One Acre Fund Written Assessment

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Assignment 2

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Business Problem

In this project, we will be focusing on Learning and exploring the *Effects* of Market Orientation to farmers in Rwanda, and suggest households characteristics of that explains market orientation.

This report will help One Acre fund in investigating those effects, improving farming households nutrient security, but also eradicating hunger.

We will use the DataScience toolbox and other researches to provide informations to stakeholders and recommend them the optimal steps to enhance farmers dietary diversity.

Data

Regarding the data we will use data collected extensively by One Acre Fund from their client through digital survey.

Methodology

The goal of this project is to analyse the effects of Market orientation on household dynamics,by considering number of food consumed by group, Income to the group and how regionality factors affect it.

First step will be identifying the number of households in every survey and their gender, this will help in preventing bias in decision making.

Secondly, we will identify and analyse percentage of sold crops, Sales income to group, location effects to dietary diversity of household.

we will use a Logistic regression Model to predict dietary using mentioned factors

Analysis

I. Data Exploration

In [1]:
```
import pandas as pd
```

In [2]:
```
# Read the data
full_data = pd.read_csv('./Data/Survey_Data.csv', index_col=0)

# View first five rows of data
full_data.head()
```

Out[2]:

	respondentNr	surveyQuestions.location.sector	surveyQuestions.location.village	surveyQuestions.location.countryGroup._geopoint_altitude
1	1	Ntyazo	Kimigunga	1540.300049
2	2	Ntyazo	Mande	1537.800049
3	3	Muyira	Rugese	1565.099976
4	4	Ntyazo	Kimigunga	1537.699951
5	5	Ntyazo	Mande	1556.400024

5 rows × 176 columns

In [3]:
```
#The shape of our data
print('Shape of our data:', full_data.shape)
```

```
Shape of our data: (240, 176)
```

We can see that we have 240 households interview from the dataset

In [4]:
```
full_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 240 entries, 1 to 240
Columns: 176 entries, respondentNr to surveyQuestions.cassavaFertGroup.fertilizer_reason_more.other.y
dtypes: bool(1), float64(69), int64(8), object(98)
memory usage: 330.2+ KB
```

In [5]:
```
full_data.dtypes.value_counts().to_frame()
```

Out[5]:

	0
object	98
float64	69
int64	8
bool	1

Before processiding to other analysis, we can do a bit of cleaning on Columns of our data, since they are too long by names and we can rename them to a short names. we can accomplish this by using `rename` methods or replacing `str` across columns. as you can see there's a repeating words across all columns surveyQuestions., we can replace this.

In [16]:
```
#rename surveyQuestions with blank in every column name
full_data.columns = full_data.columns.str.replace('surveyQuestions', '')
full_data.columns = full_data.columns.str.replace('.location', '')
full_data.columns = full_data.columns.str.replace('.HHH', '')
full_data.columns = full_data.columns.str.replace('.countryGroup', '')
full_data.columns = full_data.columns.str.replace('.livestockGroup.livestockCount', '')
full_data.columns = full_data.columns.str.replace('.cropGroup', '')
full_data.columns = full_data.columns.str.replace('.inputGroup.inputs', '')
full_data.columns = full_data.columns.str.replace('.cashGroup', '')
full_data.columns = full_data.columns.str.replace('.foodSecurity', '')
full_data.head()
```

Out[16]:

	respondentNr	.sector	.village	.countryGroup._geopoint_altitude	.countryGroup.country	.countryGroup.currency	.district	.genderHH
1	1	Ntyazo	Kimigunga	1540.300049	Rwanda	RWF	Nyanza	male
2	2	Ntyazo	Mande	1537.800049	Rwanda	RWF	Nyanza	female
3	3	Muyira	Rugese	1565.099976	Rwanda	RWF	Nyanza	male
4	4	Ntyazo	Kimigunga	1537.699951	Rwanda	RWF	Nyanza	male
5	5	Ntyazo	Mande	1556.400024	Rwanda	RWF	Nyanza	male

5 rows × 176 columns

With these new names, we can see clearly meaningfull names, but we still have a dot (.) among names, since all names are self explanatory, we can remove that too.

In [19]:
```
full_data.columns = full_data.columns.str.replace('[.]', '_')
full_data.head()
```

Out[19]:

	respondentNr	sector	village	countryGroup_geopoint_altitude	countryGroupcountry	countryGroupcurrency	district	genderHH	ag
1	1	Ntyazo	Kimigunga	1540.300049	Rwanda	RWF	Nyanza	male	
2	2	Ntyazo	Mande	1537.800049	Rwanda	RWF	Nyanza	female	
3	3	Muyira	Rugese	1565.099976	Rwanda	RWF	Nyanza	male	
4	4	Ntyazo	Kimigunga	1537.699951	Rwanda	RWF	Nyanza	male	
5	5	Ntyazo	Mande	1556.400024	Rwanda	RWF	Nyanza	male	

5 rows × 176 columns

In [26]:
```
# checking missing values
full_data.isnull().sum().sort_values().to_frame()
```

Out[26]:

	0
respondentNr	0
dietaryDiversity2legumes	0
dietaryDiversity2fish	0
dietaryDiversity1eggs	0
dietaryDiversity1meat	0
...	...
cropRepeat4cropDetailsbananaUnits	240
inputRepeat6cassavaSelected	240
inputRepeat7cassavaSelected	240
livestock_beehives	240
inputRepeatinputCropGroupinputCropRepeat_count	240

176 rows × 1 columns

We can see there is some survey questions where there was no answer across all interviewed households

In [27]:
```
full_data.describe()
```

Out[27]:

	respondentNr	countryGroup_geopoint_altitude	ageHH	assetscashSpending	farmfarmSize	farmlandOwned	travelGroupmarketTr
count	240.00000	240.000000	240.000000	239.000000	240.000000	239.000000	240.00
mean	120.50000	1638.001664	48.925000	5610.878661	81.839456	0.661506	49.78
std	69.42622	100.552246	13.678106	5675.012204	577.867443	0.389035	40.40
min	1.00000	1379.699951	24.000000	300.000000	0.015000	0.000000	0.00
25%	60.75000	1566.224976	38.000000	2000.000000	1.000000	0.250000	20.00
50%	120.50000	1647.049988	46.000000	4000.000000	3.000000	0.750000	40.00
75%	180.25000	1714.149994	58.000000	7000.000000	25.000000	1.000000	60.00
max	240.00000	1878.699951	90.000000	30000.000000	7666.000000	1.000000	180.00

8 rows × 77 columns

II. Exploratory Data Analysis

After looking in my data, I plan not to use all columns in the exploratory data analysis, I will subset some columns, those include personal data(but not *sensitive* ones ex: Marital Status), location data, etc...

In [33]:
```
#columns needed
cols = ['respondentNr',
 'sector',
 'district',
 'genderHH',
 'ageHH',
 'assetscashSpending',
 'farmfarmSize',
 'farmunitsFarmSize',
 'farmlandOwned',
 'travelGroupmarketTravel',
 'travelGroupagrodealerTravel',
 'mainCropCount',
 'cropRepeat_count',
 'cropRepeat1cropLabel',
 'cropRepeat1cropDetailscropProp',
 'cropRepeat1cropDetailscropHarvest',
 'cropRepeat1cropDetailscropUnits',
 'cropRepeat1cropDetailscropSold',
 'cropRepeat1cropSalecropIncome',
 'cropRepeat1cropSalemarketType',
 'cropRepeat2cropPosition',
 'cropRepeat2cropLabel',
 'cropRepeat2cropDetailscropProp',
 'cropRepeat2cropDetailscropHarvest',
 'cropRepeat2cropDetailscropUnits',
 'cropRepeat2cropDetailscropSold',
 'cropRepeat2cropSalecropIncome',
 'cropRepeat2cropSalemarketType',
 'cropRepeat3cropPosition',
 'cropRepeat3cropLabel',
 'cropRepeat3cropDetailscropProp',
 'cropRepeat3cropDetailscropHarvest',
 'cropRepeat3cropDetailscropUnits',
 'cropRepeat3cropDetailscropSold',
 'cropRepeat3cropSalecropIncome',
 'cropRepeat3cropSalemarketType',
 'cropRepeat3cropSalecontract',
 'cropRepeat4cropPosition',
 'cropRepeat4cropLabel',
 'cropRepeat4cropDetailscropProp',
 'cropRepeat4cropDetailscropHarvest',
 'cropRepeat4cropDetailscropUnits',
 'cropRepeat4cropDetailscropSold',
 'cropRepeat4cropSalecropIncome',
 'cropRepeat5cropPosition',
 'cropRepeat5cropLabel',
 'cropRepeat5cropDetailscropProp',
 'cropRepeat5cropDetailscropHarvest',
 'cropRepeat5cropDetailscropUnits',
 'cropRepeat5cropDetailscropSold',
 'cropRepeat5cropSalecropIncome']
#subsetting data
sub_data = full_data.loc[:, cols].copy()
sub_data
```

Out[33]:

	respondentNr	sector	district	genderHH	ageHH	assetscashSpending	farmfarmSize	farmunitsFarmSize	farmlandOwned	travel
1	1	Ntyazo	Nyanza	male	45	10000.0	2300.0	m2	0.75	
2	2	Ntyazo	Nyanza	female	45	5000.0	1.0	ha	0.75	
3	3	Muyira	Nyanza	male	54	15000.0	2.0	ha	1.00	
4	4	Ntyazo	Nyanza	male	65	2000.0	15.0	are	0.50	
5	5	Ntyazo	Nyanza	male	35	1000.0	12.6	are	0.50	
...	...	...	...	...	...	...	...	...	...	
236	236	Rugarika	Kamonyi	female	31	8000.0	2.0	ha	0.75	
237	237	Rugarika	Kamonyi	male	36	30000.0	2.0	ha	0.25	
238	238	Rugarika	Kamonyi	female	60	2000.0	20.0	are	0.25	
239	239	Rugarika	Kamonyi	male	30	5000.0	2.5	are	0.50	
240	240	Rugarika	Kamonyi	female	64	3000.0	1.5	are	0.75	

240 rows × 51 columns

In [34]:
```
#summary of our subset
sub_data.describe()
```

Out[34]:

	respondentNr	ageHH	assetscashSpending	farmfarmSize	farmlandOwned	travelGroupmarketTravel	travelGroupagrodealerTrave
count	240.00000	240.000000	239.000000	240.000000	239.000000	240.000000	240.000000
mean	120.50000	48.925000	5610.878661	81.839456	0.661506	49.783333	37.225000
std	69.42622	13.678106	5675.012204	577.867443	0.389035	40.409863	34.396157
min	1.00000	24.000000	300.000000	0.015000	0.000000	0.000000	1.000000
25%	60.75000	38.000000	2000.000000	1.000000	0.250000	20.000000	10.000000
50%	120.50000	46.000000	4000.000000	3.000000	0.750000	40.000000	30.000000
75%	180.25000	58.000000	7000.000000	25.000000	1.000000	60.000000	60.000000
max	240.00000	90.000000	30000.000000	7666.000000	1.000000	180.000000	180.000000

8 rows × 29 columns

Crop Data

We can start exploring the subset of Our data using Data visualization with help of Matplotlib and seaborn library

In [43]:
```
#columns needed
crops_cols = ['respondentNr',
  'cropRepeat_count',
 'cropRepeat1cropLabel',
 'cropRepeat1cropDetailscropProp',
 'cropRepeat1cropDetailscropHarvest',
 'cropRepeat1cropDetailscropSold',
 'cropRepeat1cropSalecropIncome',
 'cropRepeat1cropSalemarketType',
 'cropRepeat2cropPosition',
 'cropRepeat2cropLabel',
 'cropRepeat2cropDetailscropProp',
 'cropRepeat2cropDetailscropHarvest',
 'cropRepeat2cropDetailscropSold',
 'cropRepeat2cropSalecropIncome',
 'cropRepeat2cropSalemarketType',
 'cropRepeat3cropPosition',
 'cropRepeat3cropLabel',
 'cropRepeat3cropDetailscropProp',
 'cropRepeat3cropDetailscropHarvest',
 'cropRepeat3cropDetailscropSold',
 'cropRepeat3cropSalecropIncome',
 'cropRepeat3cropSalemarketType',
 'cropRepeat3cropSalecontract',
 'cropRepeat4cropPosition',
 'cropRepeat4cropLabel',
 'cropRepeat4cropDetailscropProp',
 'cropRepeat4cropDetailscropHarvest',
 'cropRepeat4cropDetailscropSold',
 'cropRepeat4cropSalecropIncome',
 'cropRepeat5cropPosition',
 'cropRepeat5cropLabel',
 'cropRepeat5cropDetailscropProp',
 'cropRepeat5cropDetailscropHarvest',
 'cropRepeat5cropDetailscropSold',
 'cropRepeat5cropSalecropIncome']
crops_data = sub_data.loc[:, crops_cols].copy()
crops_data.head()
```

Out[43]:

	respondentNr	cropRepeat_count	cropRepeat1cropLabel	cropRepeat1cropDetailscropProp	cropRepeat1cropDetailscropHarvest	cropRepe
1	1	5	Ibishyimbo bigufi	0.15	20.0	
2	2	5	Ibishyimbo bigufi	0.85	200.0	
3	3	5	Ibishyimbo bigufi	0.55	400.0	
4	4	5	Imbogeri	0.05	15.0	
5	5	5	Ibishyimbo bigufi	0.75	100.0	

5 rows × 35 columns

Dietary Data

In [116]:
```
#columns needed for Dietary Data
diet_cols = ['respondentNr',
 'district',
'dietaryDiversity1starch',
 'dietaryDiversity1tubers',
 'dietaryDiversity1vegetables',
 'dietaryDiversity1fruits',
 'dietaryDiversity1meat',
 'dietaryDiversity1eggs',
 'dietaryDiversity2fish',
 'dietaryDiversity2legumes',
 'dietaryDiversity2dairy',
 'dietaryDiversity2fat',
 'dietaryDiversity2sugar',
 'dietaryDiversity2other',
]
diet_data = full_data.loc[:, diet_cols].copy()
diet_data.head()
```

Out[116]:

	respondentNr	district	dietaryDiversity1starch	dietaryDiversity1tubers	dietaryDiversity1vegetables	dietaryDiversity1fruits	dietaryDiversity
1	1	Nyanza	yes	no	no	no	
2	2	Nyanza	yes	yes	yes	yes	
3	3	Nyanza	yes	yes	yes	yes	
4	4	Nyanza	yes	no	yes	no	
5	5	Nyanza	yes	no	yes	no	

In [54]:
```
# dropping missing values
crops_data.dropna()
crops_data.shape
```

Out[54]:
```
(240, 35)
```

In [55]:
```
crops_data.head()
```

Out[55]:

	respondentNr	cropRepeat_count	cropRepeat1cropLabel	cropRepeat1cropDetailscropProp	cropRepeat1cropDetailscropHarvest	cropRepe
1	1	5	Ibishyimbo bigufi	0.15	20.0	
2	2	5	Ibishyimbo bigufi	0.85	200.0	
3	3	5	Ibishyimbo bigufi	0.55	400.0	
4	4	5	Imbogeri	0.05	15.0	
5	5	5	Ibishyimbo bigufi	0.75	100.0	

5 rows × 35 columns

In [83]:
```
crops_data.cropRepeat1cropSalecropIncome.isnull().value_counts()
```

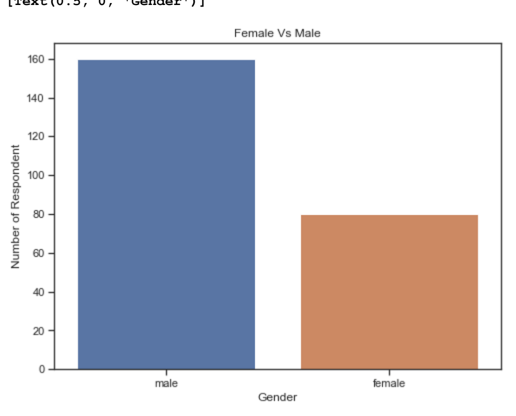
Out[83]:
```
True     122
False    118
Name: cropRepeat1cropSalecropIncome, dtype: int64
```

The Above shows that there is *no data available* to 122 Entries about Crop Sale Income

In [36]:
```
# Importing libraries
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set(style="ticks")
```

In [60]:
```
# Barplot
plt.figure(figsize=(8, 6))
plt.title("Female Vs Male")
ax = sns.countplot(x = sub_data['genderHH'])
# Naming labels
ax.set(ylabel = 'Number of Respondent')
ax.set(xlabel='Gender')
```

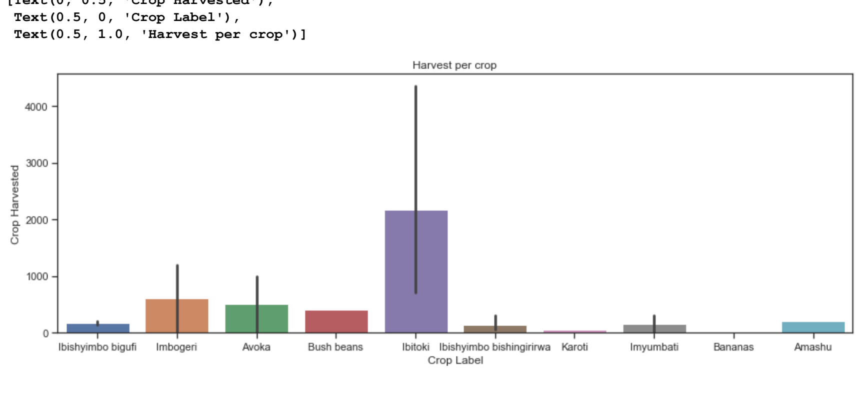
Out[60]:
```
[Text(0.5, 0, 'Gender')]
```



Observation1: We can see the Number Respondent of `female` is half of `Male` respondent.

In [92]:
```
plt.figure(figsize = (15,5))
# plotting relationship of Harvest and crops
ax = sns.barplot(x = crops_data['cropRepeat1cropLabel'], y = crops_data['cropRepeat1cropDetailscropHar
vest'])
ax.set(xlabel='Crop Label', ylabel='Crop Harvested', Title = 'Harvest per crop')
```

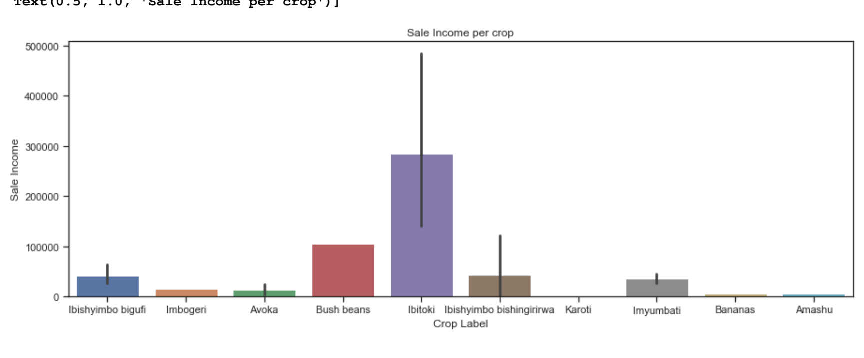
Out[92]:
```
[Text(0, 0.5, 'Crop Harvested'),
 Text(0.5, 0, 'Crop Label'),
 Text(0.5, 1.0, 'Harvest per crop')]
```



Observation 2: The Harvest Number Of Banana(Ibitoki) is high. Which led to another question, to see if they provide income to farmers.

In [89]:
```
plt.figure(figsize = (15,5))
# plotting relationship of income and crops
ax = sns.barplot(x = crops_data['cropRepeat1cropLabel'], y = crops_data['cropRepeat1cropSalecropIncom
e'])
ax.set(xlabel='Crop Label', ylabel='Sale Income', Title = 'Sale Income per crop')
```

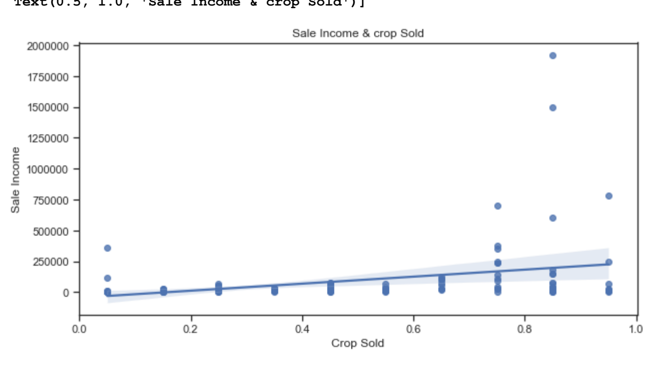
Out[89]:
```
[Text(0, 0.5, 'Sale Income'),
 Text(0.5, 0, 'Crop Label'),
 Text(0.5, 1.0, 'Sale Income per crop')]
```



Observation 3: Banana (Ibitoki) is the crop that brings more income to Households than other crops.

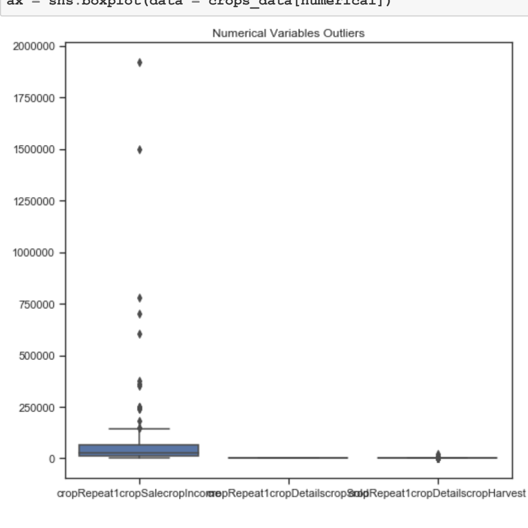
In [96]:
```
plt.figure(figsize = (10,5))
# plotting relationship of income and crops
ax = sns.regplot(x = crops_data['cropRepeat1cropDetailscropSold'], y = crops_data['cropRepeat1cropSale
cropIncome'])
ax.set(xlabel='% Crop Sold', ylabel='Sale Income', Title = 'Sale Income & Percentage Crops Sold')
```

Out[96]:
```
[Text(0, 0.5, 'Sale Income'),
 Text(0.5, 0, 'Crop Sold'),
 Text(0.5, 1.0, 'Sale Income & crop Sold')]
```



Observation 4: They seem to be a linear relationship Between `Sale Income` and percentage `Crop Sold`.

In [100]:
```
 # Checking outliers
numerical = ['cropRepeat1cropSalecropIncome','cropRepeat1cropDetailscropSold','cropRepeat1cropDetailsc
ropHarvest']
plt.figure(figsize=(10,5))
plt.title("Numerical Variables Outliers")
ax = sns.boxplot(data = crops_data[numerical])
```

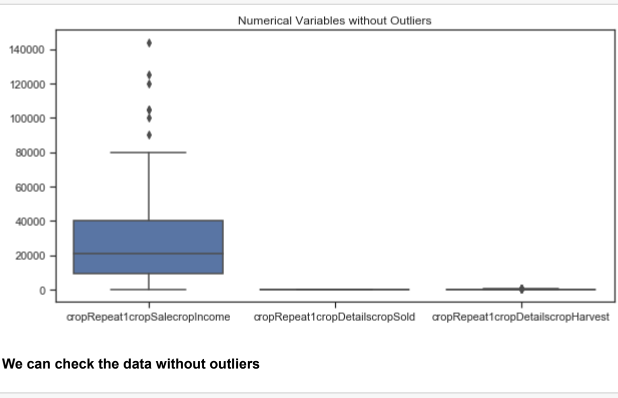


Obviously The data contains Outliers, We can check if we might reduce them, but it's not always a good idea to remove them but further investigate the reason why they are in dataset.

In [102]:
```
import numpy as np
# functions that removing outliers
def remove_outliers(data, numerical):
    for i in data[numerical]:
        Q1 = data[i].quantile(0.25)
        Q3 = data[i].quantile(0.75)
        interQ = Q3-Q1
        LowerT = Q1 - 1.5 * interQ
        UpperT = Q3 + 1.5 * interQ
        median = np.median(crops_data[i])
        for j in data[i]:
            if j > UpperT or j < LowerT:
                data[i] = data[i].replace(j, median)
```

In [ ]:
```
remove_outliers(crops_data, numerical)
```

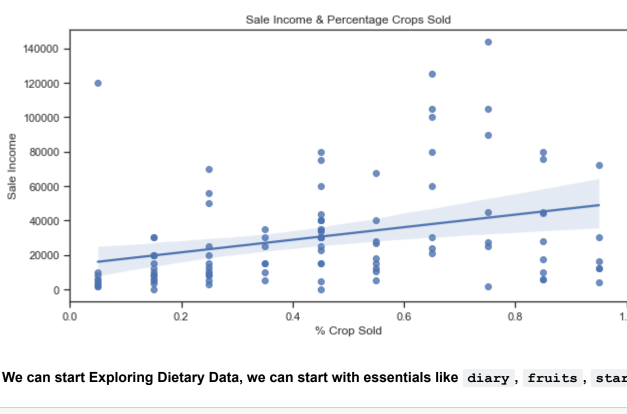
In [105]:
```
plt.figure(figsize=(10, 5))
plt.title("Numerical Variables without Outliers")
ax = sns.boxplot(data = crops_data[numerical])
```



We can check the data without outliers

In [127]:
```
plt.figure(figsize = (10,5))
# plotting relationship of income and crops sold
ax = sns.regplot(x = crops_data['cropRepeat1cropDetailscropSold'], y = crops_data['cropRepeat1cropSale
cropIncome'])
ax.set(xlabel='% Crop Sold', ylabel='Sale Income', Title = 'Sale Income & Percentage Crops Sold')
```

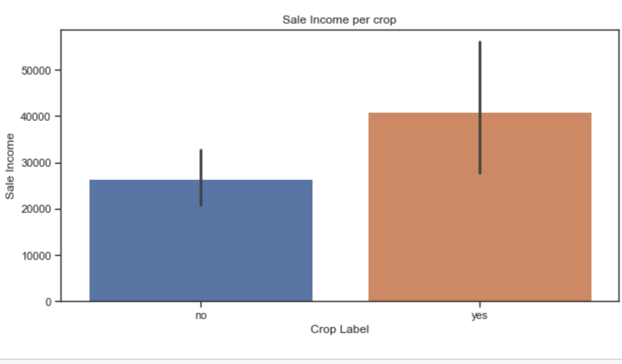
Out[127]:
```
[Text(0, 0.5, 'Sale Income'),
 Text(0.5, 0, '% Crop Sold'),
 Text(0.5, 1.0, 'Sale Income & Percentage Crops Sold')]
```



We can start Exploring Dietary Data, we can start with essentials like `diary`, `fruits`, `starch`, and `eggs`.

In [126]:
```
plt.figure(figsize = (10,5))
# plotting relationship of income and crops
ax = sns.barplot(x = diet_data['dietaryDiversity2dairy'], y = crops_data['cropRepeat1cropSalecropIncom
e'])
ax.set(xlabel='Crop Label', ylabel='Sale Income', Title = 'Sale Income per crop')
```

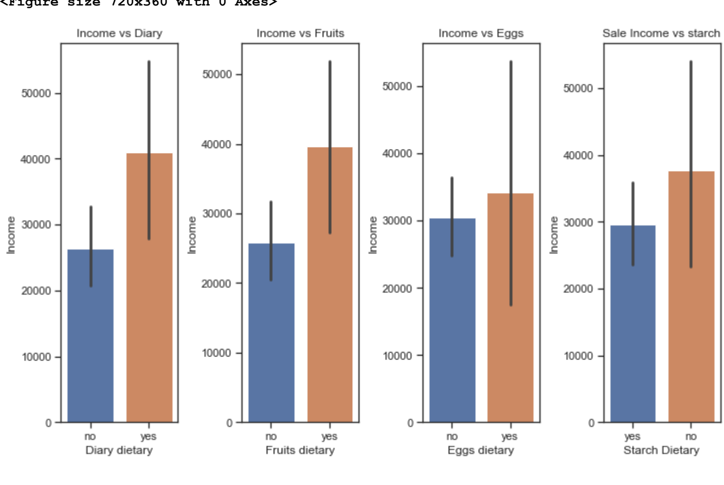
Out[126]:
```
[Text(0, 0.5, 'Sale Income'),
 Text(0.5, 0, 'Crop Label'),
 Text(0.5, 1.0, 'Sale Income per crop')]
```



In [151]:
```
# multiple plots about dietary and income
plt.figure(figsize = (10,5))
fig, axis = plt.subplots(ncols=4, figsize =(10, 6), constrained_layout = True)

# For Diary and Income
sns.barplot(x = diet_data['dietaryDiversity2dairy'], y = crops_data['cropRepeat1cropSalecropIncome'],
ax = axis[0])
axis[0].set(xlabel='Diary dietary', ylabel='Income', Title = 'Income vs Diary')

# For Fruits and income
sns.barplot(x = diet_data['dietaryDiversity1fruits'], y = crops_data['cropRepeat1cropSalecropIncome'],
 ax = axis[1])
axis[1].set(xlabel='Fruits dietary', ylabel='Income', Title = 'Income vs Fruits')

# For Eggs and Income
sns.barplot(x = diet_data['dietaryDiversity1eggs'], y = crops_data['cropRepeat1cropSalecropIncome'], a
x= axis[2])
axis[2].set(xlabel='Eggs dietary', ylabel='Income', Title = 'Income vs Eggs')

# For Starch and Income
sns.barplot(x = diet_data['dietaryDiversity1starch'], y = crops_data['cropRepeat1cropSalecropIncome'],
 ax = axis[3])
axis[3].set(xlabel='Starch Dietary', ylabel='Income', Title = 'Sale Income vs starch')
```

Out[151]:
```
[Text(0, 0.5, 'Income'),
 Text(0.5, 0, 'Starch Dietary'),
 Text(0.5, 1.0, 'Sale Income vs starch')]
```

```
<Figure size 720x360 with 0 Axes>
```



Observation 5: We can see that the more income leads to the stability in dietary per houselholds.

III. Market Orientation

After exploring the whole dataset we can turn back to the question of Market orientation. where we will focus on its effects on household dynamics, especially *dietary diversity* and Income but also considering *regionality* factor.

For Market orientation, we will subset data with these columns, `diet data, income, % crop sold, and regional data`.

In [153]:
```
#market orientation data
mo_cols = [
    'respondentNr',
 'district',
'cropRepeat1cropPosition',
 'cropRepeat1cropLabel',
 'cropRepeat1cropDetailscropProp',
 'cropRepeat1cropDetailscropHarvest',
 'cropRepeat1cropDetailscropUnits',
 'cropRepeat1cropDetailsbananaUnits',
 'cropRepeat1cropDetailscropSold',
 'cropRepeat1cropSalecropIncome',
 'cropRepeat1cropSalemarketType',
    'dietaryDiversity1starch',
 'dietaryDiversity1tubers',
 'dietaryDiversity1vegetables',
 'dietaryDiversity1fruits',
 'dietaryDiversity1meat',
 'dietaryDiversity1eggs',
 'dietaryDiversity2fish',
 'dietaryDiversity2legumes',
 'dietaryDiversity2dairy',
 'dietaryDiversity2fat',
 'dietaryDiversity2sugar',
 'dietaryDiversity2other'
]
MO_data = full_data.loc[:, mo_cols].copy()
MO_data.head()
```

Out[153]:

	respondentNr	district	cropRepeat1cropPosition	cropRepeat1cropLabel	cropRepeat1cropDetailscropProp	cropRepeat1cropDetailscropHa
1	1	Nyanza	beansBush	Ibishyimbo bigufi	0.15	
2	2	Nyanza	beansBush	Ibishyimbo bigufi	0.85	
3	3	Nyanza	beansBush	Ibishyimbo bigufi	0.55	
4	4	Nyanza	amaranth	Imbogeri	0.05	
5	5	Nyanza	beansBush	Ibishyimbo bigufi	0.75	

5 rows × 23 columns

In [154]:
```
MO_data.district.value_counts()
```

Out[154]:
```
Nyanza     80
Ruhango    80
Kamonyi    80
Name: district, dtype: int64
```

The above district will be our regional focus in this analysis. Also in this analysis the crops to be based used are in `Crop Position 1` as show below.

In [155]:
```
MO_data.cropRepeat1cropPosition.value_counts()
```

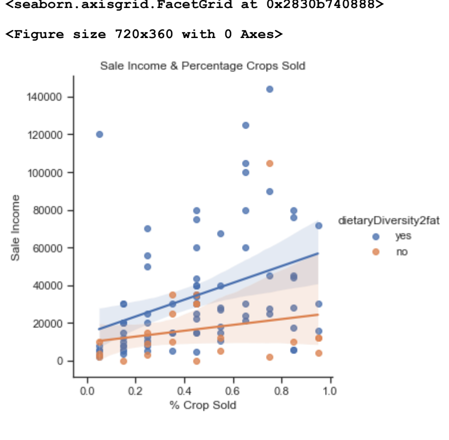
Out[155]:
```
beansBush        185
bananas           33
beansClimbing     10
cassava            6
amaranth           2
avocado            2
carrots            1
cabbage            1
Name: cropRepeat1cropPosition, dtype: int64
```

In [163]:
```
numerical_1 = ['cropRepeat1cropSalecropIncome']
remove_outliers(MO_data, numerical_1)
```

In [178]:
```
plt.figure(figsize = (10,5))
# plotting relationship of income and crops sold to diary diet
ax = sns.lmplot(x ='cropRepeat1cropDetailscropSold', y = 'cropRepeat1cropSalecropIncome', hue = 'dieta
ryDiversity2fat', data = MO_data)
ax.set(xlabel='% Crop Sold', ylabel='Sale Income', Title = 'Sale Income & Percentage Crops Sold')
```

Out[178]: <seaborn.axisgrid.FacetGrid at 0x2830b740888>

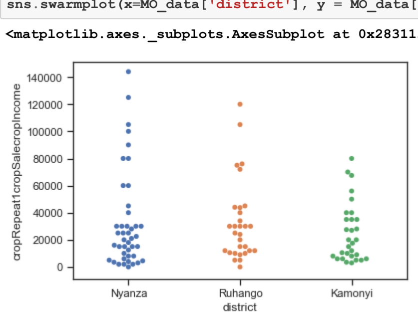
<Figure size 720x360 with 0 Axes>



To understand how dietary is affected by the relationship between Crop sold and Income, we can use `categorical scatter plots` since dietary is a *categorical variable*.

In [252]:
```
sns.swarmplot(x=MO_data['district'], y = MO_data['cropRepeat1cropSalecropIncome'])
```

Out[252]: <matplotlib.axes._subplots.AxesSubplot at 0x28311381788>



From the above we can see `Nyanza` has more sale income then other districts

Modelling

In [199]:
```
col = ['district',
       'cropRepeat1cropDetailscropProp',
       'cropRepeat1cropDetailscropHarvest',
       'cropRepeat1cropDetailscropSold',
       'cropRepeat1cropSalecropIncome',
       'dietaryDiversity1fruits']
data = MO_data.loc[:, col].copy()
```

We are going to build a model to predict dietary stability of fruits, if we have sold crops, income variables and other variables.

We start by separating data into features and target valiable. `X` is going to be our feature and `Y` as our target valiable.

In [200]:
```
#dropping the fruits column
X = data.drop(['dietaryDiversity1fruits'], axis = 1)
Y = data[['dietaryDiversity1fruits']]
```

In [201]:
```
#Selecting categorical columns using cardinality
low_cardinality_cols = [colName for colName in X.columns if X[colName].nunique() < 6 or X[colName].dty
pe == 'object']
```

==> Encoding Data: Let's Perform One Hot Encoding to feature data. Why? => most model don't accept "words" written variables they prefer numbers, and we are trying to transform districts into numbers.

In [202]:
```
X = pd.get_dummies(X, columns = low_cardinality_cols, drop_first=True)
X.head()
```

Out[202]:

	cropRepeat1cropDetailscropProp	cropRepeat1cropDetailscropHarvest	cropRepeat1cropDetailscropSold	cropRepeat1cropSalecropIncome
1	0.15	20.0	0.00	NaN
2	0.85	200.0	0.45	30000.0
3	0.55	400.0	0.45	60000.0
4	0.05	15.0	0.00	NaN
5	0.75	100.0	0.15	20000.0

In [206]:
```
# we will fill NaN values with 0 since no data is available
X.fillna(0, inplace=True)
X.head()
```

Out[206]:

	cropRepeat1cropDetailscropProp	cropRepeat1cropDetailscropHarvest	cropRepeat1cropDetailscropSold	cropRepeat1cropSalecropIncome
1	0.15	20.0	0.00	0.0
2	0.85	200.0	0.45	30000.0
3	0.55	400.0	0.45	60000.0
4	0.05	15.0	0.00	0.0
5	0.75	100.0	0.15	20000.0

Now with Features ready, we can convert The "Yes" and "No" in Target Valiable with "1s" and "0s" instead.

In [229]:
```
Y = Y.replace({'dietaryDiversity1fruits': {'yes': 1, 'no': 0}})
Y.dietaryDiversity1fruits.value_counts()
```

Out[229]:
```
0    167
1     73
Name: dietaryDiversity1fruits, dtype: int64
```

==>Splitting data: To understand model performance, we divide our dataset into training and testing datasets.

Let's split dataset by using function train_test_split.

In [231]:
```
# split X and y into training and testing sets
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,Y,test_size=0.25,random_state=0)
```

Here, the Dataset is broken into two parts in a ratio of 75:25. It means 75% data will be used for model training and 25% for model testing.

==>Model Development and Prediction: On this task we will use `logistic regression model`, then fit it with training dataset and test it with testing dataset using `predict()` methods.

In [244]:
```
# import the class
from sklearn.linear_model import LogisticRegression as LogReg

# instantiate the model (using the default parameters) & fit  the model
logisticReg = LogReg().fit(X_train, y_train.values.reshape(-1,))

# testing the model
y_pred=logisticReg.predict(X_test)
```

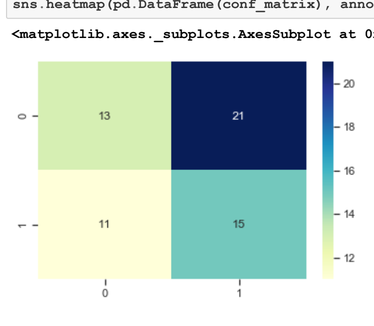
==>Model Evaluation using Confusion Matrix: We will use the confusion matrix to evaluate the performance of our classification model.

In [245]:
```
# import the metrics class
from sklearn import metrics
conf_matrix = metrics.confusion_matrix(y_test, y_pred)
conf_matrix
```

Out[245]:
```
array([[13, 21],
       [11, 15]], dtype=int64)
```

In [247]:
```
sns.heatmap(pd.DataFrame(conf_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
```

Out[247]: <matplotlib.axes._subplots.AxesSubplot at 0x2831110a608>



Diagonal values represent accurate predictions, while non-diagonal elements are inaccurate predictions. In the output, 13 and 15 are actual predictions, and 21 and 11 are incorrect predictions.

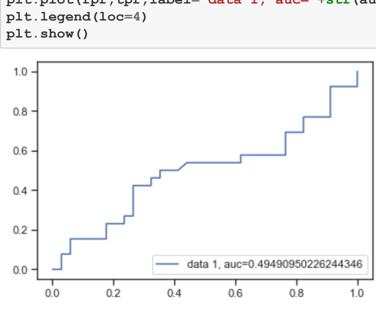
==>Confusion Matrix Evaluation Metrics

In [248]:
```
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
print("Precision:",metrics.precision_score(y_test, y_pred))
print("Recall:",metrics.recall_score(y_test, y_pred))
```

```
Accuracy: 0.4666666666666667
Precision: 0.4166666666666667
Recall: 0.5769230769230769
```

With the accuracy of `46%` we can say the classification modal fails to classify, means there is still a big room to grow our model. we can also see that on `Receiver Operating Characteristic(ROC) curve`, that shows a tradeoff between sensitivity and specificity of our model.

In [250]:
```
y_pred_proba = logisticReg.predict_proba(X_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test,  y_pred_proba)
auc = metrics.roc_auc_score(y_test, y_pred_proba)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```



With `AUC` score less than 0.5, means this classifier is not a good classifier.

==>There are ways to Improve our Model:

1. Feature Scaling and Normalization: where we normalize all features to the same scale.
2. Class Imbalance: we can look for number of yes and no, if one is higher than other.
3. Optimizing Log loss & F1 scores.
4. Tuning Hyperparameter: To improve our accuracy, we can perform Grid-search to tune hyperparameter of our model.
5. Explore other classifiers: such as Support vector machines and Tree-based classifiers.
6. Increase number of features in our model.

Results and Discussion

Through this analysis, we found that there are entries of `240` households, across three districts of Rwanda, *Nyanza, Ruhango and Kamonyi* and There are 160 men and 80 women participated in the survey.

While some of entries were left with no data, We did fill them with `0` for the purpose of analysis. From the provided data, we found that `Banana (Igitoki)` crop has a big number of Harvest and It is also the crop that generate High Sale Income to farmers.

Data had `Outliers` in Sale Income, in this case it is a good idea to investigate the outliers in Income data rather than ignoring them, since this might show different prices on market on a specific crop.

Regarding Market Orientation, there is a linear relationship between Crop sold and Income per households. The more Market orientation the more Income to farmers. This blings to another subject of `Dietary diversity`, which also seems to be impacted by the `Sale income`.

For Example: The Households with more income seems to have essential and healthy meal like `Diary, Eggs, Fruits and Starch`, and even expensive foods like `Meat` and `Fish`. From This we can say that, having a Good Market Orientation affects positively farmers and improves their `diatary` since they have more `Sales income`.

The regionality factor shows that Farmers in *Nyanza* earns more than their colleagues in *Ruhango and Kamonyi*.

The houshold that have more than `0.5` percentage of sold crops, that farms Banana(Ibitoki) and Lives in Nyanza will have a good dietary and this is the characteristics of households that explains market orientation.

Conclusion

The project's purpose was to analyse the effects of Market orientation on household dynamics.

By conducting rough and quick analysis, we found the effect of market orientation to farmers which is positive. However, we can't say a hundred percent that we reached the goal of eradicating hunger. There are couple steps One Acre Fund will take to investigate effects of Market orientation as highlighted below and How One Acre fund(OAF) will use these information.

- Conducting customer orientation analysis, from this OAF will understand how farmers could statisfy their clients or market, and create farmers value in a continuous basis for their sustainable growth.
- Conducting competitor orientation analysis, where OAF will understand competitors strengths and weaknesses and make strategies to produce competitive advantage to organization itself and its clients (Farmers).
- Regarding Nutritient security, OAF would collect that on `How often` farmers get access to essential and healthy dietary in a month and/or weekly, where this information will show if there is a huge *positive impact* on farmers nutrient security and *stability* in their dietary adverstity.
- Farmers face overproduction and marketing among other risks that impact their income, helping them to overcome this by Learning and conducting market analysis for them could impact them positively and hence improve their income.

OAF has done a tremendous work for farmers in past years and it is a good time to be with farmers especially in these where there is new challenges that are being surfaced in different sectors including technology, health and economy. OAF will have to make a data-driven decision to farmers without bias and clear vision and goal to sustain farmers growth.

The link is for Repository of The assessment here.

Change Log

Date (YYYY-MM-DD)	Change Description
2022-03-30	Understanding Business Problem
2022-03-30	Methodology & Conducting Analysis
2022-03-31	Modelling
2022-03-31	Results and Conclusion