar (tur)	g	Monthly	1000.0	3350.0	17.0	223.0	arhar (tur)	1977550
1	421001202	arhar (tur)	g	Monthly	1000.0	3350.0	17.0	223.0	arhar (tur)	1977550
2	421002201	arhar (tur)	g	Monthly	1000.0	3350.0	17.0	223.0	arhar (tur)	1977550
3	421002202	arhar (tur)	g	Monthly	1000.0	3350.0	17.0	223.0	arhar (tur)	1977550
4	421002203	arhar (tur)	g	Monthly	1000.0	3350.0	17.0	223.0	arhar (tur)	1977550
...	...	...	...	...	...	...	...	...	...	...
233493	756361201	barley & products	g	Monthly	2000.0	3360.0	13.0	115.0	barley & products	2072684
233494	756361202	barley & products	g	Monthly	3000.0	3360.0	13.0	115.0	barley & products	2072684
233495	756361203	barley & products	g	Monthly	2000.0	3360.0	13.0	115.0	barley & products	2072684
233496	756361204	barley & products	g	Monthly	4000.0	3360.0	13.0	115.0	barley & products	2072684
233497	756361301	barley & products	g	Monthly	10000.0	3360.0	13.0	115.0	barley & products	2072684

233498 rows × 10 columns

In [46]:
```
food_items = N['i'].sort_values(ascending=True)
q_1000 = pd.DataFrame()
q_1000['i'] = food_items
```

```
q_1000['q'] = [1000]*len(food_items)
q_1000 = q_1000.reset_index().drop(['index'], axis=1)
q_1000 = q_1000[q_1000['i'].isin(fdc_codes['Item'])]
q_1000 = fdc_codes.merge(q_1000, left_on = 'Item', right_on = 'i' )
q_1000
```

Out[46]:

	Item	ID	i	q
0	apple	1102644	apple	1000
1	arhar (tur)	1977550	arhar (tur)	1000
2	baby food	1102843	baby food	1000
3	bajra & products	1799770	bajra & products	1000
4	banana	1102653	banana	1000
...	...	...	...	...
80	urd	1898206	urd	1000
81	vanaspati, margarine	1103828	vanaspati, margarine	1000
82	walnut	2118446	walnut	1000
83	watermelon	1102698	watermelon	1000
84	wheat/atta - other sources	522973	wheat/atta - other sources	1000

85 rows × 4 columns

In [47]:

```
fdc_codes = fdc_codes[fdc_codes['Item'].isin(q_1000['i'])]
fdc_codes
```

Out[47]:

	Item	ID
0	apple	1102644
1	arhar (tur)	1977550
2	baby food	1102843
3	bajra & products	1799770
4	banana	1102653
...	...	...
90	urd	1898206
91	vanaspati, margarine	1103828
92	walnut	2118446
93	watermelon	1102698
94	wheat/atta - other sources	522973

85 rows × 2 columns

After matching all of the food items across the different dataframes for uniformity, we ran the following cell to produce a dataframe that has the nutritional content of each food item we're looking at. We will use the information in this dataframe to map the nutrientients to the predicted consumption per household, qhat.

In [48]:

```
import fooddatacentral as fdc
apikey = 'CDXgPa1HVqJab8EFllem1ikOF75m2ELYwziKtICr'
D = {}
count = 0
for food in q_1000.i.tolist():
```

```
    try:
        FDC = q_1000.loc[q_1000.i==food,:].ID[count]
        count+=1
        print(FDC)
        D[food] = fdc.nutrients(apikey,FDC).Quantity
    except AttributeError:
        warnings.warn("Couldn't find FDC Code %s for food %s." % (food,FDC))

D = pd.DataFrame(D,dtype=float).fillna(0)

D
```

```
1102644
1977550
1102843
1799770
1102653
2072684
2038522
547462
1102699
2091506
170931
1100621
2024758
171314
1103343
1103193
1100517
1103345
2029648
170497
1100523
1103857
1100522
422335
1104484
1919204
1155520
1102631
170922
168570
2216557
2121048
1103354
1103844
1937534
175304
168448
1102665
1100536
1750348
1102666
1942595
1103956
1607231
174687
1915741
2058624
1102655
1103366
1886719
2008520
1102668
1102594
2091229
```

```
2155640
1102670
172420
508611
1909132
1100404
172337
598232
1103364
1102597
1103153
169926
170419
1103686
1102688
168287
1103374
1144812
2129576
2077766
2031743
1126152
1102697
561783
1103276
172231
1898206
1103828
2118446
1102698
522973
```

Out[48]:

	apple	arhar (tur)	baby food	bajra & products	banana	barley & products	beef	beer	berries	besan	...	suji, rawa	tamari
Alanine	0.00	0.0	0.00	0.0	0.00	0.0	0.0	0.0	0.00	0.0	...	0.0	
Alcohol, ethyl	0.00	0.0	0.00	0.0	0.00	0.0	0.0	0.0	0.00	0.0	...	0.0	
Amino acids	0.00	0.0	0.00	0.0	0.00	0.0	0.0	0.0	0.00	0.0	...	0.0	
Arginine	0.00	0.0	0.00	0.0	0.00	0.0	0.0	0.0	0.00	0.0	...	0.0	
Ash	0.00	0.0	0.00	0.0	0.00	0.0	0.0	0.0	0.00	0.0	...	0.0	
...	...	...	...	...	...	...	...	...	...	...	...	...	
Vitamin K (Menaquinone-4)	0.00	0.0	0.00	0.0	0.00	0.0	0.0	0.0	0.00	0.0	...	0.0	
Vitamin K (phylloquinone)	2.20	0.0	0.40	0.0	0.50	0.0	0.0	0.0	7.30	0.0	...	0.0	
Vitamins and Other Components	0.00	0.0	0.00	0.0	0.00	0.0	0.0	0.0	0.00	0.0	...	0.0	
Water	85.56	0.0	82.10	0.0	74.91	0.0	0.0	0.0	88.93	0.0	...	0.0	3
Zinc, Zn	0.04	0.0	0.04	0.0	0.15	0.0	0.0	0.0	0.15	0.0	...	0.0	

182 rows × 85 columns

In [135…

```python
food_list = qhat.columns.values.tolist()
d_list = D.columns.values.tolist()

#cross filter and match the two dfs; replace NaN values with 0
```

```
final_q = qhat.filter(items=d_list).replace(np.nan,0)/30 #convert monthly predicted inta
final_d = D.filter(items=food_list).replace(np.nan,0)
```

Below, predicted_consumption shows nutritional content mapped to each household.

In [136…

```
predicted_consumption = final_q@final_d.T
predicted_consumption
```

Out[136]:

t	m	j	Alanine	Alcohol, ethyl	Amino acids	Arginine	Ash	Aspartic acid	Beta-sitostanol	Beta-sitosterol
1	1	421001201	36.535100	0.0	0.0	135.684709	216.678193	94.564400	426.290455	14538.848338
		421001202	30.633055	0.0	0.0	131.496218	200.705723	79.928233	328.905466	11217.484762
		421001203	0.000000	0.0	0.0	0.000000	0.000000	0.000000	0.000000	0.000000
		421001204	33.721344	0.0	0.0	134.185935	204.408984	87.067603	456.107117	15555.760444
		421002201	33.899246	0.0	0.0	130.658442	205.059762	87.702233	436.010458	14870.353889
		...	...	...	...	...	...	...	...	...
		756991202	16.700813	0.0	0.0	61.118263	94.200028	43.900674	235.606372	8035.472699
		756991203	14.374527	0.0	0.0	50.805302	79.703840	37.876841	245.374795	8368.629614
		756991204	15.168937	0.0	0.0	56.449140	82.072721	40.576162	209.638969	7149.841470
		756991301	23.491333	0.0	0.0	88.867892	133.005919	62.136230	593.866146	20254.100779
		756991302	28.954558	0.0	0.0	110.592773	165.808526	75.843433	520.787389	17761.713346

8043 rows × 182 columns

Finally, we created a dataframe, comparison, that compares the nutritional content mapped to each household (predicted_consumption) with the recommended daily nutritional intake per household (nutrient_by_house). We included a column in the dataframe that compares these values, comparison, that takes the sum of all of the nutrients per household. Negative values in this column indicate that the households are malnourished/taking in less than the recommended daily allowances.

In [137…

```
nutrition_by_house_filtered = nutrition_by_house.filter(items=predicted_consumption).rep
predicted_consumption_filtered = predicted_consumption.filter(items=nutrition_by_house).
```

In [138…

```
predicted_consumption_filtered = predicted_consumption_filtered.reset_index().drop(['t',
predicted_consumption_filtered = predicted_consumption_filtered.rename({'j':'Household'}
predicted_consumption_filtered = predicted_consumption_filtered.set_index('Household')
```

In [140…

```
predicted_consumption_filtered = predicted_consumption_filtered.sort_index(axis=1, ascen
nutrition_by_house_filtered = nutrition_by_house_filtered.sort_index(axis=1, ascending=F
```

In [141…

```
comparison = predicted_consumption_filtered - nutrition_by_house_filtered
comparison['Sum'] = comparison.sum(axis=1)
```

In [143…

```
negative_values = comparison[comparison['Sum'] < 0]
negative_values
```

Out[143]:

	Zinc, Zn	Vitamin K (phylloquinone)	Vitamin E (alpha-tocopherol)	Vitamin C, total ascorbic acid	Vitamin B-6	Vitamin B-12	Vitamin A, RAE	Thiamin	Riboflavin	Prot

Household										
421001203	-6.5	-57.5	-9.0	-35.0	-0.80	-1.50	-500.0	-0.75	-0.75	-2
421011101	-6.5	-57.5	-9.0	-35.0	-0.80	-1.50	-500.0	-0.75	-0.75	-2
421031205	-8.0	-90.0	-15.0	-75.0	-1.50	-2.40	-700.0	-1.10	-1.10	-4
421071201	-9.5	-67.5	-13.0	-60.0	-1.15	-2.10	-750.0	-1.05	-1.10	-4
421111204	-13.0	-115.0	-18.0	-70.0	-1.60	-3.00	-1000.0	-1.50	-1.50	-5
...	...	...	...	...	...	...	...	...	...	
756842301	-8.5	-67.5	-13.0	-55.0	-1.10	-2.10	-650.0	-0.95	-0.95	-4
756911301	-4.0	-42.5	-6.5	-20.0	-0.55	-1.05	-350.0	-0.55	-0.55	-1
756911302	-11.0	-120.0	-15.0	-90.0	-1.30	-2.40	-900.0	-1.20	-1.30	-5
756932301	-4.0	-42.5	-6.5	-20.0	-0.55	-1.05	-350.0	-0.55	-0.55	-1
756971202	-9.5	-67.5	-13.0	-60.0	-1.15	-2.10	-750.0	-1.05	-1.10	-4

256 rows × 21 columns

Based our computations above, we found that 3.18% of the households in Maharashtra are malnourished relative to the recommended daily nutritional intake.

In [144…

```
#proportion of households not getting enough nutrients:
len(negative_values)/len(comparison) * 100
```

Out[144]:

```
3.1828919557379085
```

In [ ]: