The Import/Export Agricultural Dataset

The import/export agricultural dataset is a time series data set with per-year information about the crops and livestocks products imported and exported in Europe for 2015-2021. It recorded the domain Code, domain, area Code (M49), area, element Code, element, Item Code (CPC), Item, Year Code, Year, Unit, Value, domain area, domain, flag, and flag description. The dataset is a CSV file, and it was downloaded from The Food and Agriculture Organization Statistical data set(FAOSTAT) website. It is available at: https://www.fao.org/faostat/en/#data/TCL (https://www.fao.org/faostat/en/#data/TCL)

International trade mainly includes import and export processing. Importing is the act of a nation's people, corporations, and government purchasing goods and services from elsewhere, regardless of how they are delivered to the home country. while export refers to selling products/goods from the home country to other countries. A nation experiences a trade deficit when its imports exceed its exports. A nation that imports less than it exports develops a trade surplus. Simultaneously, increasing the Gross domestic product (GDP) became the main target for all countries to expand their exports[1].

my Github account: https://github.com/RehamTousoun/Agri_InIreland (https://github.com/RehamTousoun/Agri_InIreland)

Loading the neccessary libraries and packages

In [1]:
```
# Import standard packages
import pandas as pd
import numpy as np                      # Numerical Python, the fundamental package for scientific computing in Python.
import seaborn as sns
from statsmodels.stats import weightstats
import scipy.stats as stats
from scipy.stats import shapiro
import geopandas as gpd
import plotly.express as px
import plotly.graph_objs as go
import matplotlib                   # pyplot module
import pprint                       # pretty-print lists, tuples, & dictionaries recursively
import matplotlib.pyplot as plt

from matplotlib.figure import Figure
from matplotlib.backends.backend_agg import FigureCanvas

```

In [2]:
```
# Taking care of jupyter environment
# show graphs in-Line, and turn on/off pretty_printing of lists
%matplotlib inline
%pprint
```

```
Pretty printing has been turned OFF
```

In [3]:
```
#ignore warning
import warnings
warnings.filterwarnings("ignore")
```

In [4]:
```
# retina quality: to better display the plots. Any display with retina resolution will make the figures look better
# if your monitor's resolution is sub-retina than the improvement will be less noticeable [2].
%config InlineBackend.figure_format = 'retina'
sns.set_context('talk')
```

In [5]:
```
# Find the current working directory.
import os
os.getcwd()
# for dirname, _, filenames in os.walk('C:\Users\Reham\Desktop\Agriculture2022'):
#     for filename in filenames:
#         print(os.path.join(dirname, filename))
```

Out[5]:
```
'C:\\Users\\Reham\\Desktop\\CA2@Agriculture'
```

Exploratory Data Analysis(EDA)

Reading Data from Files

In [6]:
```
# Read the dataset from the CSV file
df = pd.read_csv('EU-AgriTrade.csv')       #https://www.fao.org/faostat/en/#data/TCL
```

In [7]:
```
# df-copy = df.copy()             # Keep a copy from the original dataframe
```

Observing and describing data

In [8]:
```
# Display the first five obsevations on the dataframe
df.head()
```

Out[8]:

	Domain Code	Domain	Area Code	Area	Item Code (CPC)	Item(M49)	Flag	Flag Description	Unit	2015	2016	2017	2018	2019	2020	2
0	TCL	Crops and livestock products	40	Austria	F2071	Bovine Meat	A	Official figure	1000 US$	543817.90	500433.84	550245.07	561087.62	546331.84	526121.43	58937
1	TCL	Crops and livestock products	40	Austria	F1944	Cereals	A	Official figure	1000 US$	413436.91	416309.32	451317.42	433067.23	461881.52	527424.05	59232
2	TCL	Crops and livestock products	40	Austria	F1887	Dairy Products	A	Official figure	1000 US$	1219787.92	1196282.33	1314954.84	1423163.86	1369810.97	1483644.97	153273
3	TCL	Crops and livestock products	40	Austria	F1782	Eggs	A	Official figure	1000 US$	22726.14	25483.68	33349.16	44926.90	44929.20	43546.00	3024
4	TCL	Crops and livestock products	40	Austria	F1892	Fodder and Feeding Stuff	A	Official figure	1000 US$	756577.02	748014.60	838420.14	961041.09	949072.54	1041044.61	119488

In [9]:
```
# Display the last five obsevations on the dataframe
df.tail()
```

Out[9]:

	Domain Code	Domain	Area Code	Area	Item Code (CPC)	Item(M49)	Flag	Flag Description	Unit	2015	2016	2017	2018	2019	2020
589	TCL	Crops and livestock products	752	Sweden	F1773	Nuts	A	Official figure	1000 US$	251063.81	225130.63	220816.01	227193.19	209162.45	224364.57
590	TCL	Crops and livestock products	752	Sweden	F2073	Pigmeat (meat equivalent)	A	Official figure	1000 US$	424883.07	427979.44	440407.52	422689.69	382819.55	343641.80
591	TCL	Crops and livestock products	752	Sweden	F2074	Poultry Meat	A	Official figure	1000 US$	307418.85	316147.55	312791.25	314796.00	297301.27	276413.82
592	TCL	Crops and	752	Sweden	F1719	Roots and	A	Official	1000	100054.45	105071.86	107971.08	120492.54	125109.90	112131.92

In [10]:
```
# .shape() method returns a tuple representing the dimensionality of the DataFrame,
# which means the number of rows and columns in our data frame[5].
df.shape
```

Out[10]: (594, 18)

The dataset contains 594 rows and 18 columns.

In [11]:
```
df.columns
```

Out[11]:
```
Index(['Domain Code', 'Domain', 'Area Code', 'Area', 'Item Code (CPC)',
       'Item(M49)', 'Flag', 'Flag Description', 'Unit', '2015', '2016', '2017',
       '2018', '2019', '2020', '2021', 'Element', 'Element Code'],
      dtype='object')
```

The dataset contains 594 rows and 18 columns: Domain Code: TCL Domain: Crops and livestock products
Area Code (M49): the code for each country in EU region. Area: EU-countries Item Code (CPC): the code for each production. Item(M49): The production exported by each country in EU region. Flag: The flag for this dataset has 7 values: E --> Estimated value X --> Figure from international organizations F --> Forecast value I --> Imputed value M --> Missing value (data cannot exist, not applicable) A --> Official figure T --> Unofficial figure

Flag Description: display the flag discreption Unit: 1000 United States dollars
Year: 2015-2021 the values of commodities exported in 1000$ over 2015-2021 Element: Import or export Element Code: code for import and export

1- Dropping the redundant columns.

We will drop the redundant columns to make the data easier to visualise.

To determine which columns are not necessary for the analysis. We defined a **displayColumnsValues()** function to have a deep look at all the columns' values in our data set.

In [12]:
```
# Python Docstrings [6]: is an in-built feature for commenting on functions, modules, methods, objects, and classes.
# They are written between three quotation marks (‘’ or “”) in the first line after defining a  function, method, etc.
# We can access a docstrings by utilising the \__doc__ attribute.
def displayColumnsValues(data):
    '''displayColumnsValues() is a function with one argument (dataframe). When the function is called,
        we pass along the dataframe, which is used inside the function to print the unique values for each feature (column)
        .nunique(): Count number of distinct elements in each column.
        .unique() method returns an array with the unique values.'''
    for i in data.columns:
        print(80*'=','\n',i,'has',
          df[i].nunique(),'value/s:\n',
          df[i].unique())
```

In [13]:
```
# calling the displayColumnsValues() function
displayColumnsValues(df)
```

```
================================================================================
 Domain Code has 1 value/s:
 ['TCL']
================================================================================
 Domain has 1 value/s:
 ['Crops and livestock products']
================================================================================
 Area Code has 27 value/s:
 [ 40  56 100 191 196 203 208 233 246 250 276 300 348 372 380 428 440 442
 470 528 616 620 642 703 705 724 752]
================================================================================
 Area has 27 value/s:
 ['Austria' 'Belgium' 'Bulgaria' 'Croatia' 'Cyprus' 'Czechia' 'Denmark'
 'Estonia' 'Finland' 'France' 'Germany' 'Greece' 'Hungary' 'Ireland'
 'Italy' 'Latvia' 'Lithuania' 'Luxembourg' 'Malta' 'Netherlands' 'Poland'
 'Portugal' 'Romania' 'Slovakia' 'Slovenia' 'Spain' 'Sweden']
================================================================================
 Item Code (CPC) has 11 value/s:
 ['F2071' 'F1944' 'F1887' 'F1782' 'F1892' 'F1802' 'F1773' 'F2073' 'F2074'
```

We have missing values in some columns, We clean the data later on.

Now we can drop unuseful columns that do not help in our analysis like:

- 'Area Code (M49)'
- Flag','Flag Description','Unit' --> contain only one value, not add any new information for the analysis,
- 'Domain Code', 'Area Code','Item Code (CPC)', 'Element Code' --> will use the 'Domain', 'Area', 'Item' and 'Element' instead,

Which method del or .drop() to drop the columns?

- del is an in-place operation, delete one column at a time.
- .drop() can use on both columns or rows, drop one on multiple items at a time, and operate in-place or return a copy [4]. We are going to use .drop() to drop the previous columns.

In [14]:
```
# Display the dataframe heading
df.columns
```

Out[14]:
```
Index(['Domain Code', 'Domain', 'Area Code', 'Area', 'Item Code (CPC)',
       'Item(M49)', 'Flag', 'Flag Description', 'Unit', '2015', '2016', '2017',
       '2018', '2019', '2020', '2021', 'Element', 'Element Code'],
      dtype='object')
```

In [15]:
```
# Unnecessary columns dropped from the data frame to make the focus on the remaining columns easier using .drop() method.
df.drop(['Domain Code','Area Code', 'Item Code (CPC)', 'Flag','Flag Description','Unit', 'Element Code'],axis=1,inplace=True
```

In [16]:
```
df.head()
```

Out[16]:

	Domain	Area	Item(M49)	2015	2016	2017	2018	2019	2020	2021	Element
0	Crops and livestock products	Austria	Bovine Meat	543817.90	500433.84	550245.07	561087.62	546331.84	526121.43	589371.34	Export Value
1	Crops and livestock products	Austria	Cereals	413436.91	416309.32	451317.42	433067.23	461881.52	527424.05	592326.72	Export Value
2	Crops and livestock products	Austria	Dairy Products	1219787.92	1196282.33	1314954.84	1423163.86	1369810.97	1483644.97	1532730.09	Export Value
3	Crops and livestock products	Austria	Eggs	22726.14	25483.68	33349.16	44926.90	44929.20	43546.00	30247.17	Export Value
4	Crops and livestock products	Austria	Fodder and Feeding Stuff	756577.02	748014.60	838420.14	961041.09	949072.54	1041044.61	1194880.85	Export Value

In [ ]:
```

```

2- Renaming the columns for clarity.

In [17]:
```
New_headers = ['Domain','Region','Production','2015', '2016',
               '2017', '2018', '2019','2020', '2021','Trade']
df.columns = New_headers
```

In [18]:
```
df.head(2)
```

Out[18]:

	Domain	Region	Production	2015	2016	2017	2018	2019	2020	2021	Trade
0	Crops and livestock products	Austria	Bovine Meat	543817.90	500433.84	550245.07	561087.62	546331.84	526121.43	589371.34	Export Value
1	Crops and livestock products	Austria	Cereals	413436.91	416309.32	451317.42	433067.23	461881.52	527424.05	592326.72	Export Value

In [ ]:
```

```

Put all the price in Millions $ instead of Thousand $.

In [19]:
```
df.iloc[:,3:10] = df.iloc[:,3:10]/10**3
```

In [20]:
```
df.head()
```

Out[20]:

	Domain	Region	Production	2015	2016	2017	2018	2019	2020	2021	Trade
0	Crops and livestock products	Austria	Bovine Meat	543.81790	500.43384	550.24507	561.08762	546.33184	526.12143	589.37134	Export Value
1	Crops and livestock products	Austria	Cereals	413.43691	416.30932	451.31742	433.06723	461.88152	527.42405	592.32672	Export Value
2	Crops and livestock products	Austria	Dairy Products	1219.78792	1196.28233	1314.95484	1423.16386	1369.81097	1483.64497	1532.73009	Export Value
3	Crops and livestock products	Austria	Eggs	22.72614	25.48368	33.34916	44.92690	44.92920	43.54600	30.24717	Export Value
4	Crops and livestock products	Austria	Fodder and Feeding Stuff	756.57702	748.01460	838.42014	961.04109	949.07254	1041.04461	1194.88085	Export Value

3- Replace the values in 'Element' column for easier reading.

In [21]:
```
# .replace() method applied to the 'Element' column to replace the 'Import Value' to'Import', andthe'Export Value' to 'Expor
df['Trade'].replace({'Import Value':'Import',
                     'Export Value':'Export'},inplace=True)
```

In [22]:
```
# Display the first two rows
df.head(2)
```

Out[22]:

	Domain	Region	Production	2015	2016	2017	2018	2019	2020	2021	Trade
0	Crops and livestock products	Austria	Bovine Meat	543.81790	500.43384	550.24507	561.08762	546.33184	526.12143	589.37134	Export
1	Crops and livestock products	Austria	Cereals	413.43691	416.30932	451.31742	433.06723	461.88152	527.42405	592.32672	Export

4- Add new column 'Total Groos'

In [23]:
```
# .insert() method used to insert the new column 'Price' in a specific position 12, that contain the import/export price in
# .sum() to Sum the rows f each column
df.insert(10, 'Total Gross',(df.iloc[:,3:10].sum(1)))
```

In [24]:
```
df.head(2)
```

Out[24]:

	Domain	Region	Production	2015	2016	2017	2018	2019	2020	2021	Total Gross	Trade
0	Crops and livestock products	Austria	Bovine Meat	543.81790	500.43384	550.24507	561.08762	546.33184	526.12143	589.37134	3817.40904	Export
1	Crops and livestock products	Austria	Cereals	413.43691	416.30932	451.31742	433.06723	461.88152	527.42405	592.32672	3295.76317	Export

5- Observing the dataset.

A quick look at our data again.

In [25]:
```
# .info(): return all information about the dataframe
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 594 entries, 0 to 593
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Domain       594 non-null    object
 1   Region       594 non-null    object
 2   Production   594 non-null    object
 3   2015         592 non-null    float64
 4   2016         593 non-null    float64
 5   2017         592 non-null    float64
 6   2018         592 non-null    float64
 7   2019         593 non-null    float64
 8   2020         594 non-null    float64
 9   2021         593 non-null    float64
 10  Total Gross  594 non-null    float64
 11  Trade        594 non-null    object
dtypes: float64(8), object(4)
memory usage: 55.8+ KB
```

Will change the dtypes for some columns after cleaning the data.
The data set contains a mixed type of data (object, int64, and float64). Some null/missing values observed.

In [26]:
```
# Generate descriptive statistics for the numeric columns, it summarize the central tendency,
# dispersion and shape of a dataset's distribution, excluding NaN values [7].
df.describe()
```

Out[26]:

	2015	2016	2017	2018	2019	2020	2021	Total Gross
count	592.000000	593.000000	592.000000	592.000000	593.000000	594.000000	593.000000	594.000000
mean	687.317309	689.661844	769.439332	814.081723	797.700898	832.426772	916.516747	5495.451768
std	1316.090477	1327.257521	1492.595449	1572.892742	1531.633828	1632.579736	1765.817321	10596.788948
min	0.000600	0.000310	0.002520	0.016480	0.000710	0.000110	0.000220	0.000110
25%	42.687753	44.433390	48.397645	54.088843	53.574240	52.633567	63.424490	360.912648
50%	171.322585	173.633290	188.064680	213.988355	213.815980	205.034715	239.113390	1390.165370
75%	638.632627	638.602640	727.363137	777.405805	769.523470	782.629365	858.300350	5255.910488
max	9418.755030	9833.310610	10637.496440	11379.889380	10322.373430	11761.589200	12043.376210	75396.790300

count: gives the total values for each column. It appears that '2015','2017','2018' have 2 missing values and '2016','2019','2021'contain one missing value each.

Range = max - min the range of data for: '2015' is 0-9418.7 '2016' is 0-9833.3 '2017' is 0-10637.4 '2018' is 0-11379.8 '2019' is 0-10322.3 '2020' is 0-11761.5 '2021' is 0-12043.3 'Total Gross' is 5495.45 - 75396.790

All the year features have the minimum value of zero because some of the import and export productions over the time series from 2015-2021 may not be traded in any EU country at a specific year.

IQ3 or 75% values for the year columns '2015'-'2021' are considered small regarding its maximum values, which indicates an outlier not clear if this outlier on the import prices or export prices will see later.

In [27]:
```
# Select the categorical columns
df.describe(include='O')
```

Out[27]:

	Domain	Region	Production	Trade
count	594	594	594	594
unique	1	27	11	2
top	Crops and livestock products	Austria	Bovine Meat	Export
freq	594	22	54	297

For the object data type. The result includes 'count', 'unique', 'top', and 'freq' 'top' gives the most common values while 'freq' gives the most common value frequency.

In [28]:
```
# .count() non-NA cells for each column or row
df.count()
```

Out[28]:
```
Domain         594
Region         594
Production     594
2015           592
2016           593
2017           592
2018           592
2019           593
2020           594
2021           593
Total Gross    594
Trade          594
dtype: int64
```

6- Cleaning Data.

In [29]:
```
#checking the duplicated values
df.duplicated().any()
```

Out[29]:
```
False
```

No duplicated rows were observed in our data set.

In [30]:
```
# Null values, the totall number of missing values at each column
df.isnull().sum()
```

Out[30]:
```
Domain         0
Region         0
Production     0
2015           2
2016           1
2017           2
2018           2
2019           1
2020           0
2021           1
Total Gross    0
Trade          0
dtype: int64
```

Our data set contain missing values, Let's have a deep look to the missing values by displaying the percentage of the missing values.

In [31]:
```
# Percentege of missing values in the data frame
df.isna().sum()/(len(df))*100
```

Out[31]:
```
Domain         0.00000
Region         0.00000
Production     0.00000
2015           0.33670
2016           0.16835
2017           0.33670
2018           0.33670
2019           0.16835
2020           0.00000
2021           0.16835
Total Gross    0.00000
Trade          0.00000
dtype: float64
```

The percentage of missing values between 0.16% to 0.33%, which can be dropped without any effect on our analysis

In [32]:
```
# drop the missing value for O Connell St and Henrt street
df.dropna(axis = 0,inplace = True)
```

In [ ]:
```

```

7- Change the data type for some features

In [33]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 591 entries, 0 to 593
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   Domain       591 non-null    object 
 1   Region       591 non-null    object 
 2   Production   591 non-null    object 
 3   2015         591 non-null    float64
 4   2016         591 non-null    float64
 5   2017         591 non-null    float64
 6   2018         591 non-null    float64
 7   2019         591 non-null    float64
 8   2020         591 non-null    float64
 9   2021         591 non-null    float64
 10  Total Gross  591 non-null    float64
 11  Trade        591 non-null    object 
dtypes: float64(8), object(4)
memory usage: 60.0+ KB
```

For the data visualisation and graphing purpose, the price(€m) for the exported crops and livestock productions displayed on the columns '2015' to '2021' dtype changed from float64 to int64, Python rounds down when it converts from floating point to integer.

In [34]:
```
# .astype() method used to change the datatypes of columns in our data frame.
df.iloc[:,3:10] = df.iloc[:,3:10].astype('int64')
```

In [35]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 591 entries, 0 to 593
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   Domain       591 non-null    object 
 1   Region       591 non-null    object 
 2   Production   591 non-null    object 
 3   2015         591 non-null    int64  
 4   2016         591 non-null    int64  
 5   2017         591 non-null    int64  
 6   2018         591 non-null    int64  
 7   2019         591 non-null    int64  
 8   2020         591 non-null    int64  
 9   2021         591 non-null    int64  
 10  Total Gross  591 non-null    float64
 11  Trade        591 non-null    object 
dtypes: float64(1), int64(7), object(4)
memory usage: 60.0+ KB
```

In [36]:
```
df.head()
```

Out[36]:

	Domain	Region	Production	2015	2016	2017	2018	2019	2020	2021	Total Gross	Trade
0	Crops and livestock products	Austria	Bovine Meat	543	500	550	561	546	526	589	3817.40904	Export
1	Crops and livestock products	Austria	Cereals	413	416	451	433	461	527	592	3295.76317	Export
2	Crops and livestock products	Austria	Dairy Products	1219	1196	1314	1423	1369	1483	1532	9540.37498	Export
3	Crops and livestock products	Austria	Eggs	22	25	33	44	44	43	30	245.20825	Export
4	Crops and livestock products	Austria	Fodder and Feeding Stuff	756	748	838	961	949	1041	1194	6489.05085	Export

Data Visualization

Why is color significant when displaying data?

Yi, M. (n.d.). How to Choose Colors for Data Visualizations. [online] Chartio. Available at: https://chartio.com/learn/charts/how-to-choose-colors-data-visualization/ (https://chartio.com/learn/charts/how-to-choose-colors-data-visualization/).

Schloss, K.B., Gramazio, C.C., Silverman, A.T., Parker, M.L. and Wang, A.S. (2019). Mapping Color to Meaning in Colormap Data Visualizations. IEEE Transactions on Visualization and Computer Graphics, 25(1), pp.810–819. doi:10.1109/tvcg.2018.2865147.

Color is crucial in data visualization because it enables you to draw attention to specific information and recall information later. In order for viewers to clearly see major differences or similarities in values, different colors can be used to separate and define different data points within a visualization. To make presented data more memorable, color choices for data visualization should take into account color theories and frequent color associations. Depending on the goal of the visualization report, colors might affect how viewers see data and convince them to feel either positively or adversely.

In [ ]:
```
1
```

In [ ]:
```
1
```

We filtered the data To show the Import and export commodities in Ireland only

In [37]:
```
# Selecting all rows crossponding to Ireland area and store them in a new dataframe df_Ireland
df_Ireland = df.loc[df['Region']=='Ireland']
```

In [38]:
```
# display the first five observations from the new data frame df_Ireland
df_Ireland.head()
```

Out[38]:

	Domain	Region	Production	2015	2016	2017	2018	2019	2020	2021	Total Gross	Trade
286	Crops and livestock products	Ireland	Bovine Meat	2454	2508	2716	2874	2601	2660	2838	18653.84379	Export
287	Crops and livestock products	Ireland	Cereals	40	18	21	22	36	45	64	249.10032	Export
288	Crops and livestock products	Ireland	Dairy Products	1869	1868	2627	3013	3270	3314	3682	19647.23284	Export
289	Crops and livestock products	Ireland	Eggs	18	13	15	14	17	20	41	141.71600	Export
290	Crops and livestock products	Ireland	Fodder and Feeding Stuff	306	290	339	375	377	416	505	2610.96716	Export

In [39]:
```
# display the last five observations from the new data frame df_Ireland
df_Ireland.tail()
```

Out[39]:

	Domain	Region	Production	2015	2016	2017	2018	2019	2020	2021	Total Gross	Trade
303	Crops and livestock products	Ireland	Nuts	68	65	66	67	65	65	66	464.35743	Import
304	Crops and livestock products	Ireland	Pigmeat (meat equivalent)	242	233	276	278	253	312	302	1897.07626	Import
305	Crops and livestock products	Ireland	Poultry Meat	501	497	501	560	520	439	433	3454.39360	Import
306	Crops and livestock products	Ireland	Roots and Tubers	131	157	163	184	185	164	141	1127.96901	Import
307	Crops and livestock products	Ireland	Vegetables	465	488	507	553	538	567	570	3691.90916	Import

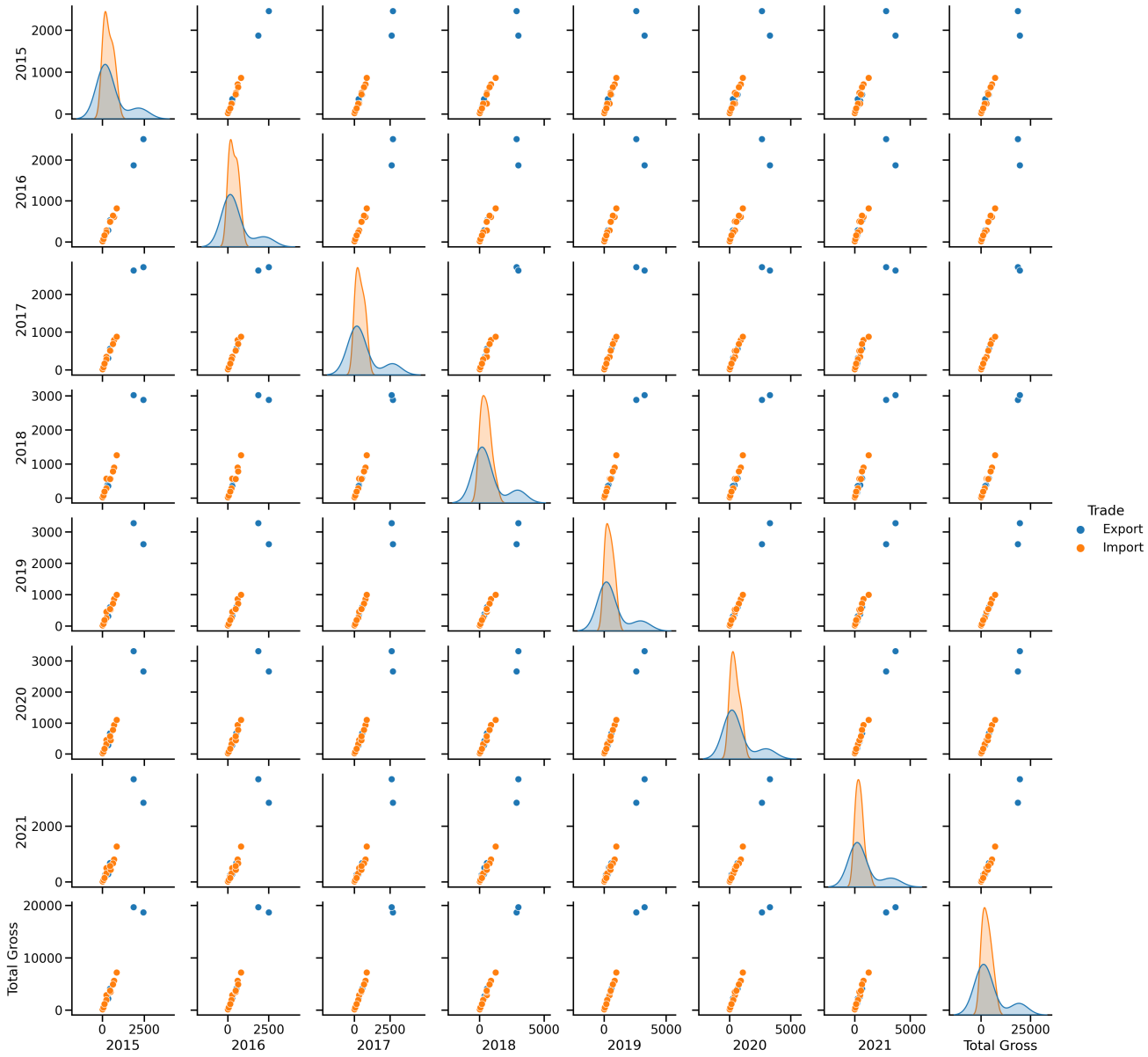
In [40]:
```
# Reset the default index [7]
df_Ireland.reset_index(inplace=True, drop=True)
```

In [ ]:
```
1
```

The pairplot method from the seaborn library used to get a nice visualisation plot for the pairwise correlation between all the variables on our dataset. the pairplot considered a simple tool to understand the data set by summarizing it in one figure.

Let's have a look at the correllation between features:

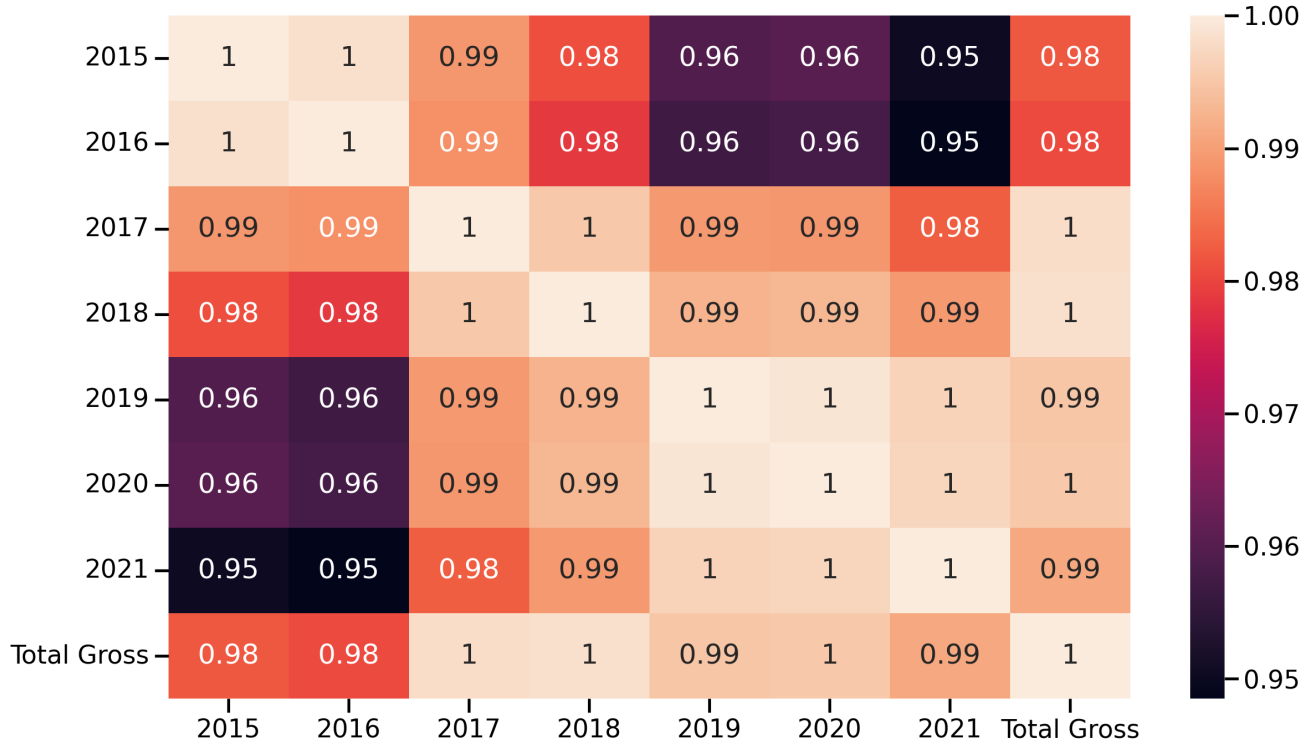
In [41]:
```
1 sns.pairplot(df_Ireland,hue='Trade');
```



We dissplay the correlation between each column in our data frame. A heat map is a two-dimensional plot of the correlation strength (a measure of dependence) between the variables represented by colour. The correlation amount is represented by the colour intensity variation on the heat map. The correlation range is between -1 and +1. There are two types of correlation positive correlation (closer to 1) and negative correlation (closer to -1). The correlation between every two columns on the data set can be represented by a square. All the values on the diagonal are 1 because it is correlating each variable to itself

Szabo, B. (2020). How to Create a Seaborn Correlation Heatmap in Python? [online] Medium. Available at: https://medium.com/@szabo.bibor/how-to-create-a-seaborn-correlation-heatmap-in-python-834c0686b88e (https://medium.com/@szabo.bibor/how-to-create-a-seaborn-correlation-heatmap-in-python-834c0686b88e).

In [42]:
```
c = df_Ireland.corr()            # Calculate the coerrelation matrix
plt.figure(figsize=(14,8))
sns.heatmap(c,annot=True)
plt.show()
```



The heatmap shows a strong positive correklation between the columns in our data set.

In [43]:
```
df_Ireland.corr()
```

Out[43]:

	2015	2016	2017	2018	2019	2020	2021	Total Gross
2015	1.000000	0.998405	0.989026	0.981010	0.959202	0.960364	0.950255	0.982093
2016	0.998405	1.000000	0.988305	0.978809	0.957060	0.957859	0.948503	0.980624
2017	0.989026	0.988305	1.000000	0.995201	0.989251	0.989055	0.982700	0.998135
2018	0.981010	0.978809	0.995201	1.000000	0.992517	0.993115	0.989244	0.998479
2019	0.959202	0.957060	0.989251	0.992517	1.000000	0.999020	0.996717	0.994851
2020	0.960364	0.957859	0.989055	0.993115	0.999020	1.000000	0.997095	0.995209
2021	0.950255	0.948503	0.982700	0.989244	0.996717	0.997095	1.000000	0.991175
Total Gross	0.982093	0.980624	0.998135	0.998479	0.994851	0.995209	0.991175	1.000000

Q1: What is Ireland's total external trade of crops and livestock products over 2015-2021?

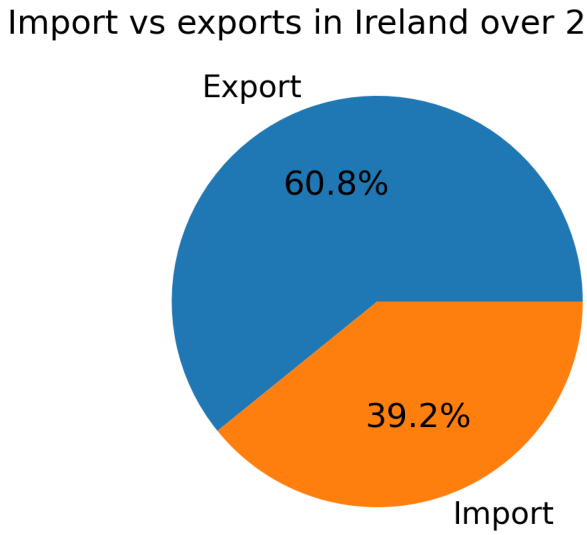
Stack Overflow. (n.d.). pandas - Matplotlib - Adding value labels to bar graph. [online] Available at: https://stackoverflow.com/questions/70235487/matplotlib-adding-value-labels-to-bar-graph (https://stackoverflow.com/questions/70235487/matplotlib-adding-value-labels-to-bar-graph) [Accessed 4 Jan. 2023].

In [44]:
```
# Bar Plot shows the crops and livestock productions import vs export values in United state $M
ax = df_Ireland.groupby('Trade').sum().plot(y = 'Total Gross',kind='bar', figsize=(8,6), ylabel='Total Gross $ M',
                                            title = 'Import Vs Export in Ireland over 2015-2021')
ax.bar_label(ax.containers[0], label_type='center')
plt.tight_layout()
```

The %matplotlib magic function configures its integration with the IPython shell or Jupyter notebook. This is important, as otherwise plots you create will either not appear (notebook) or take control of the session until closed (shell).[Python for Data Analysis Data Wrangling with Pandas, NumPy, and IPython, Wes McKinney]

print('Ireland's total external trade over 2015-2017 is: Euro',df_Ireland['Total Gross'].sum(),'million')

In [45]:
```
df_Ireland.groupby('Trade').sum().plot.pie(title='Import vs exports in Ireland over 2015-2021',
                                           y='Total Gross', figsize=(5, 5), autopct='%.1f%%', legend=False, ylabel='');

```



The pie chart shows Ireland's total external trade in crops and livestock products over 2015-2021 amounted to Euro $82250 million. Of this total external trade, Euro $50027 million (60.8%) Were exported crops and livestock products, while Euro $32223 million (39.2) were imported crops and livestock products.

To study the relationship between the import and export products, We filter the data frame df_Ireland into two datasets, one for import items and the other for export items in Ireland. Let us display the highest crops/livestock production imported and exported in Ireland.

In [46]:
```
df_Ireland.head()
```

Out[46]:

	Domain	Region	Production	2015	2016	2017	2018	2019	2020	2021	Total Gross	Trade
0	Crops and livestock products	Ireland	Bovine Meat	2454	2508	2716	2874	2601	2660	2838	18653.84379	Export
1	Crops and livestock products	Ireland	Cereals	40	18	21	22	36	45	64	249.10032	Export
2	Crops and livestock products	Ireland	Dairy Products	1869	1868	2627	3013	3270	3314	3682	19647.23284	Export
3	Crops and livestock products	Ireland	Eggs	18	13	15	14	17	20	41	141.71600	Export
4	Crops and livestock products	Ireland	Fodder and Feeding Stuff	306	290	339	375	377	416	505	2610.96716	Export

To know the highest crops/livestock production in Ireland:

- Drop the 'Total Gross' column.
- Melt the df_Ireland to include all the Years 2015-2021 in one column 'Year'.
- Split to two datasets df_Ireland_import, df_Ireland_export one for Import and the other for export
- Sort the dataframe df_Ireland

In [47]:
```
df_Ireland.drop(['Total Gross'],axis = 1, inplace = True)
df_Ireland_melted = df_Ireland.melt(id_vars=['Domain','Region','Production','Trade'],
                                    var_name='Year', value_name='Value $M')
```

In [48]:
```
# Again we filter the data into two datasets one for import items and the other for export items in Ireland.
df_Ireland_import = df_Ireland_melted.loc[df_Ireland_melted['Trade']=='Import']
df_Ireland_export = df_Ireland_melted.loc[df_Ireland_melted['Trade']=='Export']
# df_Ireland_import.reset_index(drop= True,inplace=True)
# df_Ireland_import
```

In [49]:
```
# .sort_values() method sorts the data in descending order to display the highest crops/livestocks production
IRL_ImportedOrded = df_Ireland_import.sort_values(by=['Value $M'], ascending=False)
IRL_ExportedOrded = df_Ireland_export.sort_values(by=['Value $M'], ascending=False)
```

For clarity, we rename 'Element' column with 'Import' in df_Ireland_import and 'Export' in 'df_Ireland_export'

In [50]:
```
df_Ireland_import.rename(columns = {'Trade':'Import'}, inplace = True)
df_Ireland_export.rename(columns = {'Trade':'Export'}, inplace = True)
```

In [51]:
```
# df_Ireland_melted.head()
```

In [52]:
```
# df_Ireland_melted.info()
```

In [53]:
```
# df_Ireland_melted['Year'] = df_Ireland_melted['Year'].astype('int')
```

Pie char

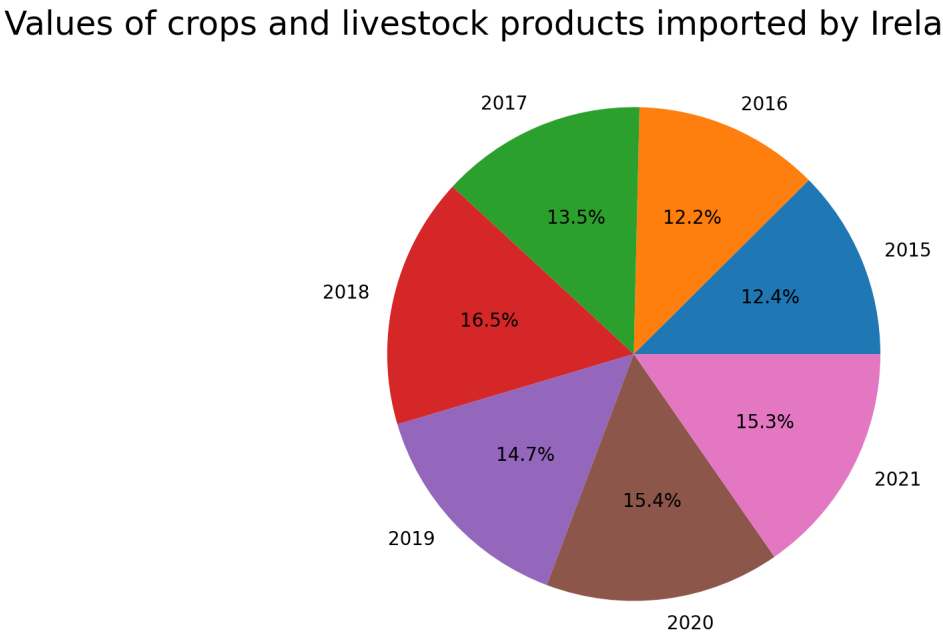
Now the data is much more organised but is long when it should be wide. Looking at the IRL_Import_Inorder and IRL_Export_Inorder, the 'Item' column contains duplicated values, so we will pivot them to make a wide data frame with no repeated crops/ livestock products in the 'Item' column.
[pandas.pydata.org. (n.d.). pandas.DataFrame.pivot — pandas 1.3.5 documentation. [online] Available at:
https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.pivot.html.]
(https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.pivot.html.%5D)

In [54]:
```
IRL_Import = df_Ireland_import.pivot(index='Production', columns='Year', values='Value $M');
# IRL_Import.head()
```

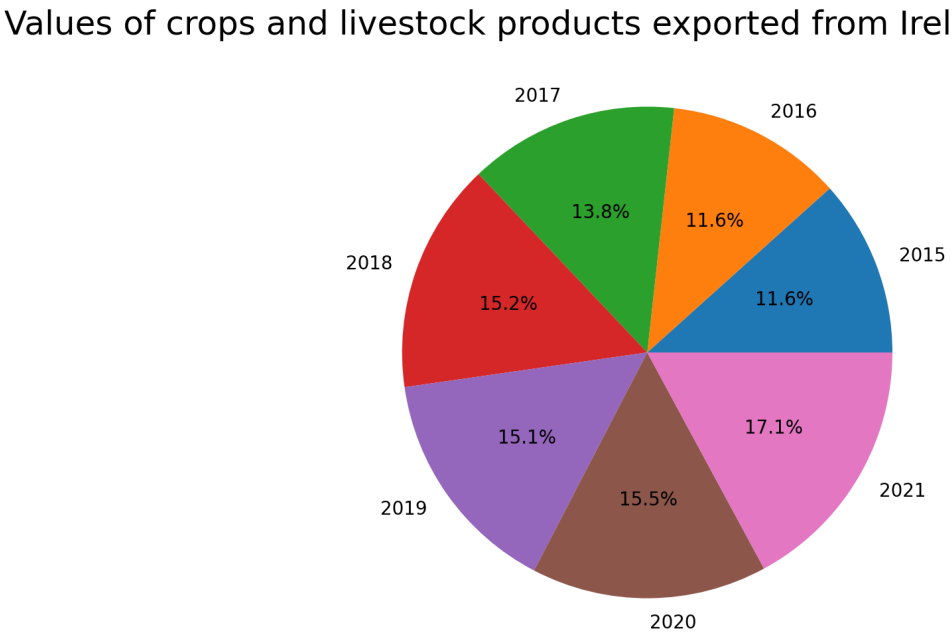
In [55]:
```
IRL_Export= df_Ireland_export.pivot(index='Production', columns='Year', values='Value $M');
# IRL_Export.head()
```

In [56]:
```
# Pie plot for the imported products in Ireland
ax=IRL_Import.sum(axis = 0).plot.pie(title='Values of crops and livestock products imported by Ireland over 2015-2021',
                                     legend=False, autopct='%1.1f%%',
                                     fontsize=10, figsize=(8,6),ylabel='');
ax
```

Out[56]: <AxesSubplot: title={'center': 'Values of crops and livestock products imported by Ireland over 2015-2021'}>



In [57]:
```
# Pie plot for the exported products in Ireland
ax =IRL_Export.sum(axis = 0).plot.pie(title='Values of crops and livestock products exported from Ireland over 2015-2021',
                                      legend=False, autopct='%1.1f%%', fontsize=10, figsize=(8,6), ylabel = '')
plt.show()
```



This pie chart for the imported crops and livestock products in Ireland over 2015-202 shows a gradually increased from 12.4% in 2015 to 15.3% in 2021. on the other hand, the pie chart for export products depicts an increment rate percentage in Ireland's exported crops and livestock products over 2015-202. it was 11.6% in 2015 and was increased to 17.1% in 2021.

Q2: What is the top agricultural production in Ireland?

The most imported produsts in Ireland is the 'Fodder and feeding stuff' While the 'DiaryProducts' is the most livestock products exported from Ireland. That dairy products include (Butter of cow milk, Buttermilk, curdled and acidified milk, Cheese from whole cow milk, Cream, fresh, Processed cheese, Raw milk of cattle, Skim milk and whey powder, Skim milk of cows, whey(condensed), Whey(dry), Whole milk powder, Whole milk(condensed), Whole milk(evaporated), and Yoghurt(with additives)).

Let us display the highest crops/livestock production in Ireland by sorting the datasets for df_Ireland)import and df_Ireland_export on descending order.

Top 10 crops and livestock products imported & exported by Ireland

In [58]:
```
# .sort_values() method sorts the data in descending order to display the highest crops/livestocks production
IRL_ImportedOrded = df_Ireland_import.sort_values(by=['Value $M'], ascending=False)
IRL_ImportedOrded.head(10)
```

Out[58]:

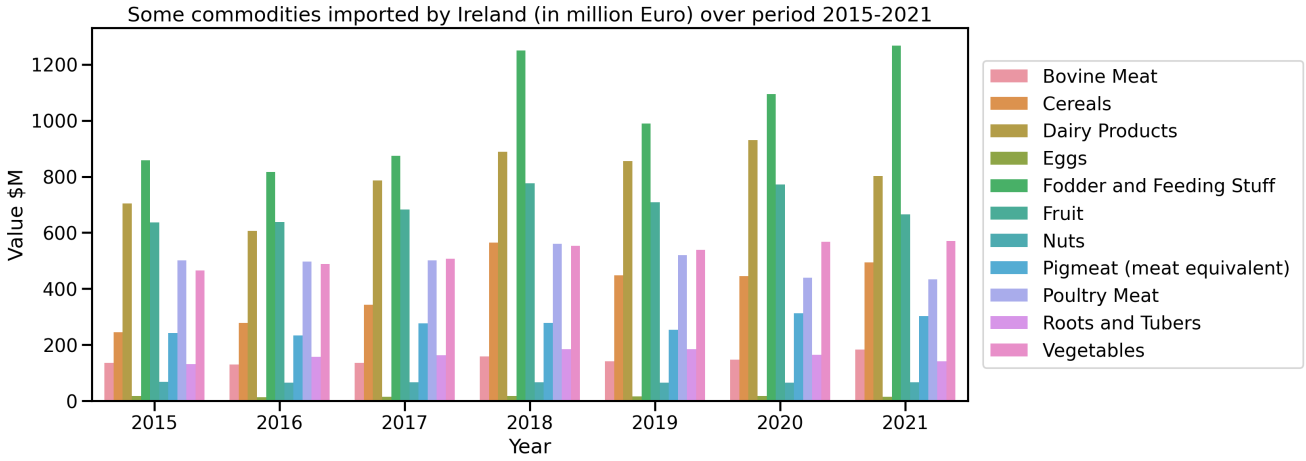
	Domain	Region	Production	Import	Year	Value $M
147	Crops and livestock products	Ireland	Fodder and Feeding Stuff	Import	2021	1267
81	Crops and livestock products	Ireland	Fodder and Feeding Stuff	Import	2018	1250
125	Crops and livestock products	Ireland	Fodder and Feeding Stuff	Import	2020	1095
103	Crops and livestock products	Ireland	Fodder and Feeding Stuff	Import	2019	990
123	Crops and livestock products	Ireland	Dairy Products	Import	2020	930
79	Crops and livestock products	Ireland	Dairy Products	Import	2018	888
59	Crops and livestock products	Ireland	Fodder and Feeding Stuff	Import	2017	874
15	Crops and livestock products	Ireland	Fodder and Feeding Stuff	Import	2015	859
101	Crops and livestock products	Ireland	Dairy Products	Import	2019	855
37	Crops and livestock products	Ireland	Fodder and Feeding Stuff	Import	2016	816

In [59]:
```
# .sort_values() method sorts the data in descending order to display the highest crops/livestocks production
IRL_ExportedOrded = df_Ireland_export.sort_values(by=['Value $M'], ascending=False)
# df_Ireland_export.reset_index(drop= True,inplace=True)
IRL_ExportedOrded.head(10)
```

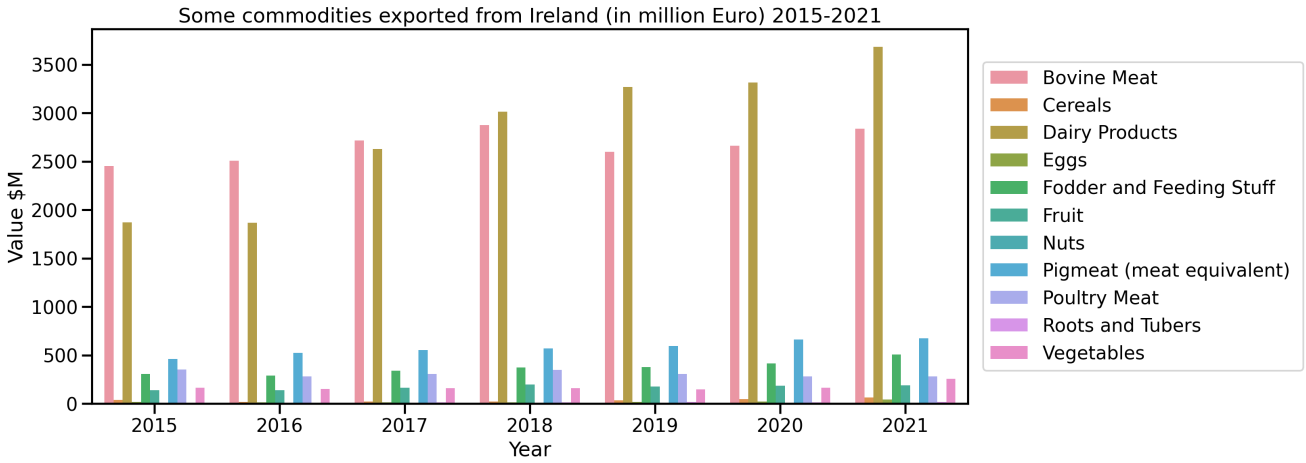
Out[59]:

	Domain	Region	Production	Export	Year	Value $M
134	Crops and livestock products	Ireland	Dairy Products	Export	2021	3682
112	Crops and livestock products	Ireland	Dairy Products	Export	2020	3314
90	Crops and livestock products	Ireland	Dairy Products	Export	2019	3270
68	Crops and livestock products	Ireland	Dairy Products	Export	2018	3013
66	Crops and livestock products	Ireland	Bovine Meat	Export	2018	2874
132	Crops and livestock products	Ireland	Bovine Meat	Export	2021	2838
44	Crops and livestock products	Ireland	Bovine Meat	Export	2017	2716
110	Crops and livestock products	Ireland	Bovine Meat	Export	2020	2660
46	Crops and livestock products	Ireland	Dairy Products	Export	2017	2627
88	Crops and livestock products	Ireland	Bovine Meat	Export	2019	2601

In [60]:
```
plt.figure(figsize=(14,6))
sns.barplot(data=df_Ireland_import, x='Year', y='Value $M',hue='Production',linewidth=2.5)
# plt.ylim([0, 900])
plt.legend(ncol=1, loc='center', bbox_to_anchor=(1.2,0.5))
plt.title('Some commodities imported by Ireland (in million Euro) over period 2015-2021')
plt.show()
```

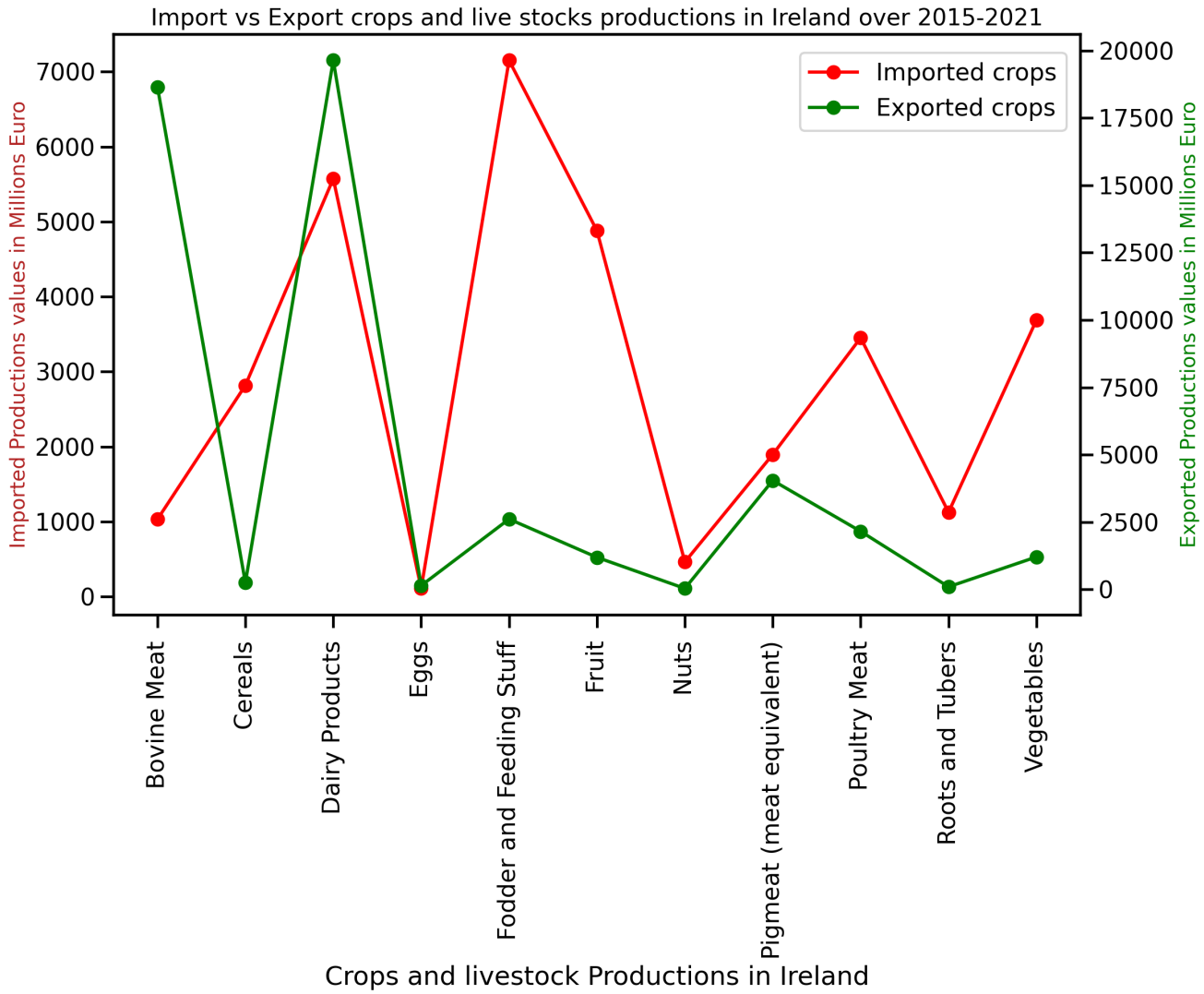


In [61]:
```
plt.figure(figsize=(14,6))
sns.barplot(data=df_Ireland_export, x='Year', y='Value $M',hue='Production')
plt.legend(ncol=1, loc='center', bbox_to_anchor=(1.2,0.5))
plt.title('Some commodities exported from Ireland (in million Euro) 2015-2021')
plt.show()
```



In [62]:

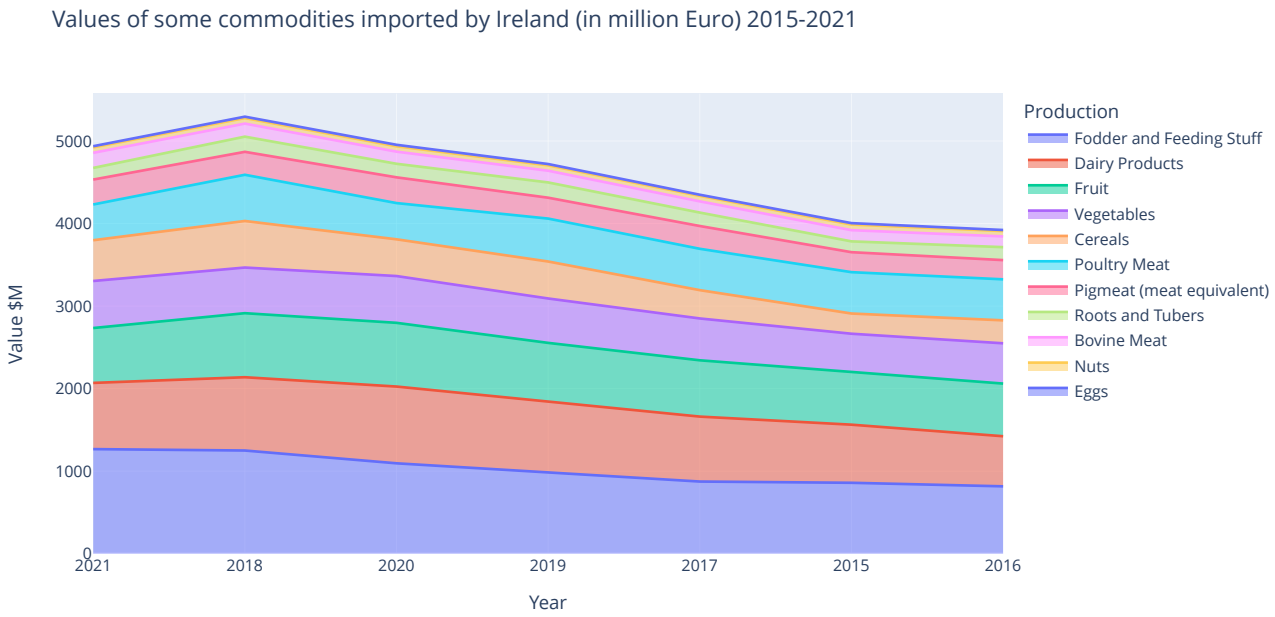
```
# plotting figures by creating axes object
# using subplots() function
fig, ax = plt.subplots(figsize = (12,10 ))

# using the twinx() for creating another
# axes object for secondary y-Axis
ax2 = ax.twinx()

# Creating the line plots
# Creating the line plots
ax.plot(IRL_Import.index,IRL_Import.sum(1),label='Imported crops',marker= 'o', color='r')
ax2.plot(IRL_Export.index, IRL_Export.sum(1), label='Exported crops', marker = 'o',color ='g')



# Place legend on the figure
fig.legend(bbox_to_anchor=(0.88, .94))

# Setting the figure title
ax.set_title('Import vs Export crops and live stocks productions in Ireland over 2015-2021',fontsize=16)

# giving labels to x and y axises
ax.set_xlabel('Crops and livestock Productions in Ireland')
ax.set_ylabel('Imported Productions values in Millions Euro',fontsize=14,color='firebrick')


# secondary y-axis label
ax2.set_ylabel('Exported Productions values in Millions Euro',fontsize=14,color='green')

# Rotate x-axis label by 75 degree
ax.tick_params(axis='x', rotation=90)

# defining display layout
plt.tight_layout()

# show plot
plt.show()
```



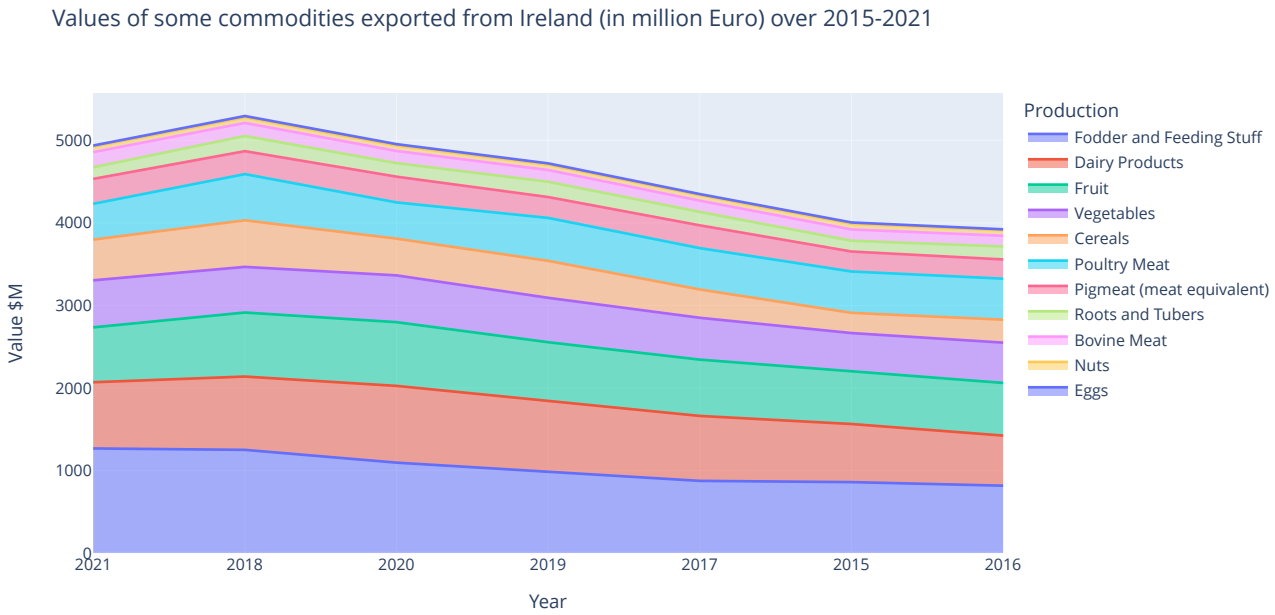
The stacked area plots were created for both import and export ordered data frames for Ireland, each row of the data frames is represented as the vertex of a polyline mark in 2D space. The area between successive polylines is filled [8].

In [63]:

```
# stacked area plot for df_Ireland_import data-frame
# fig = px.area(df_Ireland_import.sort_values(by=['Value $M'],ascending=False),
#               x='Year',y='Value $M', color='Production',
#               line_group='Production',
#               title = 'Values of some commodities imported by Ireland (in million Euro) 2015-2021'
#              )
# fig.show()

# To add to the dashboard later we use chart
px.area(df_Ireland_import.sort_values(by=['Value $M'],ascending=False),
              x='Year',y='Value $M', color='Production',
              line_group='Production',
              title = 'Values of some commodities imported by Ireland (in million Euro) 2015-2021'
             )
```



In [64]:
```
# stacked area plot for df_Ireland_export data-frame
chart = px.area(df_Ireland_import.sort_values(by=['Value $M'],ascending=False),
                x='Year', y='Value $M', color='Production',
                line_group='Production',
                title='Values of some commodities exported from Ireland (in million Euro) over 2015-2021'
               )
# fig.show()
chart
```

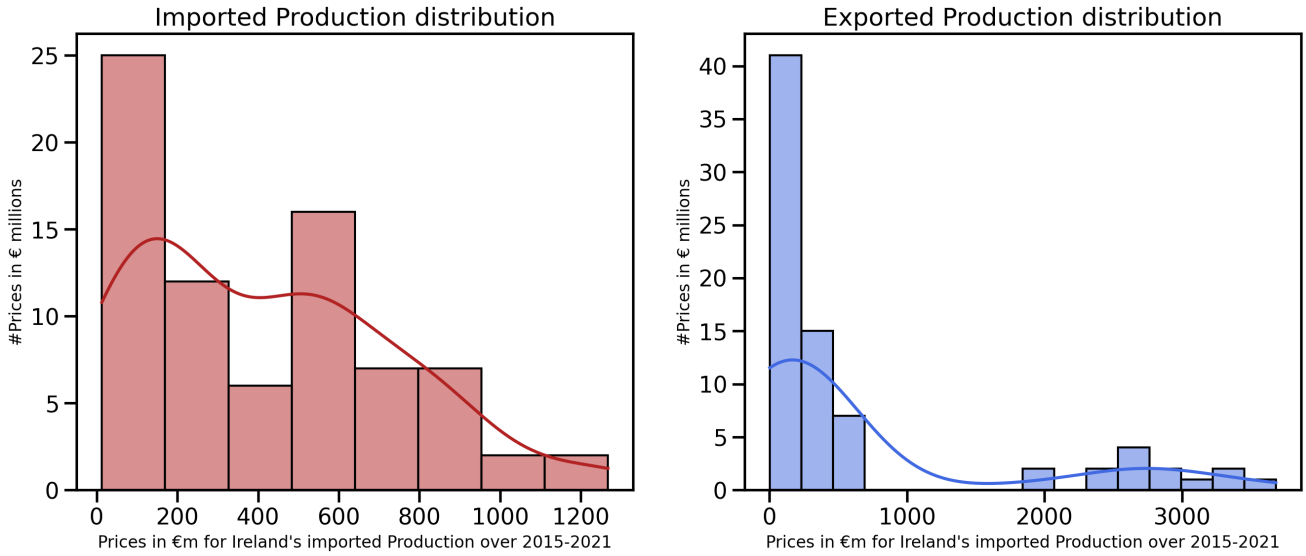


Histogram

A histogram provides a visual representation of the frequency at which each value in a data collection occurs relatively unbiasedly. Histograms are plots that show the distribution of a numeric variable, grouping data into bins. The height of the bar represents the number of observations per bin.

In [65]:
```
# set up figure & axes
fig, axes = plt.subplots(nrows=1, ncols=2,figsize=(16,6))

sns.histplot(data=df_Ireland_import, x='Value $M', kde=True, color='firebrick', ax=axes[0])
axes[0].set_title('Imported Production distribution')
axes[0].set_xlabel('Prices in €m for Ireland\'s imported Production over 2015-2021',fontsize=12)
axes[0].set_ylabel('#Prices in € millions',fontsize=12)


sns.histplot(data=df_Ireland_export, x='Value $M', kde=True, color='royalblue', ax=axes[1])
axes[1].set_title('Exported Production distribution')
axes[1].set_xlabel('Prices in €m for Ireland\'s imported Production over 2015-2021',fontsize=12)
axes[1].set_ylabel('#Prices in € millions',fontsize=12)
```

Out[65]:
```
Text(0, 0.5, '#Prices in € millions')
```



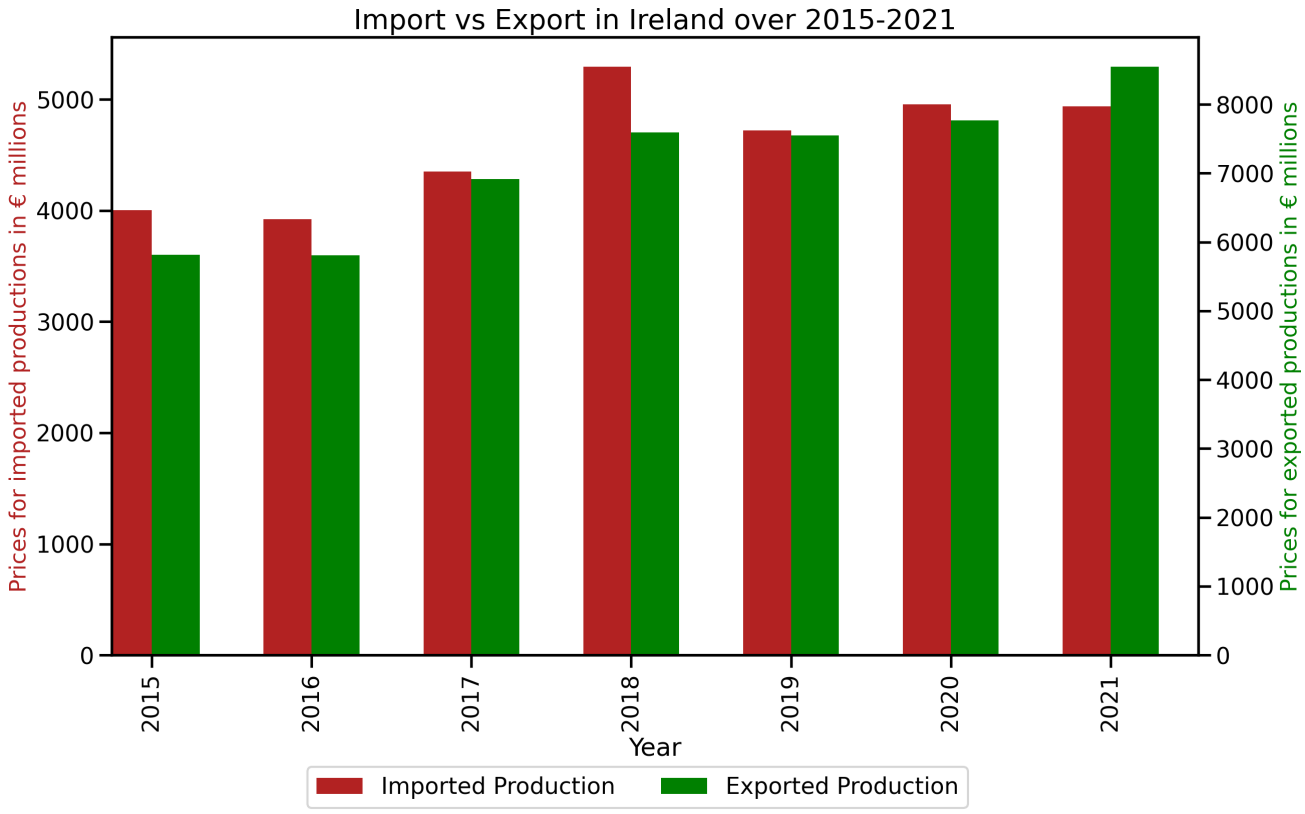
We can determine the number of evenly sized bins to be used in the by using the bin parameters.

Bar-Plot

To create a bar plot for the import/export counts we can use plot function or seaborn plot() is another pandas function that requires to get the intermediate count table from pd.crosstab() before, in dispute with seaborn, sns.catplot plot the count in one step.

Stack Overflow. (n.d.). python - Pandas: Bar-Plot with two bars and two y-axis. [online] Available at: https://stackoverflow.com/questions/24183101/pandas-bar-plot-with-two-bars-and-two-y-axis (https://stackoverflow.com/questions/24183101/pandas-bar-plot-with-two-bars-and-two-y-axis) [Accessed 6 Jan. 2023].

In [66]:
```
fig = plt.figure(figsize=(14,8))          # Create matplotlib figure
ax = fig.add_subplot(111)   # Create matplotlib axes
ax2 = ax.twinx()            # Create another axes that shares the same x-axis as ax.
width = 0.30

imp = IRL_Import.sum().plot(kind='bar',color='firebrick', ax=ax, width=width, position=1,label='Imported Production')
exp = IRL_Export.sum().plot(kind='bar',color='green',ax=ax2, width=width, position=0,label='Exported Production')

plt.title('Import vs Export in Ireland over 2015-2021',fontsize=20)
ax.set_ylabel('Prices for imported productions in € millions',fontsize=16,color='firebrick')
ax2.set_ylabel('Prices for exported productions in € millions',fontsize=16,color='green')
fig.legend(ncol=2,loc='center', bbox_to_anchor=(0.5, -0.055))
plt.show()
```



The bar graph depicts that In general the Import is more than the export as we can see in 2015,2016, 2020. A small trade defecit between import and export are noticed in 2017 and 2019. So proud to see that after the taugh time of Covid-19. Ireland exported exceeded the imported values.

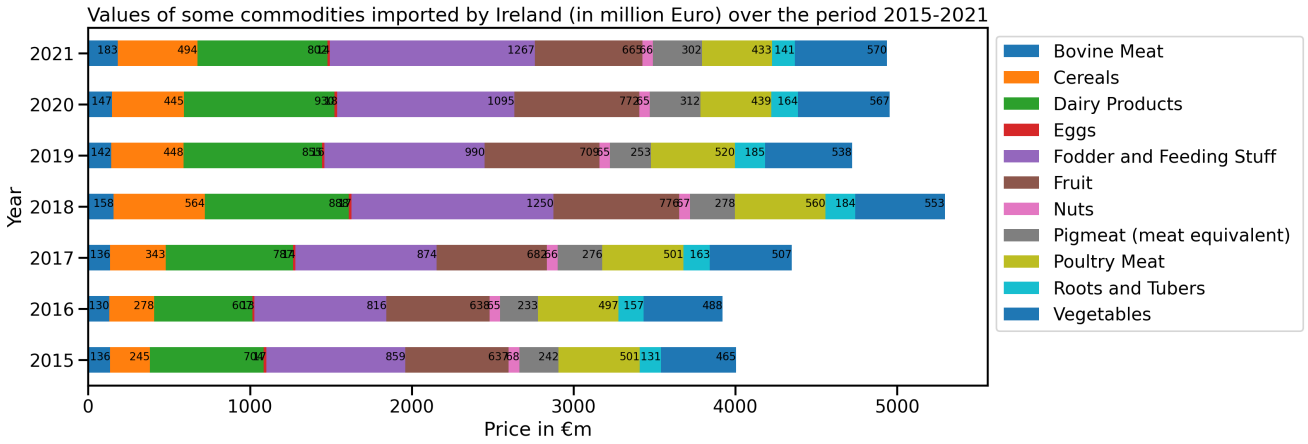
In [67]:
```
# IRL_Import.head(2)
```

Stack Overflow. (n.d.). python - How to display data values in stacked horizontal bar chart in Matplotlib. [online] Available at: https://stackoverflow.com/questions/54162981/how-to-display-data-values-in-stacked-horizontal-bar-chart-in-matplotlib (https://stackoverflow.com/questions/54162981/how-to-display-data-values-in-stacked-horizontal-bar-chart-in-matplotlib) [Accessed 30 Dec. 2022].

Creating a stacked horizontal bar chart with the data values displayed on it for the crops and livestock productions in Ireland over 2015-2021.

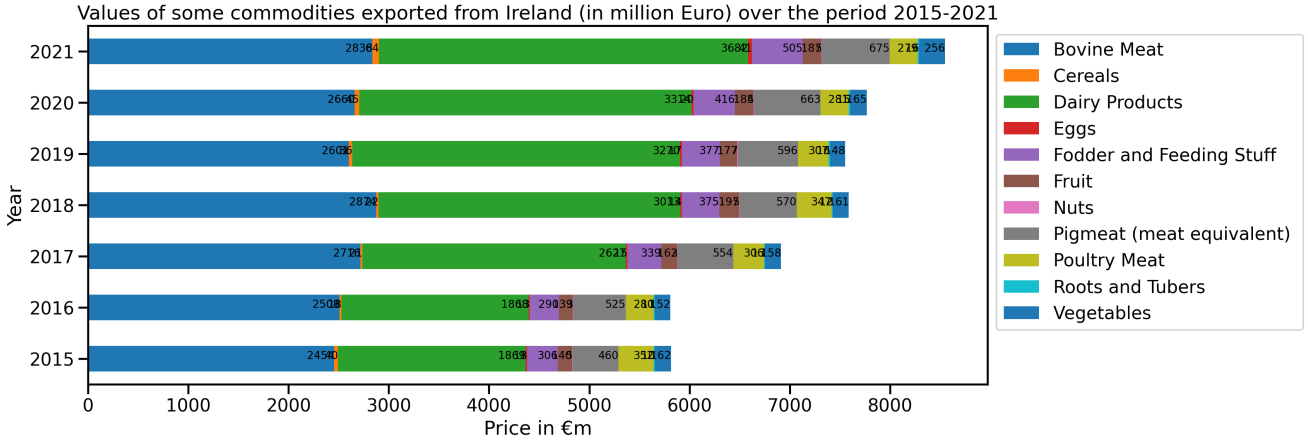
In [68]:
```
Item_count = df_Ireland_import.pivot(index='Year', columns='Production', values='Value $M')

ax = Item_count.plot.barh(stacked=True,figsize=(15, 6))
plt.legend(ncol=1, bbox_to_anchor=(1, 1))
plt.xlabel('Price in €m')
plt.ylabel('Year')

plt.title('Values of some commodities imported by Ireland (in million Euro) over the period 2015-2021',
          loc='center', fontsize=18)

for n, x in enumerate(Item_count.values):
    xpos = 0
    for val in x:
        xpos += val
        ax.text(xpos + 1, n, str(val), fontsize = 10,ha='right')
    xpos = 0
display(ax)
plt.show()
```

```
<AxesSubplot: title={'center': 'Values of some commodities imported by Ireland (in million Euro) over the period 2015-2021'}, x
label='Price in €m', ylabel='Year'>
```



In [69]:
```
Item_count_export = df_Ireland_export.pivot(index='Year', columns='Production', values='Value $M')

ax = Item_count_export.plot.barh(stacked=True,figsize=(15, 6))
plt.legend(ncol=1, bbox_to_anchor=(1, 1))
plt.xlabel('Price in €m')
plt.ylabel('Year')
plt.title('Values of some commodities exported from Ireland (in million Euro) over the period 2015-2021',
          loc='center',fontsize=18)

for n, x in enumerate(Item_count_export.values):
    xpos = 0
    for val in x:
        xpos += val
        ax.text(xpos + 1, n, str(val), fontsize = 10,ha='right')
    xpos = 0
display(ax)
plt.show()
```

```
<AxesSubplot: title={'center': 'Values of some commodities exported from Ireland (in million Euro) over the period 2015-2021'},
xlabel='Price in €m', ylabel='Year'>
```



GeeksforGeeks. (2020). How to Add a Y-Axis Label to the Secondary Y-Axis in Matplotlib? [online] Available at: https://www.geeksforgeeks.org/how-to-add-a-y-axis-label-to-the-secondary-y-axis-in-matplotlib/ (https://www.geeksforgeeks.org/how-to-add-a-y-axis-label-to-the-secondary-y-axis-in-matplotlib/) [Accessed 7 Jan. 2023].

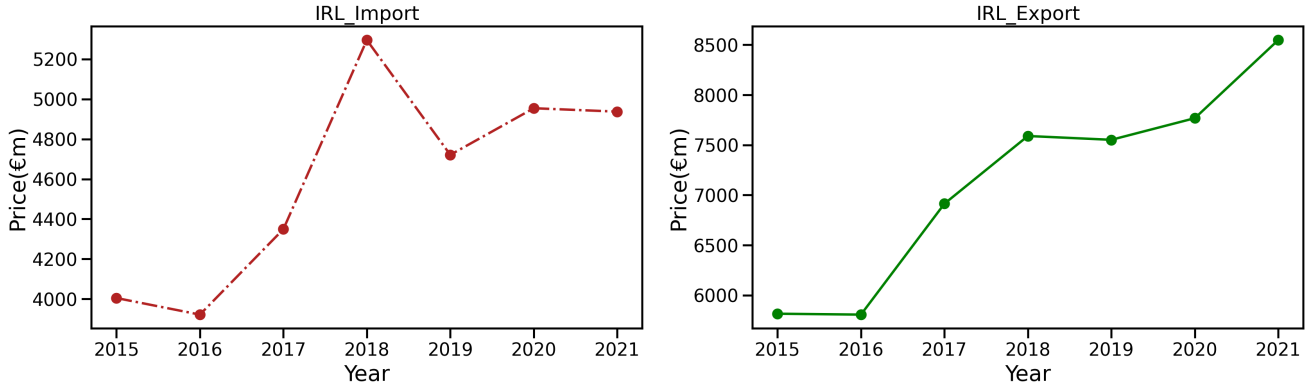
In [70]:
```
df_Ireland_import.head(2)
```

Out[70]:

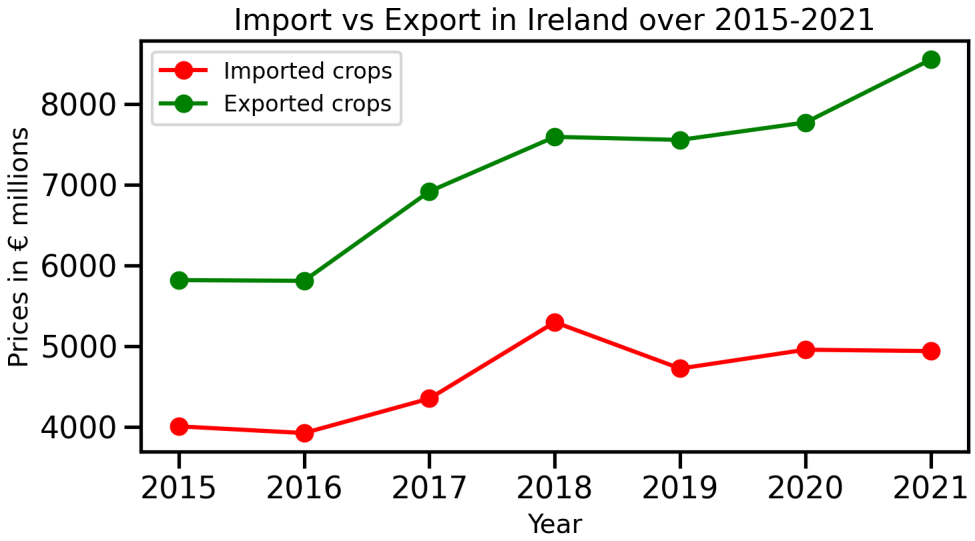
	Domain	Region	Production	Import	Year	Value $M
11	Crops and livestock products	Ireland	Bovine Meat	Import	2015	136
12	Crops and livestock products	Ireland	Cereals	Import	2015	245

Line Plot

In [71]:
```
fig,ax =plt.subplots(1,2,figsize=(20,5))

# figure, ax = plt.xticks(rotation = 90)

ax[0].plot(IRL_Import.sum(),c='firebrick',marker='o',ls='-.')
ax[0].set_title('IRL_Import')
ax[0].set_xlabel('Year',fontsize=20)
ax[0].set_ylabel('Price(€m)',fontsize=20)

# plt.xticks(rotation = 90)
ax[1].plot(IRL_Export.sum(),c = 'green',marker = 'o')
ax[1].set_title('IRL_Export')
ax[1].set_xlabel('Year',fontsize=20)
ax[1].set_ylabel('Price(€m)',fontsize=20)


# IRL_Import.sum().plot(kind='bar',figsize=(8,4))
# IRL_Export.sum().plot(kind='bar',figsize=(8,4))
plt.show()
```



In [72]:
```
# Line plot for Ireland total trade over 2015-2021
plt.figure(figsize=(8,4))
IRL_Import.sum().plot(label='Imported crops',marker= 'o', color='r')     # line plot for impoted products
IRL_Export.sum().plot(label='Exported crops',marker= 'o', color='g')     # line plot for exported products
plt.legend(fontsize=12)
plt.title('Import vs Export in Ireland over 2015-2021',fontsize=16)
plt.xlabel('Year',fontsize =14)
plt.ylabel('Prices in € millions',fontsize =14)
plt.show()
```

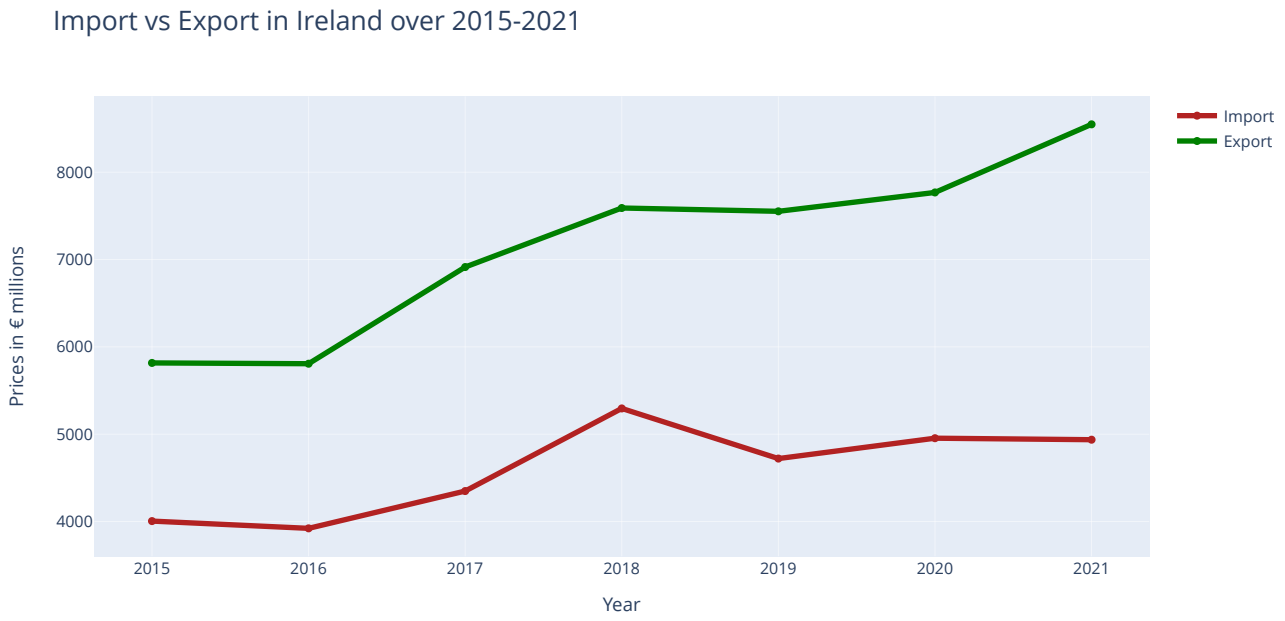


kaggle.com. (n.d.). Analysis on Indian Import Export. [online] Available at: https://www.kaggle.com/code/shubhamsinghgharsele/analysis-on-indian-import-export (https://www.kaggle.com/code/shubhamsinghgharsele/analysis-on-indian-import-export).

In 2018, the trade rate for imports and export increased. The imported products reached 5259 million Euro, the highest import rate from 2015-2021. at the same time, the exports became 7590 million Euro. In 2019 the trade rate began to decrease again. In 2021, the exported trade reached its highest rate of 8548 million Euro.

GO-Figure! is a great tool that can use to create a visual summaries of lists of GO terms. This is useful for data analysis and comparisons of different datasets. created to add to the dashboard later

In [73]:
```
fig = go.Figure()
# Create and style traces
fig.add_trace(go.Scatter(x= IRL_Import.columns, y=IRL_Import.sum(), name='Import',mode='lines+markers',
                         line=dict(color='firebrick', width=4)))
fig.add_trace(go.Scatter(x= IRL_Export.columns, y=IRL_Export.sum(), name = 'Export',mode='lines+markers',
                         line=dict(color='green', width=4)))

fig.update_layout(
    title=go.layout.Title(text='Import vs Export in Ireland over 2015-2021',
                          font=dict(
                              size=20
                          )),
    xaxis=go.layout.XAxis(title=go.layout.xaxis.Title(text='Year')),
    yaxis=go.layout.YAxis(title=go.layout.yaxis.Title(text='Prices in € millions'))
                )
fig.show()
```



Compare export commodities for Ireland with other Europe Country

Instead of filtering the main dataframe to extract the export items only. We are going to read the export file

In [74]:
```
df_export = pd.read_csv('FAOSTAT_data_Export_EU.csv')
```

In [75]:
```
df_export.head()
```

Out[75]:

	Domain Code	Domain	Area Code (M49)	Area	Element Code	Element	Item Code (FAO)	Item	Year Code	Year	Unit	Value
0	TCL	Crops and livestock products	40	Austria	5922	Export Value	1944	Cereals	2015	2015	1000 US$	413436.91
1	TCL	Crops and livestock products	40	Austria	5922	Export Value	1944	Cereals	2016	2016	1000 US$	416309.32
2	TCL	Crops and livestock products	40	Austria	5922	Export Value	1944	Cereals	2017	2017	1000 US$	451317.42
3	TCL	Crops and livestock products	40	Austria	5922	Export Value	1944	Cereals	2018	2018	1000 US$	433067.23
4	TCL	Crops and livestock products	40	Austria	5922	Export Value	1944	Cereals	2019	2019	1000 US$	461881.52

In [76]:
```
lll = df_export.Value /1000
lll
```

Out[76]:
```
0       413.43691
1       416.30932
2       451.31742
3       433.06723
4       461.88152
          ...
2419    199.21434
2420    199.96462
2421    209.35856
2422    248.78600
2423    321.39627
Name: Value, Length: 2424, dtype: float64
```

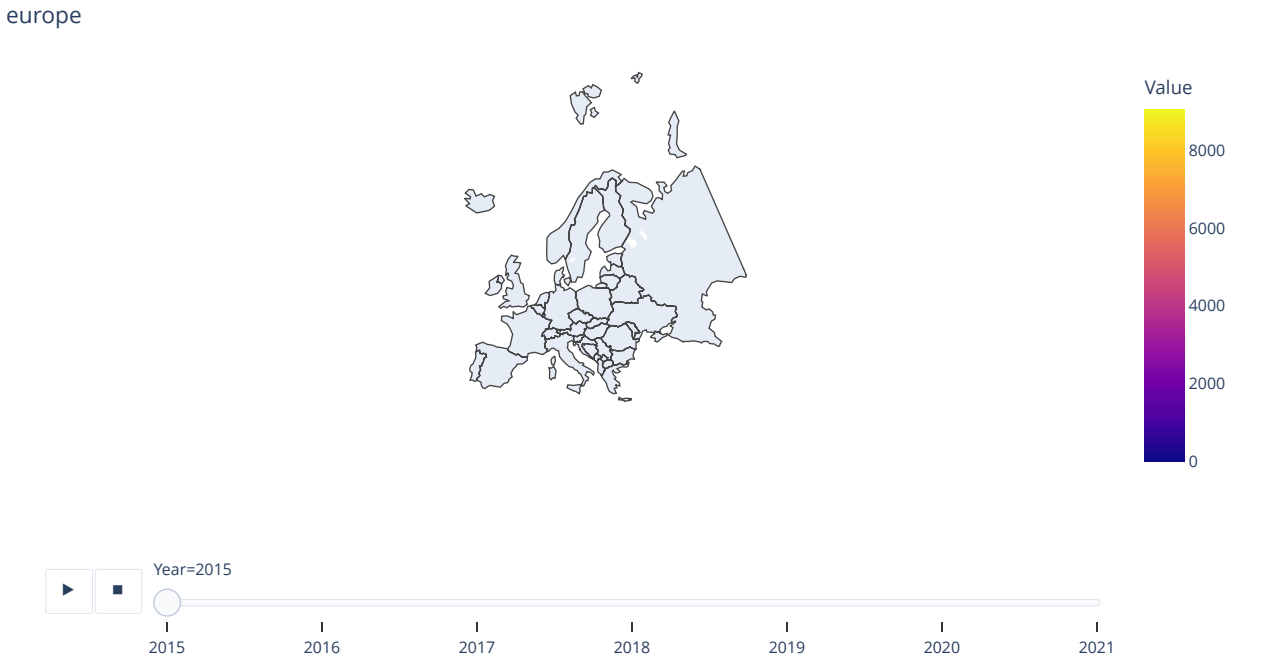
We compare the export commodities for Ireland with all European Union countries over 2015-2021

In [77]:
```
# Again, we put the price in $M instead of $K
df_export.Value = df_export['Value']/1000
df_export.head()
```

Out[77]:

	Domain Code	Domain	Area Code (M49)	Area	Element Code	Element	Item Code (FAO)	Item	Year Code	Year	Unit	Value
0	TCL	Crops and livestock products	40	Austria	5922	Export Value	1944	Cereals	2015	2015	1000 US$	413.43691
1	TCL	Crops and livestock products	40	Austria	5922	Export Value	1944	Cereals	2016	2016	1000 US$	416.30932
2	TCL	Crops and livestock products	40	Austria	5922	Export Value	1944	Cereals	2017	2017	1000 US$	451.31742
3	TCL	Crops and livestock products	40	Austria	5922	Export Value	1944	Cereals	2018	2018	1000 US$	433.06723
4	TCL	Crops and livestock products	40	Austria	5922	Export Value	1944	Cereals	2019	2019	1000 US$	461.88152

In [78]:
```
fig = px.choropleth(df_export,
                    locations='Area Code (M49)',
                    color='Value',
                    hover_name='Area',
                    animation_frame= 'Year',
                   color_continuous_scale=px.colors.sequential.Plasma)

fig.update_layout( title_text = 'europe', geo_scope = 'europe')
fig.show()
```



It seems the choropleth plot is not displaying any colours for any country. It may be for using the numeric code of the country 'Area Code (M49)'. Let's try to use the country abbreviations according to the International Organization for Standardization (ISO)- ISO 3166-1 alpha-3.

Read a new CSV file containing the Europe country codes for the International Organization for Standardization (ISO)- ISO 3166-1

In [79]:
```
CountryCode_df = pd.read_csv('EU_CountryCodes.csv')
CountryCode_df.head()
```

Out[79]:

	Country	alpha-2	alpha-3	country-code
0	Austria	AT	AUT	40
1	Belgium	BE	BEL	56
2	Bulgaria	BG	BGR	100
3	Croatia	HR	HRV	191
4	Cyprus	CY	CYP	196

We Convert the two columns 'Country' and 'alpha-3' to a dictionary to add a new column 'alpha-3' to the data frame 'df_export'

cmdlinetips (2021). How To Convert Two Columns from Pandas Dataframe to a Dictionary. [online] Python and R Tips. Available at: https://cmdlinetips.com/2021/04/convert-two-column-values-from-pandas-dataframe-to-a-dictionary/ (https://cmdlinetips.com/2021/04/convert-two-column-values-from-pandas-dataframe-to-a-dictionary/) [Accessed 9 Jan. 2023].

In [80]:
```
# dict() function on the zip object with two iterables gives us the dictionary we need.
# zip() function takes iterables as its argument and returns iterator.
EuCountries_abbreviations_3 = dict(zip(CountryCode_df.Country, CountryCode_df['alpha-3']))
```

In [81]:
```
# EuCountries_abbreviations_3
```

Now, we add a new column 'Alpha-3' to map the countries' names in the 'Area' column to their abbreviations using an area map dictionary Countries_abbreviations_3

In [82]:
```
df_export['Alpha-3'] = df_export['Area'].map(EuCountries_abbreviations_3)
```

In [83]:
```
df_export.head()
```

Out[83]:

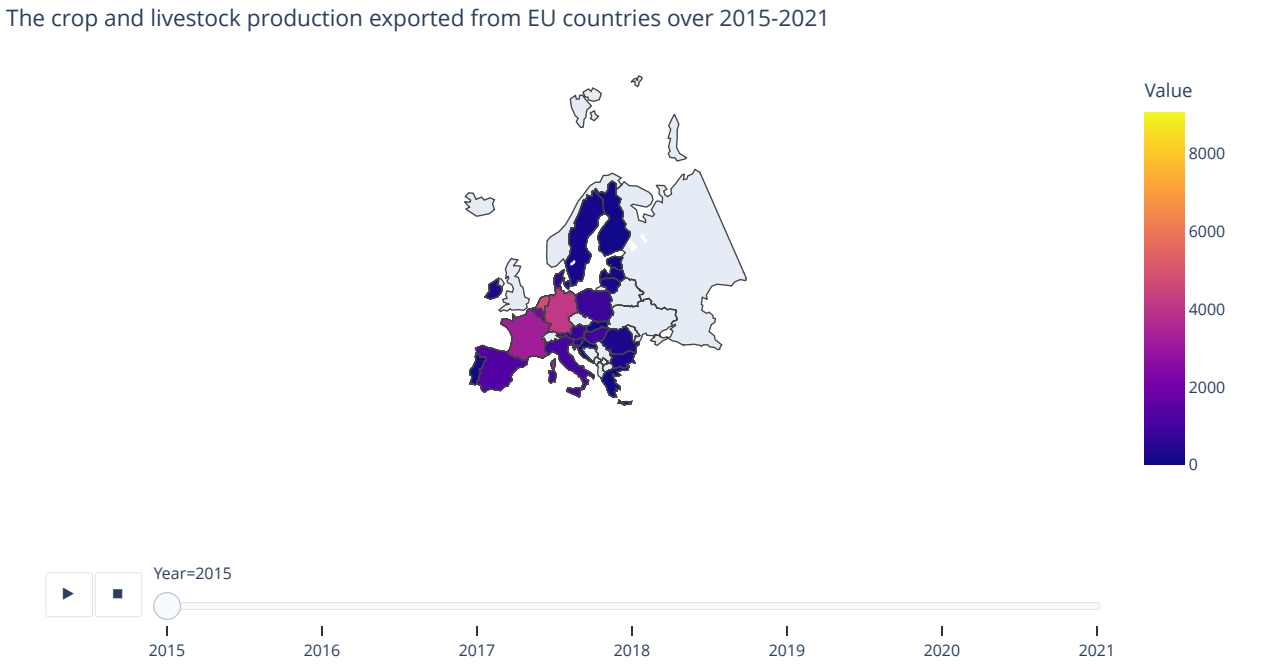
	Domain Code	Domain	Area Code (M49)	Area	Element Code	Element	Item Code (FAO)	Item	Year Code	Year	Unit	Value	Alpha-3
0	TCL	Crops and livestock products	40	Austria	5922	Export Value	1944	Cereals	2015	2015	1000 US$	413.43691	AUT
1	TCL	Crops and livestock products	40	Austria	5922	Export Value	1944	Cereals	2016	2016	1000 US$	416.30932	AUT
2	TCL	Crops and livestock products	40	Austria	5922	Export Value	1944	Cereals	2017	2017	1000 US$	451.31742	AUT
3	TCL	Crops and livestock products	40	Austria	5922	Export Value	1944	Cereals	2018	2018	1000 US$	433.06723	AUT
4	TCL	Crops and livestock products	40	Austria	5922	Export Value	1944	Cereals	2019	2019	1000 US$	461.88152	AUT

In [84]:
```
df_export_2021 = df_export.query("Year == 2021")
df_export_2021.head()
```

Out[84]:

	Domain Code	Domain	Area Code (M49)	Area	Element Code	Element	Item Code (FAO)	Item	Year Code	Year	Unit	Value	Alpha-3
6	TCL	Crops and livestock products	40	Austria	5922	Export Value	1944	Cereals	2021	2021	1000 US$	592.32672	AUT
13	TCL	Crops and livestock products	40	Austria	5922	Export Value	1941	Cereal preparations total	2021	2021	1000 US$	1385.61272	AUT
20	TCL	Crops and livestock products	40	Austria	5922	Export Value	2071	Bovine Meat	2021	2021	1000 US$	589.37134	AUT
27	TCL	Crops and livestock products	40	Austria	5922	Export Value	2074	Poultry Meat	2021	2021	1000 US$	379.17957	AUT
34	TCL	Crops and livestock products	40	Austria	5922	Export Value	2073	Pigmeat (meat equivalent)	2021	2021	1000 US$	915.28358	AUT

In [85]:
```
# choropleth plot
fig = px.choropleth(df_export,
                    locations='Alpha-3',
                    color='Value',
                    hover_name='Area',
                    animation_frame='Year',
                    color_continuous_scale=px.colors.sequential.Plasma)

fig.update_layout( title_text = 'The crop and livestock production exported from EU countries over 2015-2021',
                  geo_scope = 'europe' )
fig.show()
chart1 = fig

```



In [86]:
```
df_export
```

Out[86]:

	Domain Code	Domain	Area Code (M49)	Area	Element Code	Element	Item Code (FAO)	Item	Year Code	Year	Unit	Value	Alpha-3
0	TCL	Crops and livestock products	40	Austria	5922	Export Value	1944	Cereals	2015	2015	1000 US$	413.43691	AUT
1	TCL	Crops and livestock products	40	Austria	5922	Export Value	1944	Cereals	2016	2016	1000 US$	416.30932	AUT
2	TCL	Crops and livestock products	40	Austria	5922	Export Value	1944	Cereals	2017	2017	1000 US$	451.31742	AUT
3	TCL	Crops and livestock products	40	Austria	5922	Export Value	1944	Cereals	2018	2018	1000 US$	433.06723	AUT
4	TCL	Crops and livestock products	40	Austria	5922	Export Value	1944	Cereals	2019	2019	1000 US$	461.88152	AUT
...	...	...	...	...	...	...	...	...	...	...	...	...	...
2419	TCL	Crops and livestock products	752	Sweden	5922	Export Value	1892	Fodder and Feeding Stuff	2017	2017	1000 US$	199.21434	SWE
2420	TCL	Crops and livestock products	752	Sweden	5922	Export Value	1892	Fodder and Feeding Stuff	2018	2018	1000 US$	199.96462	SWE
2421	TCL	Crops and livestock products	752	Sweden	5922	Export Value	1892	Fodder and Feeding Stuff	2019	2019	1000 US$	209.35856	SWE
2422	TCL	Crops and livestock products	752	Sweden	5922	Export Value	1892	Fodder and Feeding Stuff	2020	2020	1000 US$	248.78600	SWE
2423	TCL	Crops and livestock products	752	Sweden	5922	Export Value	1892	Fodder and Feeding Stuff	2021	2021	1000 US$	321.39627	SWE

2424 rows × 13 columns

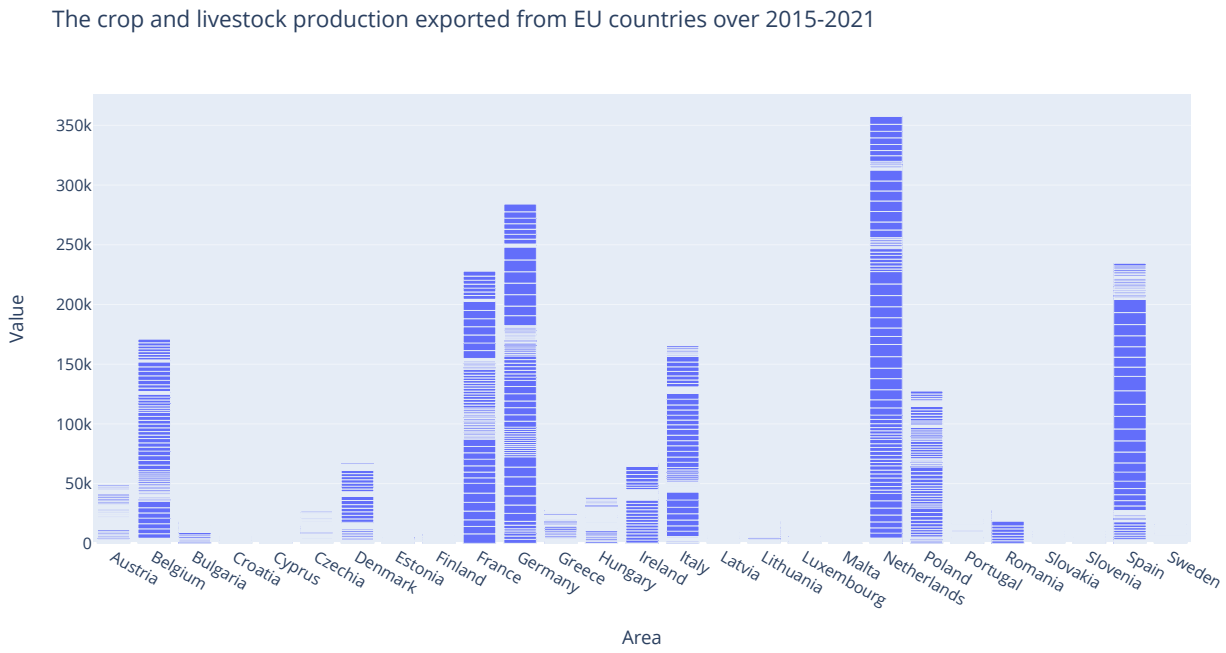
Get the top 5 countries that exported the crops and livestock production in the EU

In [87]:
```
# Get the top 5 countries that exported the crops and livestock production in The EU
Top5 = df_export.groupby('Area').sum().sort_values(by=['Value'], ascending=False)
Top5.head()
```

Out[87]:

Area	Area Code (M49)	Element Code	Item Code (FAO)	Year Code	Year	Value
Netherlands	48048	538902	170905	183638	183638	357428.65093
Germany	25116	538902	170905	183638	183638	284083.60565
Spain	65884	538902	170905	183638	183638	234477.18214
France	22750	538902	170905	183638	183638	227848.75099
Belgium	5096	538902	170905	183638	183638	170947.12601

In [88]:
```
# We display a bar plot for all EU countries
chart2 = px.bar(data_frame=df_export,
                x='Area',
                y='Value',
                title='The crop and livestock production exported from EU countries over 2015-2021',
                )
chart2
```



The figure shows that the Netherlands has the highest European Union export rate from 2015-2021. The Top five countries are the Netherlands, Germany, Spain, France, and Belgium.

In [89]:
```
# fig = go.Figure(
#                 data = go.Choropleth(locations=df_export['Alpha-3'],
#                                      z = df_export['Value'].astype(int) ,
#                                      locationmode='ISO-3',
#                                      colorbar_title='Price in $'))


# fig.update_layout(
#                   title_text = ' ',
#                    geo_scope='europe'
# )
# fig.show()
```

An Interactive Dashboard with Panel

panel.holoviz.org. (n.d.). Overview — Panel v0.14.1. [online] Available at: https://panel.holoviz.org/ (https://panel.holoviz.org/).

What iS Panel? Panel is an open source python library that can be used to create interactive web apps and dashboards.

In [90]:
```
import panel as pn
pn.extension('tabulator')       # Creating interactive table
import hvplot.pandas
# pn.interact(find_outliers)
```

In [91]:
```
df1 = df_Ireland_melted.copy()
```

In [92]:
```
df1.head()
```

Out[92]:

	Domain	Region	Production	Trade	Year	Value $M
0	Crops and livestock products	Ireland	Bovine Meat	Export	2015	2454
1	Crops and livestock products	Ireland	Cereals	Export	2015	40
2	Crops and livestock products	Ireland	Dairy Products	Export	2015	1869
3	Crops and livestock products	Ireland	Eggs	Export	2015	18
4	Crops and livestock products	Ireland	Fodder and Feeding Stuff	Export	2015	306

In [93]:
```
IRL_Import_df1 = df1.loc[df1['Trade']=='Import']
IRL_Export_df1= df1.loc[df1['Trade']=='Export']
```

In [94]:
```
IRL_Import_df1.head()
```

Out[94]:

	Domain	Region	Production	Trade	Year	Value $M
11	Crops and livestock products	Ireland	Bovine Meat	Import	2015	136
12	Crops and livestock products	Ireland	Cereals	Import	2015	245
13	Crops and livestock products	Ireland	Dairy Products	Import	2015	704
14	Crops and livestock products	Ireland	Eggs	Import	2015	17
15	Crops and livestock products	Ireland	Fodder and Feeding Stuff	Import	2015	859

We need to merge the import and export have a dataset ??????????/

In [95]:
```
IRL_Import_df1.drop('Trade',axis = 1, inplace = True)
IRL_Import_df1.rename(columns = {'Value $M':'Import'}, inplace = True)

IRL_Export_df1.drop('Trade',axis = 1, inplace = True)
IRL_Export_df1.rename(columns = {'Value $M':'Export'}, inplace = True)
```

In [ ]:
```

```

In [96]:
```
All_Ireland = pd.merge(IRL_Import_df1,IRL_Export_df1, on=['Domain','Production','Year'])
```

In [97]:
```
# All_Ireland.info()
```

In [98]:
```
# We change the data type of the year to int as I got an error when calculating the totalGross_Pipeline
All_Ireland['Year'] = All_Ireland['Year'].astype(int)
```

In [99]:
```
#  Make dataframe Interactive
# df_export_melted = df_melted.loc[df_melted.Trade=='Export']
idf = All_Ireland.interactive()
```

In [100]:
```
1 idf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 77 entries, 0 to 76
Data columns (total 7 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   Domain      77 non-null     object
 1   Region_x    77 non-null     object
 2   Production  77 non-null     object
 3   Year        77 non-null     int32 
 4   Import      77 non-null     int64 
 5   Region_y    77 non-null     object
 6   Export      77 non-null     int64 
dtypes: int32(1), int64(2), object(4)
memory usage: 4.5+ KB
<class 'pandas.core.frame.DataFrame'>
Int64Index: 77 entries, 0 to 76
Data columns (total 7 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   Domain      77 non-null     object
 1   Region_x    77 non-null     object
 2   Production  77 non-null     object
 3   Year        77 non-null     int32 
 4   Import      77 non-null     int64 
 5   Region_y    77 non-null     object
 6   Export      77 non-null     int64 
dtypes: int32(1), int64(2), object(4)
memory usage: 4.5+ KB
```

Out[100]:

Define Panel Widget

Using a slider, the IntSlider widget enables selecting an integer value within predefined bounds.

panel.holoviz.org. (n.d.). IntSlider — Panel v0.14.2. [online] Available at: https://panel.holoviz.org/reference/widgets/IntSlider.html (https://panel.holoviz.org/reference/widgets/IntSlider.html).

In [101]:
```
1 year_slider = pn.widgets.IntSlider(name='Year slider',
2                                    start= 2015, end =2021, step=1)
3 year_slider
```

Out[101]:

Year slider: **2015**

The RadioButtonGroup widget is used here to create toggle buttons to select values from a list or dictionary.

panel.holoviz.org. (n.d.). RadioButtonGroup — Panel v0.14.2. [online] Available at: https://panel.holoviz.org/reference/widgets/RadioButtonGroup.html (https://panel.holoviz.org/reference/widgets/RadioButtonGroup.html)

In [102]:
```
1 # Radio button for the total Gross of the export
2 # options parameter: is a list or dictionary of options to select from
3 
4 y_Trade = pn.widgets.RadioButtonGroup(
5 #     name = 'Total Gross for export production from Ireland',
6     options=['Import','Export'],
7     button_type = 'success'
8 )
9 y_Trade
```

Out[102]:

Import | Export

In [103]:
```
All_Ireland
```

Out[103]:

	Domain	Region_x	Production	Year	Import	Region_y	Export
0	Crops and livestock products	Ireland	Bovine Meat	2015	136	Ireland	2454
1	Crops and livestock products	Ireland	Cereals	2015	245	Ireland	40
2	Crops and livestock products	Ireland	Dairy Products	2015	704	Ireland	1869
3	Crops and livestock products	Ireland	Eggs	2015	17	Ireland	18
4	Crops and livestock products	Ireland	Fodder and Feeding Stuff	2015	859	Ireland	306
...	...	...	...	...	...	...	...
72	Crops and livestock products	Ireland	Nuts	2021	66	Ireland	5
73	Crops and livestock products	Ireland	Pigmeat (meat equivalent)	2021	302	Ireland	675
74	Crops and livestock products	Ireland	Poultry Meat	2021	433	Ireland	279
75	Crops and livestock products	Ireland	Roots and Tubers	2021	141	Ireland	16
76	Crops and livestock products	Ireland	Vegetables	2021	570	Ireland	256

77 rows × 7 columns

Now, We need to connect our data pipeline with our widgets

In [104]:
```
All_Ireland.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 77 entries, 0 to 76
Data columns (total 7 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   Domain      77 non-null     object
 1   Region_x    77 non-null     object
 2   Production  77 non-null     object
 3   Year        77 non-null     int32 
 4   Import      77 non-null     int64 
 5   Region_y    77 non-null     object
 6   Export      77 non-null     int64 
dtypes: int32(1), int64(2), object(4)
memory usage: 4.5+ KB
```

In [105]:
```
trade_Pipeline = (
    idf[
        (idf.Year <= year_slider)
    ]
    .groupby(['Production','Year'])[y_Trade].mean()
    .to_frame()
    .reset_index()
    .sort_values(by='Year')
    .reset_index(drop=True)
)
```

In [106]:
```
1 trade_Pipeline
```

Out[106]:

Year slider: **2015**

Import | Export

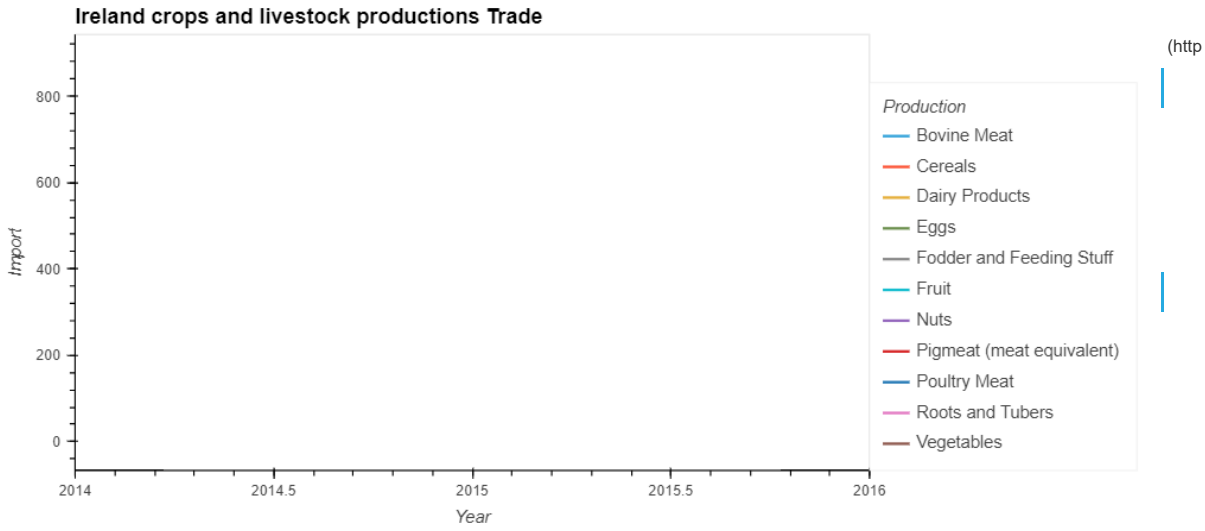
	Production	Year	Import
0	Bovine Meat	2015	136.0
1	Cereals	2015	245.0
2	Dairy Products	2015	704.0
3	Eggs	2015	17.0
4	Fodder and Feeding Stuff	2015	859.0
5	Fruit	2015	637.0
6	Nuts	2015	68.0
7	Pigmeat (meat equivalent)	2015	242.0
8	Poultry Meat	2015	501.0
9	Roots and Tubers	2015	131.0
10	Vegetables	2015	465.0

In [107]:
```
1 Productions_plot = trade_Pipeline.hvplot(x = 'Year',
2                                          by='Production',
3                                          y=y_Trade,
4                                          line_width=2,
5                                          width = 900,
6                                          height = 400,
7                                          title='Ireland crops and livestock productions Trade')
8 Productions_plot
```

Out[107]:

Year slider: **2015**

Import | Export



To create an interactive table for Ireland trade over 2015-2021. We can use the Tabulator widget to display and add the pandas dataframe.

In [108]:
```
Ireland_table = trade_Pipeline.pipe(pn.widgets.Tabulator, pagination='remote', page_size = 10, sizing_mode='stretch_width')
Ireland_table
```

Out[108]:

Year slider: **2015**

Import | Export

index	Production	Year	Import
0	Bovine Meat	2,015	136.0
1	Cereals	2,015	245.0
2	Dairy Products	2,015	704.0
3	Eggs	2,015	17.0
4	Fodder and Feeding Stuff	2,015	859.0
5	Fruit	2,015	637.0
6	Nuts	2,015	68.0
7	Pigmeat (meat equivalent)	2,015	242.0
8	Poultry Meat	2,015	501.0
9	Roots and Tubers	2,015	131.0

First Prev 1 2 Next Last

In [ ]:
```

```

Creating Dashboard

In [109]:
```
#Layout using Template
template = pn.template.FastListTemplate(
    title='Ireland crops and livestock productions Trade over 2015-2021 dashboard',

    sidebar=[pn.pane.Markdown("# Ireland Agriculture DataAnalysis"),
              pn.pane.Markdown("#### The agricultural sector can be considered the backbone of each country.\
                               Digital Agriculture (DA) spread in the last decade due to applying Information ,\
                               and Communication Technologies (ICT) in agriculture. DA established novel procedures,\
                               for farming to guarantee crop increment, efficiency, and control while protecting the environm
              pn.pane.PNG('image.png', sizing_mode='scale_both'),
              pn.pane.Markdown("## Settings"),
              year_slider],

      main=[pn.Row(pn.Column(chart2), pn.Column(chart1)),

          pn.Row(pn.Column(y_Trade,Ireland_table.panel(width=500)),
                                    pn.Column(y_Trade,
                                Productions_plot.panel(width=700,lenght=300)))]
)
template.show()

```

```
Launching server at http://localhost:53602 (http://localhost:53602)
```

Out[109]:
```
<panel.io.server.Server object at 0x00000202B2B1A580>
```

Feature Engineering

The Ireland import and export the crops and livestock production dataset contains categorical and numeric features. Before building a machine learning model, we should make preprocessing steps on the data. The regression model can be fed with numeric features only to apply. In this case, the dummy variables will replace the categorical features.

In [110]:
```
df_Ireland_melted.head()
```

Out[110]:

	Domain	Region	Production	Trade	Year	Value $M
0	Crops and livestock products	Ireland	Bovine Meat	Export	2015	2454
1	Crops and livestock products	Ireland	Cereals	Export	2015	40
2	Crops and livestock products	Ireland	Dairy Products	Export	2015	1869
3	Crops and livestock products	Ireland	Eggs	Export	2015	18
4	Crops and livestock products	Ireland	Fodder and Feeding Stuff	Export	2015	306

In [111]:
```
# Drop irrelevant columns:
df_Ireland_melted.drop(columns=['Domain'],axis=1,inplace=True)
```

1- conversion of categorical variables to numerical variables:

Scikit-learn.org. (2019). sklearn.preprocessing.OneHotEncoder — scikit-learn 0.22 documentation. [online] Available at: https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.OneHotEncoder.html (https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.OneHotEncoder.html).

Srinidhi, S. (2020). Label Encoder vs. One Hot Encoder in Machine Learning. [online] Medium. Available at: https://contactsunny.medium.com/label-encoder-vs-one-hot-encoder-in-machine-learning-3fc273365621 (https://contactsunny.medium.com/label-encoder-vs-one-hot-encoder-in-machine-learning-3fc273365621).

We have many encodings to convert the categorical data into numeric data:

- **Label Encoding:** The categorical values in the column will be encoded with a value between zero and the number of classes-1.
- **Ordinal Encoding(integer encoding):** The categorical values should be in an ordinal relationship to apply ordinal encoding. The ordinal encoding converts each unique category value into an integer value starting from zero to the number of classes-1
- **One Hot Encoding & Dummy Variable Encoding:** It splits the categorical column when no ordinal relationship exists into multiple columns(n), where n is the number of columns equal to the unique values in the categorical column. Each column contains binary values to indicate the presence or absence of a category with a value of 1 or 0, respectively.

We will build ML models for both classification and prediction. The scikit documentation advises using a label encoding with the target variable. We will use label encoding to map the target values in the 'Trade' columns. Moreover, the one-hot encoding with the feature 'Production' to avoid the ML model misunderstandings during the training stage. Scikit-Learn's DictVectorizer method will encode our categorical columns to numeric.

In [112]:
```
# Map the categorical column'Trade' into numeric valus
from sklearn import preprocessing
# define label encoding
le = preprocessing.LabelEncoder()
# transform the target column 'Trade'
df_Ireland_melted['Trade'] = le.fit_transform(df_Ireland_melted['Trade'])
df_Ireland_melted.head()
```

Out[112]:

	Region	Production	Trade	Year	Value $M
0	Ireland	Bovine Meat	0	2015	2454
1	Ireland	Cereals	0	2015	40
2	Ireland	Dairy Products	0	2015	1869
3	Ireland	Eggs	0	2015	18
4	Ireland	Fodder and Feeding Stuff	0	2015	306

In [113]:
```
# Categorical Data in the 'Production' column Conversion to numeric values
df_Ireland_melted = pd.get_dummies(df_Ireland_melted,columns=['Production'])
```

In [114]:
```
df_Ireland_melted.head()
```

Out[114]:

	Region	Trade	Year	Value $M	Production_Bovine Meat	Production_Cereals	Production_Dairy Products	Production_Eggs	Production_Fodder and Feeding Stuff	Production_Fruit	Production_Nu
0	Ireland	0	2015	2454	1	0	0	0	0	0	
1	Ireland	0	2015	40	0	1	0	0	0	0	
2	Ireland	0	2015	1869	0	0	1	0	0	0	
3	Ireland	0	2015	18	0	0	0	1	0	0	
4	Ireland	0	2015	306	0	0	0	0	1	0	

In [115]:
```
df_Ireland_melted.describe()
```

Out[115]:

	Trade	Value $M	Production_Bovine Meat	Production_Cereals	Production_Dairy Products	Production_Eggs	Production_Fodder and Feeding Stuff	Production_Fruit	Production_N
count	154.000000	154.000000	154.000000	154.000000	154.000000	154.000000	154.000000	154.000000	154.0000
mean	0.500000	533.623377	0.090909	0.090909	0.090909	0.090909	0.090909	0.090909	0.0909
std	0.501631	766.445220	0.288418	0.288418	0.288418	0.288418	0.288418	0.288418	0.2884
min	0.000000	3.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
25%	0.000000	66.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
50%	0.500000	278.500000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
75%	1.000000	570.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
max	1.000000	3682.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.0000

Scaling

The minimum for 'Value $M' is 3 while the maximum is 3680 million Euro. So the crop and livestock production trade price in the 'Value' column must scale before building a ML model.

The most popular concepts to rescale a numeric data are:

- **Normalization:** All the numeric features rescaled to the range between [0-1] using the formula:

  X_norm= (x-x_min)/(x_max- x_min)

- **Standardization:** Standardization is transforming the numeric feature with Gaussian distribution to standard normal distribution by subtracting all values from the mean value (μ) and then dividing by the standard deviation value (σ):

  X_stand= (x-μ)/(σ).

We will scale the 'Value $M' column later in Machine Learning Section.

In [116]:
```
# For Statistic Section we will melt the main dataframe df
# Melt the main dataframe
df_melted = df.melt(id_vars=['Domain','Region','Production','Total Gross','Trade'], var_name='Year', value_name='Value')
df_melted.drop(['Total Gross'],axis = 1, inplace = True)
df_melted.head()
```

Out[116]:

	Domain	Region	Production	Trade	Year	Value
0	Crops and livestock products	Austria	Bovine Meat	Export	2015	543
1	Crops and livestock products	Austria	Cereals	Export	2015	413
2	Crops and livestock products	Austria	Dairy Products	Export	2015	1219
3	Crops and livestock products	Austria	Eggs	Export	2015	22
4	Crops and livestock products	Austria	Fodder and Feeding Stuff	Export	2015	756

In [ ]:
```
1
```

In [ ]:
```
1
```

Machine Learning

We will apply the machine learning algorithms to the dataset for Ireland only. We will use the classifications algorithms to classify Ireland's crops and livestock productions according to the prices from 2015-2021 into binary classes, import and export.

Also, We apply different regression algorithms to forecast the export trade prices of various crops and livestock productions in the coming five years in Ireland.

In [117]:
```
# Import scikit-learn packages and libraries
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LinearRegression,Ridge,Lasso
from sklearn.metrics import confusion_matrix, classification_report      # import library for confusion matrix
from sklearn.model_selection import cross_val_score                      # cross validation library
from sklearn.model_selection import cross_val_predict
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import (StratifiedKFold, learning_curve)
from statsmodels.tools.eval_measures import mse, rmse
from sklearn.metrics import accuracy_score
from sklearn.metrics import r2_score
from sklearn import metrics
from sklearn.svm import SVC
from sklearn import tree
from sklearn.model_selection import (GridSearchCV, cross_val_predict, StratifiedKFold, learning_curve)
from sklearn.tree import DecisionTreeRegressor
```

In [118]:
```
df_Ireland_melted.head()
```

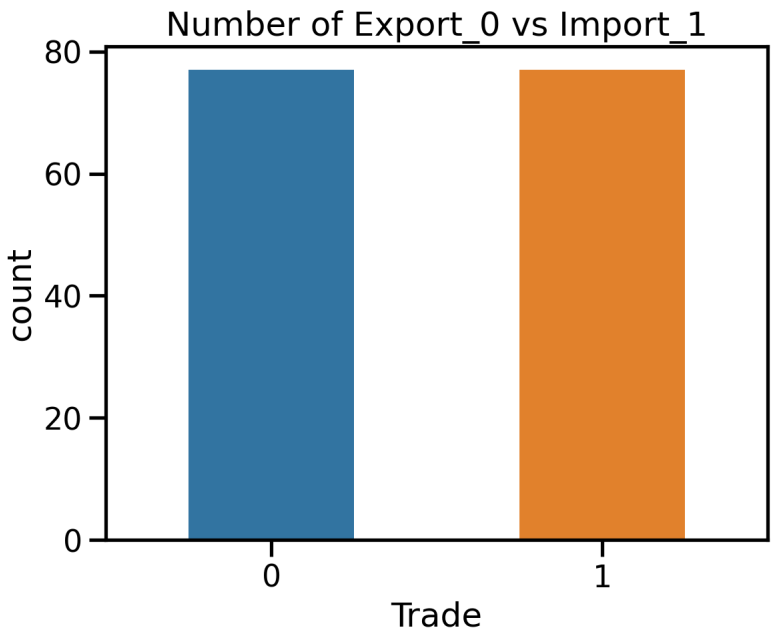
Out[118]:

	Region	Trade	Year	Value $M	Production_Bovine Meat	Production_Cereals	Production_Dairy Products	Production_Eggs	Production_Fodder and Feeding Stuff	Production_Fruit	Production_Nu
0	Ireland	0	2015	2454	1	0	0	0	0	0	
1	Ireland	0	2015	40	0	1	0	0	0	0	
2	Ireland	0	2015	1869	0	0	1	0	0	0	
3	Ireland	0	2015	18	0	0	0	1	0	0	
4	Ireland	0	2015	306	0	0	0	0	1	0	

Check the dataset if it balanced or not?

In [119]:
```
# visualizing the 'Trade' column >>> 'Export':0 & 'Import':1
sns.countplot(x='Trade',data = df_Ireland_melted,width=0.5)
plt.title('Number of Export_0 vs Import_1')
```

Out[119]: Text(0.5, 1.0, 'Number of Export_0 vs Import_1')



Great, the figure depicts that we have a balanced dataset.

In [120]:
```
1
2 df_Ireland_melted.head()
```

Out[120]:

	Region	Trade	Year	Value $M	Production_Bovine Meat	Production_Cereals	Production_Dairy Products	Production_Eggs	Production_Fodder and Feeding Stuff	Production_Fruit	Production_Nu
0	Ireland	0	2015	2454	1	0	0	0	0	0	
1	Ireland	0	2015	40	0	1	0	0	0	0	
2	Ireland	0	2015	1869	0	0	1	0	0	0	
3	Ireland	0	2015	18	0	0	0	1	0	0	
4	Ireland	0	2015	306	0	0	0	0	1	0	

In [121]:
```
1 # Drop Region column as it is Ireland only
2 df_Ireland_melted.drop(columns=['Region'],axis=1,inplace=True)
```

Determine X & y

In [122]:
```
1 X = df_Ireland_melted.drop(columns='Trade',axis=1).values     # features columns from 2015 to the Total Gross
2 y = df_Ireland_melted.Trade.values                                  # Target column
```

In [123]:
```
1 X.shape, y.shape
```

Out[123]: ((154, 13), (154,))

The dataset will be split to two datasets, the training dataset and test dataset. The data is usually tend to be split inequality because training the model usually requires as much data-points as possible.The common splits are 70/30 or 80/20 for train/test.

The training dataset is the intial dataset used to train ML algorithm to learn and produce right predictions. (70% of dataset is training dataset)The test dataset, however, is used to assess how well ML algorithm is trained with the training dataset.

kaggle.com. (n.d.). Crop Yield Prediction. [online] Available at: https://www.kaggle.com/code/aviraljain58/crop-yield-prediction (https://www.kaggle.com/code/aviraljain58/crop-yield-prediction)

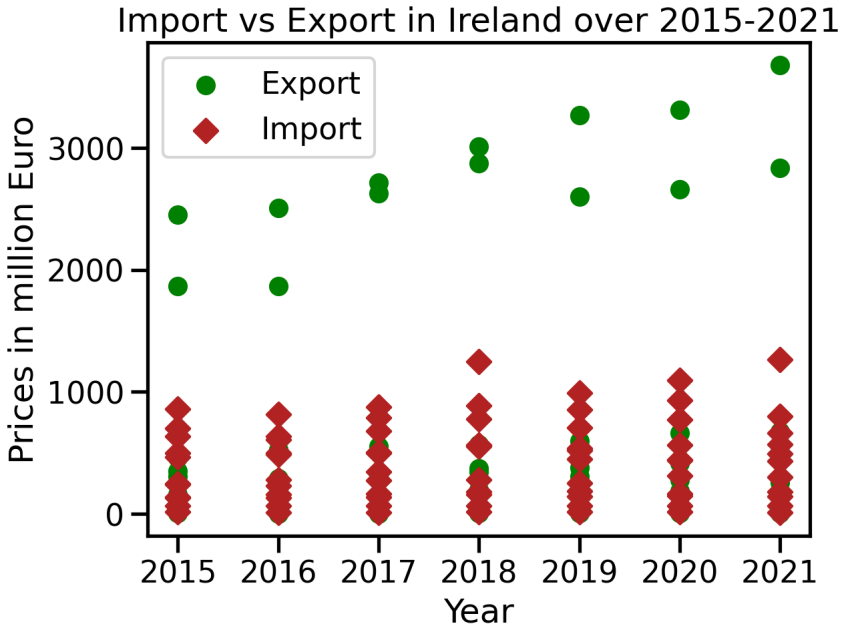
In [124]:
```
1 # Split the data into train set and test set
2 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, random_state = 0)
```

In [125]:
```
1 df_Ireland_melted.shape
```

Out[125]: (154, 14)

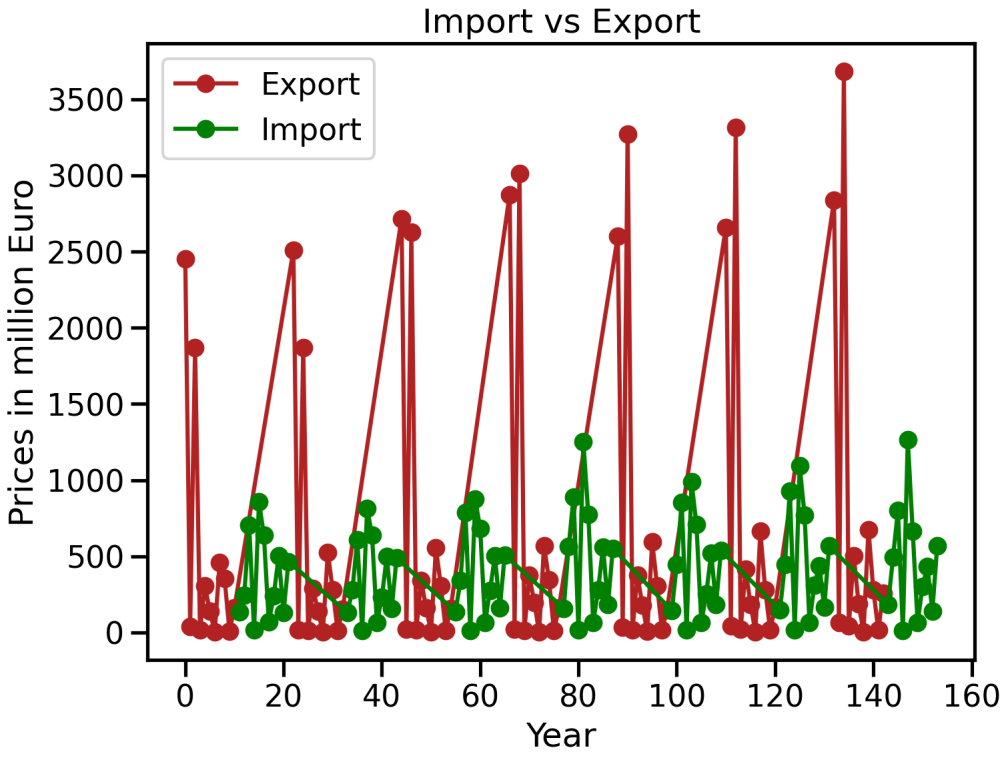
In [ ]:
```
1
```

In [126]:
```
# plt.scatter(df_Ireland_import['Value'],df_Ireland_import['Value'])
plt.scatter(df_Ireland_melted['Year'][(df_Ireland_melted.Trade == 0)],
            df_Ireland_melted['Value $M'][(df_Ireland_melted.Trade == 0)],
            label = 'Export', color = 'green', marker='o')

plt.scatter(df_Ireland_melted['Year'][(df_Ireland_melted.Trade == 1)]
            ,df_Ireland_melted['Value $M'][(df_Ireland_melted.Trade == 1)],
            label = 'Import',color='firebrick',marker='D')

plt.title('Import vs Export in Ireland over 2015-2021')
plt.xlabel('Year')
plt.ylabel('Prices in million Euro')
plt.legend()
plt.show()
```



In [127]:
```
# df_Ireland_melted['Value'][(df_Ireland_melted.Trade == 0)].plot.scatter(x='index',y='Value')
```

In [128]:
```
plt.figure(figsize=(8,6))
df_Ireland_melted['Value $M'][(df_Ireland_melted.Trade == 0)].plot(label='Export',marker= 'o', color='firebrick')     # line
df_Ireland_melted['Value $M'][(df_Ireland_melted.Trade == 1)].plot(label='Import',marker= 'o', color='green')

plt.title('Import vs Export')
plt.xlabel('Year')
plt.ylabel('Prices in million Euro')
plt.legend()
plt.show()
```



In [ ]:
```
1
```

In [129]:
```
# Scaling the numeric values of the data
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

In [130]:
```
# Display the X_train & X_test
X_train.shape, X_test.shape
```

Out[130]: ((123, 13), (31, 13))

Classifications:

K-Nearest Neighbor Classifier:
==========

An Informal kNN Algorithm The kNN algorithm can be summarized in the following simple steps:

1. Determine k (the selection of k depends on your data and project requirements; there is no magic formula for k).
2. Calculate the distances between the new input and all the training data (as with k, the selection of a distance function also depends on the type of data).
3. Sort the distance and determine the k nearest neighbors based on the kth minimum distance.
4. Gather the categories of those neighbors.
5. Determine the category based on majority vote.

In [ ]:
```
1
```

In order to decide the best value for hyperparameter k (number of neighbors), We need to train and test your model on 10 different k values and finally use the one that gives the best results. Let's initialize a variable neighbors(k) which will have values ranging from 1-9 and two numpy zero matrices namely train_accuracy and test_accuracy each for training and testing accuracy. We need them later to plot a graph to choose the best neighbor value.

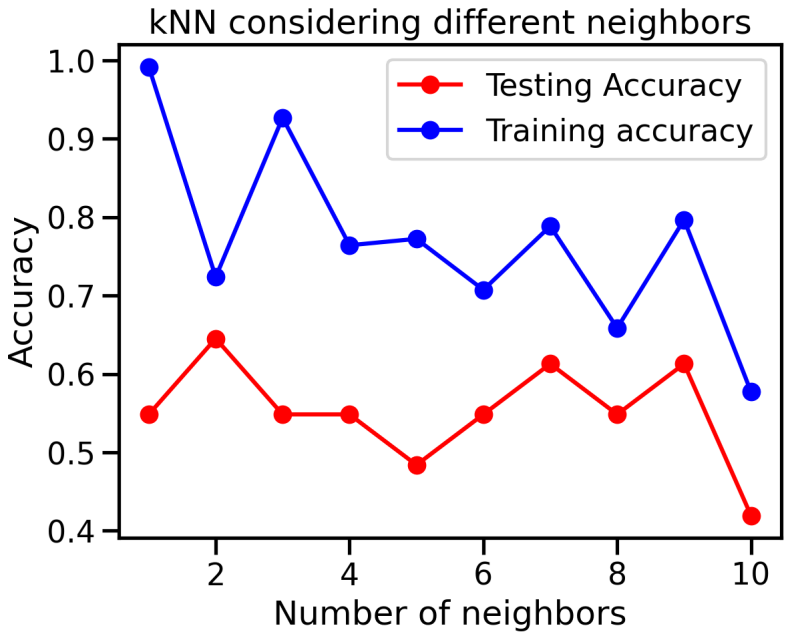
In [131]:
```
neighbors = np.arange(1, 11)                  # number of neighbors
train_accuracy = np.zeros(len(neighbors))     # Declare and initialise the matrix
test_accuracy = np.zeros(len(neighbors))      # Declare and initialise the matrix
```

In [132]:
```
for i,k in enumerate(neighbors):                          # for loop that checks the model for neighbor values 1, 2, 3, ...,
    knn = KNeighborsClassifier(n_neighbors = k)           # Initialise an object knn using KNeighborsClassifier method

    #Fit the model
    knn.fit(X_train, y_train)                       # Call fit method to implement the ML KNeighborsClassifier model

    #Compute accuracy on the training set
    train_accuracy[i] = knn.score(X_train, y_train)   # Save the score value in the train_accuracy array

    #Compute accuracy on the test set
    test_accuracy[i] = knn.score(X_test, y_test)      # Save the score value in the train_accuracy array
```

In [133]:
```
print(f'train_accuracy is: {train_accuracy*100}\n')
print(f'test_accuracy is: {test_accuracy*100}')
```

```
train_accuracy is: [99.18699187 72.35772358 92.68292683 76.42276423 77.23577236 70.73170732
 78.86178862 65.85365854 79.67479675 57.72357724]

test_accuracy is: [54.83870968 64.51612903 54.83870968 54.83870968 48.38709677 54.83870968
 61.29032258 54.83870968 61.29032258 41.93548387]
```

In [134]:
```
# Visualise the accuracy based on the number of neighbors
plt.title('kNN considering different neighbors')
plt.plot(neighbors, test_accuracy,'ro-',label = 'Testing Accuracy')
plt.plot(neighbors, train_accuracy,'bo-', label = 'Training accuracy')
plt.legend()
plt.xlabel('Number of neighbors')
plt.ylabel('Accuracy')
plt.show()
```



In [135]:
```
# Declare and initialise kNN classifier with 9 neighbors
kNN_cl = KNeighborsClassifier(n_neighbors = 2)

# Call fit() method to train the model
kNN_cl.fit(X_train, y_train)

# Calculate r2 score
print('Train Accuracy',kNN_cl.score(X_train,y_train))
print("Test Accuracy",kNN_cl.score(X_test, y_test))
```

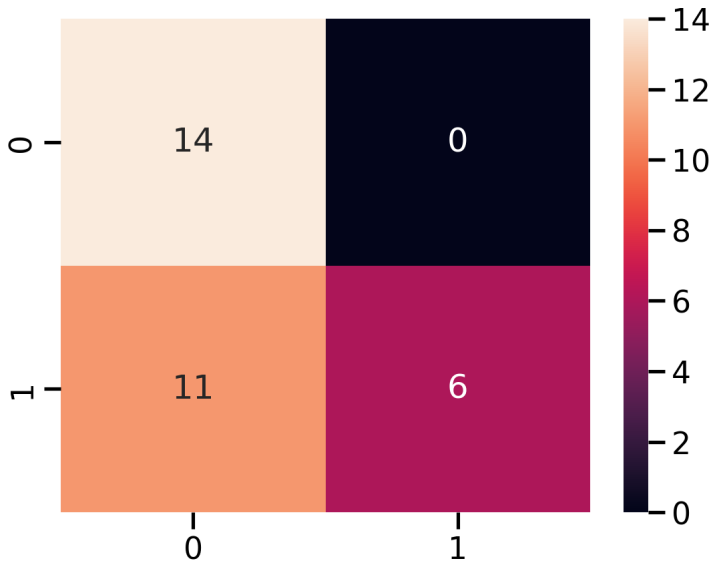
```
Train Accuracy 0.7235772357723578
Test Accuracy 0.6451612903225806
```

In [136]:
```
# kNN Parameters
pprint.pprint(kNN_cl.get_params())
```

```
{'algorithm': 'auto',
 'leaf_size': 30,
 'metric': 'minkowski',
 'metric_params': None,
 'n_jobs': None,
 'n_neighbors': 2,
 'p': 2,
 'weights': 'uniform'}
```

In [137]:
```
# Predict the results
y_pred = kNN_cl.predict(X_test)

# confusion matrix&report
cm = confusion_matrix(y_test,y_pred)
sns.heatmap(cm,annot=True);
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.56      1.00      0.72        14
           1       1.00      0.35      0.52        17

    accuracy                           0.65        31
   macro avg       0.78      0.68      0.62        31
weighted avg       0.80      0.65      0.61        31
```



In [138]:
```
# Print the confusion matrix
print(cm)
```

```
[[14  0]
 [11  6]]
```

Cross Validation:
K Fold Cross Validation We essentially perform holdout cross-validation multiple times in k-fold cross-validation. Therefore, we divide the dataset into k equal-sized samples for k-fold cross-validation. The remaining k1 subsamples are utilized as training data, and just one subsample of these many k subsamples is used as validation data for testing the model. The cross-validation procedure is then carried out k times, using the validation data from each of the k subsamples exactly once each time. Then, an estimation can be created by averaging the k results.

A visual representation of 5-fold cross-validation (k=5) is provided in the following screenshot:

In [ ]:
```

```

Use of Cross Validation with KNN:

In [139]:
```
scores=cross_val_score(knn, X,y,cv=10,scoring='accuracy')
print(scores,'\n',scores.mean())                    # The scores is a list for cross validation(cv=10)
```

```
[0.6875     0.875      0.75       0.75       0.86666667 0.8
 0.8        0.66666667 0.73333333 0.66666667]
 0.7595833333333334
```

Applying the cross validation on KNN improve the model performance as the mean accuracy with cross validation = 10 is 75.9%

In [ ]:
```
1
```

DecisionTree:
==========

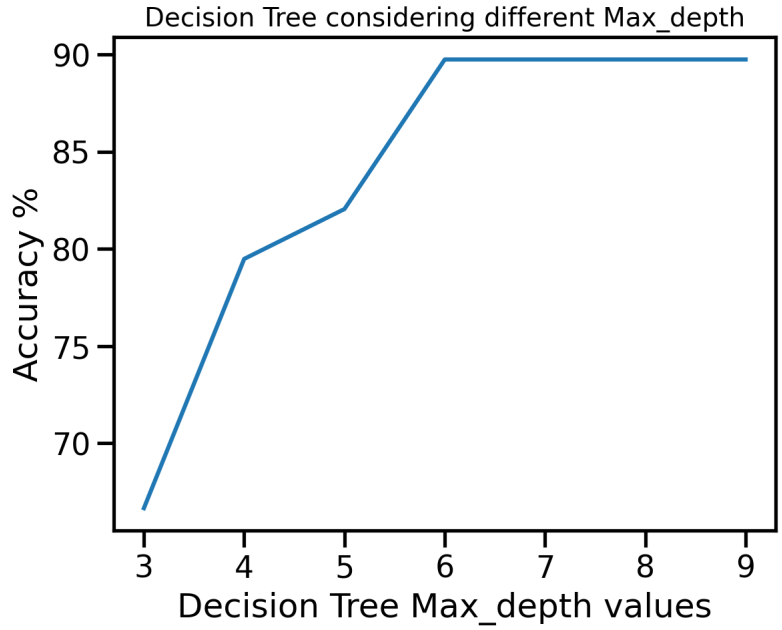
We start training and testing our model with different max depth values, We use the max_depth value which gives best result to visualize the decision tree.

In [140]:
```
1  X = df_Ireland_melted.drop(columns='Trade',axis=1).values     # features columns from 2015 to the Total Gross
2  y = df_Ireland_melted.Trade.values                                  # Target column
3
4  # Split the data into train set and test set
5  X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)
6  # Split the data into train set and test set
7  X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)
8
9  # Scaling the numeric values of the data
10 sc = StandardScaler()
11 X_train = sc.fit_transform(X_train)
12 X_test = sc.transform(X_test)
```

In [141]:

```
# Determine the best value for Max_depth
Maxdepth_list =   np.arange(3, 10)
# [3,5,7,9]
Decision_accuracy = []
for depth in Maxdepth_list:
    # creat the decisiontree classifier to train the data
    classifier = DecisionTreeClassifier(max_depth=depth, random_state=0)
    classifier.fit(X_train,y_train)

    # predicition vale
    y_pred = classifier.predict(X_test)

    # Model accuracy
    accuracy = metrics.accuracy_score(y_test,y_pred)*100
    Decision_accuracy. append(accuracy)

# Print the accuracy list
print("Accuracy:", Decision_accuracy)

# Visualise the accuracy based on the tree max_depth
plt.title('Decision Tree considering different Max_depth',fontsize = 14)
plt.plot(Maxdepth_list, Decision_accuracy)
# ,'ro-',label = 'Testing Accuracy')
# plt.plot(neighbors, train_accuracy,'bo-', label = 'Training accuracy')
# plt.legend()

plt.xlabel('Decision Tree Max_depth values')
plt.ylabel('Accuracy %')
plt.show()
```

```
Accuracy: [66.66666666666666, 79.48717948717949, 82.05128205128204, 89.74358974358975, 89.74358974358975, 89.74358974358975, 8
9.74358974358975]
```

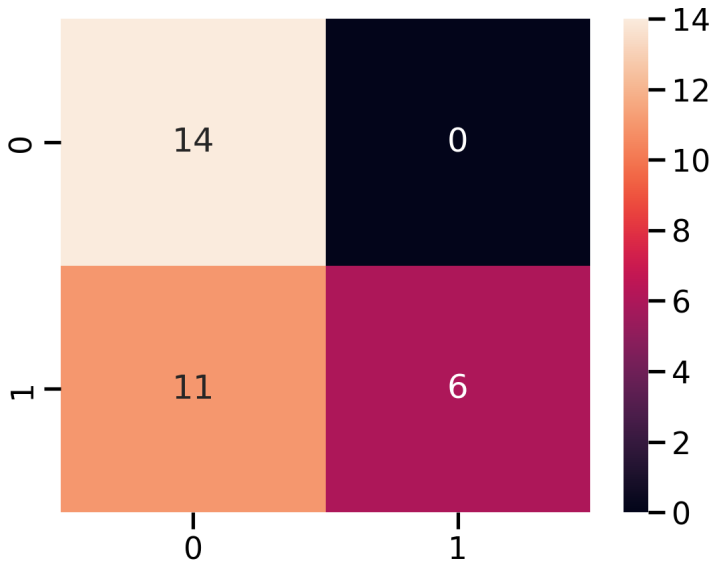


The previous figure shows that the best value for the max_depth parameter is 7

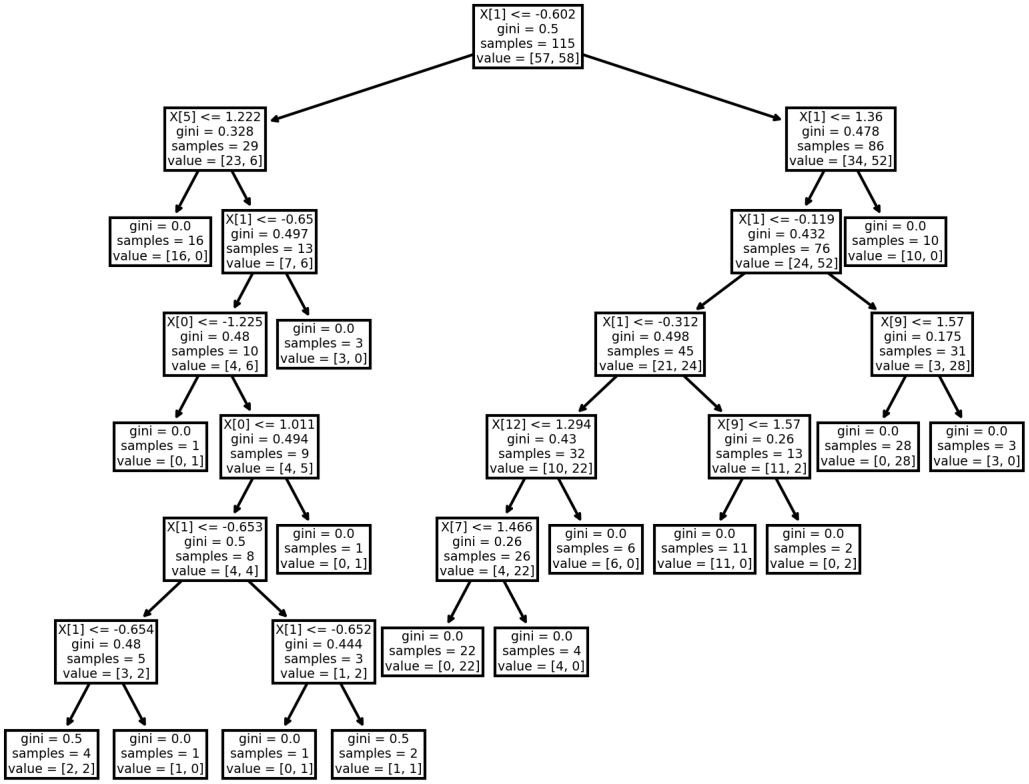
In [142]:

```
# max_depth=7
# creat the decisiontree classifier to train the data
classifier = DecisionTreeClassifier(max_depth=7, random_state=0)
classifier.fit(X_train,y_train)

#  DecisionTree Parameters
pprint.pprint(classifier.get_params())

# predicition vale
y_pred = classifier.predict(X_test)


cm1 = confusion_matrix(y_test,y_pred)
sns.heatmap(cm,annot=True);
print(classification_report(y_test,y_pred))

# Model accuracy
print("Accuracy:",metrics.accuracy_score(y_test,y_pred)*100)
```

```
{'ccp_alpha': 0.0,
 'class_weight': None,
 'criterion': 'gini',
 'max_depth': 7,
 'max_features': None,
 'max_leaf_nodes': None,
 'min_impurity_decrease': 0.0,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'random_state': 0,
 'splitter': 'best'}
              precision    recall  f1-score   support

           0       0.90      0.90      0.90        20
           1       0.89      0.89      0.89        19

    accuracy                           0.90        39
   macro avg       0.90      0.90      0.90        39
weighted avg       0.90      0.90      0.90        39

Accuracy: 89.74358974358975
```



In [143]:
```
# Plot the decission tree at max_depth = 7
plt.figure(figsize=(10,8))
tree.plot_tree(classifier.fit(X_train,y_train));
```



Use of Cross Validation with Decission Tree:

In [144]:
```
scores=cross_val_score(classifier, X,y,cv=10,scoring='accuracy')
print(scores,'\n',scores.mean())                          # The scores is a list for cross validation(cv=10)
```

```
[0.875      0.75       0.875      0.9375     0.73333333 0.86666667
 0.93333333 0.8        0.86666667 0.86666667]
 0.8504166666666668
```

The accuracy for our Decission tree classifier with max-depth = 7 is Applying the cross validation on the decission tree model did not enhance its performance as the mean accuracy with cross validation = 10 is 85%.

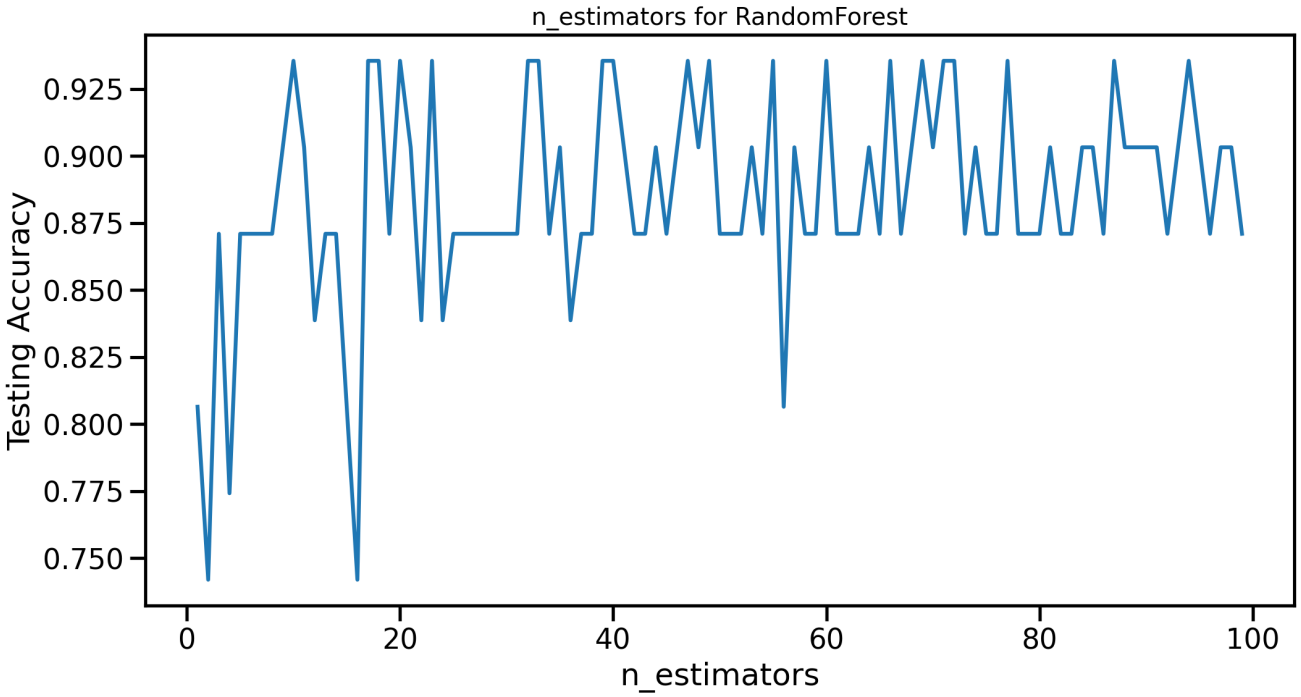
RandomForest:

In [145]:
```
X = df_Ireland_melted.drop(columns='Trade',axis=1).values     # features columns from 2015 to the Total Gross
y = df_Ireland_melted.Trade.values                                  # Target column

# Split the data into train set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)

# Scaling the numeric values of the data
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
# Split the data into train set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, random_state = 0)
```

In [146]:
```
scores= []
for k in range(1,100):
    rfc = RandomForestClassifier(n_estimators=k)
    rfc.fit(X_train, y_train)
    y_pred = rfc.predict(X_test)
    scores.append(metrics.accuracy_score(y_test, y_pred))
```

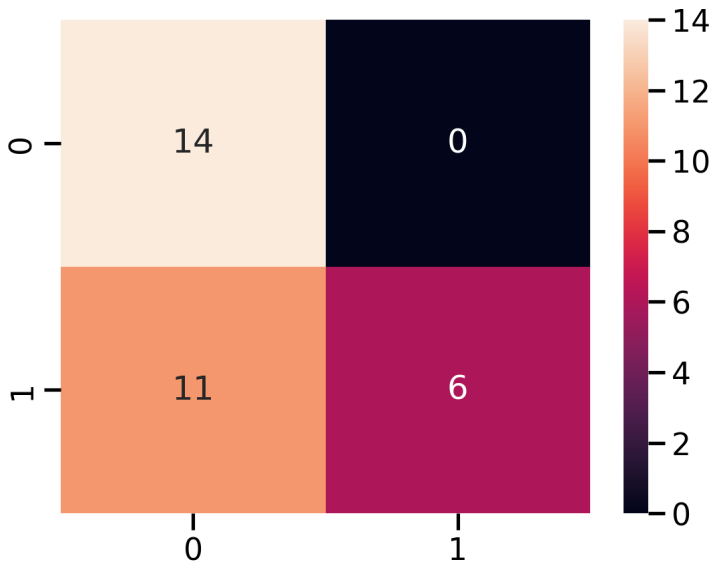
In [147]:
```
# Visualise the accuracy based on the number of estimators
plt.figure(figsize=(12,6))
plt.title('n_estimators for RandomForest',fontsize =14)
plt.plot(range(1,100),scores)
plt.xlabel('n_estimators')
plt.ylabel('Testing Accuracy')
print(f'The maximun accuracy is {max(scores)} for the n_estimatore={scores.index(max(scores))}\n')
plt.show()
```

```
The maximun accuracy is 0.9354838709677419 for the n_estimatore=9
```



In [148]:
```
# Creat the Random Forest Classifier
clf = RandomForestClassifier(n_estimators=11)
clf.fit(X_train,y_train)

# DecisionTree Parameters
# pprint.pprint(clf.get_params())

# predicition vale
y_pred = clf.predict(X_test)

print('\n Accuracy',metrics.accuracy_score(y_test,y_pred)*100)

# Plot the Confusion matrix
cm2 = confusion_matrix(y_test,y_pred)
sns.heatmap(cm,annot=True)
print(classification_report(y_test,y_pred))
```

```
 Accuracy 87.09677419354838
              precision    recall  f1-score   support

           0       0.92      0.79      0.85        14
           1       0.84      0.94      0.89        17

    accuracy                           0.87        31
   macro avg       0.88      0.86      0.87        31
weighted avg       0.88      0.87      0.87        31
```



Use of Cross Validation with Random Forest:

In [149]:
```
scores=cross_val_score(clf, X,y,cv=10,scoring='accuracy')
print(scores,'\n',scores.mean())                          # The scores is a list for cross validation(cv=10)
```

```
[0.9375     0.875      1.         0.9375     0.86666667 0.93333333
 0.93333333 0.93333333 1.         0.8       ]
 0.9216666666666669
```

The accuracy for our Random Forest classifier with n-estimator = 9 is 87%. Applying the cross validation on the decission tree model increase the model accuracy, the mean accuracy with cross validation = 10 is 92.7%.

In [ ]:
```

```

Naive Bayes:
Naive Bayes algorithms are supervised learning algorithm that uses Bayes' theorem to predict the class of a new piece of data. The algorithm assumes that the features of the data are independent, which means that the class of a data point does not depend on the values of any of the other data points.

scikit-learn.org. (n.d.). 1.9. Naive Bayes — scikit-learn 0.24.2 documentation. [online] Available at: http://scikit-learn.org/stable/modules/naive_bayes.html (http://scikit-learn.org/stable/modules/naive_bayes.html).

In [150]:
```
X = df_Ireland_melted.drop(columns='Trade',axis=1).values     # features columns from 2015 to the Total Gross
y = df_Ireland_melted.Trade.values                                  # Target column

# Split the data into train set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, random_state = 0)

# Scaling the numeric values of the data
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

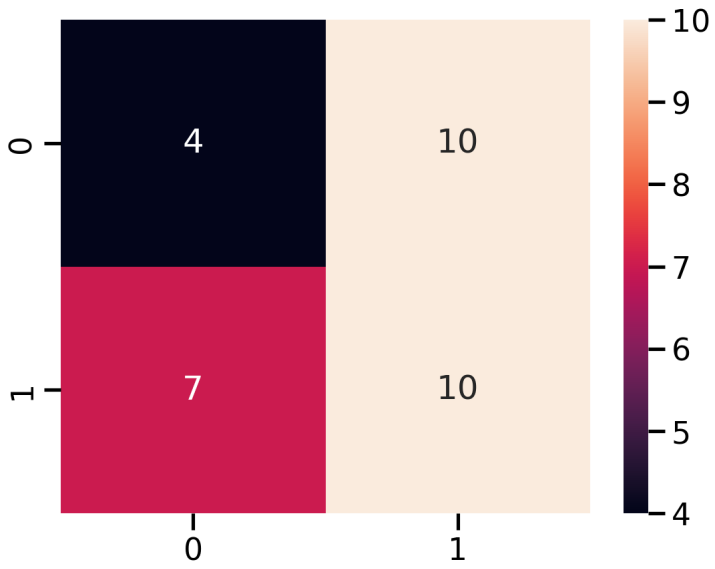
In [151]:
```
# Create and initialise an object sc by calling a method GaussianNB()
nvclassifier = GaussianNB()

# Train the model by calling a method fit()
nvclassifier.fit(X_train, y_train)
# Predicting the Test set results
y_pred = nvclassifier.predict(X_test)
```

In [152]:
```
# Check the actual and predicted value side by side
y_compare = np.vstack((y_test, y_pred)).T
# actual value on the left side and predicted value on the right hand side
y_compare[:, :]
```

Out[152]:
```
array([[0, 1],
       [0, 1],
       [1, 0],
       [1, 1],
       [0, 0],
       [0, 1],
       [0, 0],
       [1, 0],
       [1, 1],
       [1, 1],
       [0, 1],
       [1, 0],
       [0, 1],
       [0, 1],
       [1, 1],
       [1, 1],
       [1, 1],
       [0, 1],
       [0, 1],
       [1, 1],
       [0, 1],
       [0, 0],
       [0, 1],
       [1, 0],
       [1, 1],
       [1, 0],
       [1, 0],
       [1, 0],
       [0, 0],
       [1, 1],
       [1, 1]])
```

In [153]:
```
# Construct the Confusion Matrix
import seaborn as sns
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm,annot= True)
print(cm)
```

```
[[ 4 10]
 [ 7 10]]
```



In [154]:
```
# Model Accuracy, how often is the classifier correct?
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))

# Rounded upto 2 decimal places
print( "Accuracy: {:.2f}".format(metrics.accuracy_score(y_test, y_pred)*100) )
```

```
Accuracy: 0.45161290322580644
Accuracy: 45.16
```

Use of Cross Validation with Naive Bayes:

In [155]:
```
for cross in np.arange(5, 30,5):
    nvclassifier = GaussianNB()
    NB_accuracy = cross_val_score(nvclassifier, X, y, scoring='accuracy', cv = cross).mean()
    print(f'for the cross validation  = {cross} ,  the accuracy = {NB_accuracy}')
```

```
for the cross validation  = 5 ,  the accuracy = 0.5324731182795699
for the cross validation  = 10 ,  the accuracy = 0.5175
for the cross validation  = 15 ,  the accuracy = 0.5575757575757575
for the cross validation  = 20 ,  the accuracy = 0.5491071428571429
for the cross validation  = 25 ,  the accuracy = 0.5380952380952381
```

Different Cross validations values tested, Using the cross validation improve the performane of the Naive Bayes model

Support Vector Machines:
A support vector machine is a supervised machine learning algorithm that is often considered to be very accurate and efficient with less computation power. This is thanks to the way that it uses a simplified set of features to predict which class a new obbservation will belong to.

In [156]:
```
X = df_Ireland_melted.drop(columns='Trade',axis=1).values     # features columns from 2015 to the Total Gross
y = df_Ireland_melted.Trade.values                                  # Target column

# Split the data into train set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, random_state = 0)

# Scaling the numeric values of the data
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

In [157]:
```
SVM_accuracy_list = []
for c_value in range(1,9):
    # Create an object svmModel by calling a method SVC()
    svmModel = SVC(kernel = 'rbf',C = c_value, gamma = 0.9)

    # Train the model by calling a method fit()
    svmModel.fit(X_train,y_train)

    # Store the predicted values into y_pred
    Y_pred = svmModel.predict(X_test)
    SVM_accuracy_list.append(Y_pred)

    # Display the accuracy upto 2 decimal places
    print(f'for c= {c_value}, Accuracy in SVC = ', round(accuracy_score(y_test, Y_pred)*100,2))
```

```
for c= 1, Accuracy in SVC =  58.06
for c= 2, Accuracy in SVC =  61.29
for c= 3, Accuracy in SVC =  70.97
for c= 4, Accuracy in SVC =  70.97
for c= 5, Accuracy in SVC =  70.97
for c= 6, Accuracy in SVC =  74.19
for c= 7, Accuracy in SVC =  77.42
for c= 8, Accuracy in SVC =  77.42
```

In [158]:
```
scores=cross_val_score(svmModel, X,y,cv=10,scoring='accuracy')
print(scores,'\n',scores.mean())                          # The scores is a list for cross validation(cv=10)
```

```
[0.6875     0.6875     0.6875     0.75       0.53333333 0.53333333
 0.46666667 0.6        0.66666667 0.6       ]
 0.62125
```

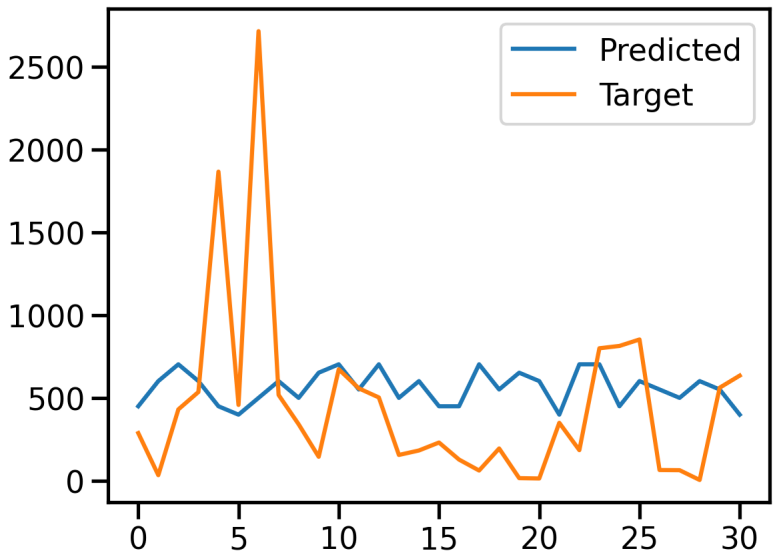
Linear Regression:

In [159]:
```
X = df_Ireland_melted[['Year']]                          # features column'Year'
y = df_Ireland_melted['Value $M']                                 # Target column 'Value'

# Split the data into train set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, random_state = 0)

# Scaling the numeric values of the data
# sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

```

In [160]:
```
# Fit the model
my_lm = LinearRegression()
my_lm.fit(X = X_train, y = y_train)

# Calculate the train and test Forecasting
train_fcst = my_lm.predict(X_train)
test_fcst = my_lm.predict(X_test)

# Calculate the r2 score for train and test
train_r2 = r2_score(y_train, train_fcst)
test_r2 = r2_score(y_test, test_fcst)

# Display the results for train and test
print(train_r2, test_r2)

# Plot result
# plt.plot(list(y_train),label='Train')
plt.plot(list(test_fcst),label='Predicted')
plt.plot(list(y_test),label='Target')

plt.legend()
```

```
0.01585074081876292 -0.13406265586178812
```

Out[160]:
```
<matplotlib.legend.Legend object at 0x00000202BAE27DF0>
```



The R-squared of the model in training set is: 0.0158 and R-squared of the model in test set is: -0.1241. That means linear regression performance is inferior and not suitable for our dataset. The Linear regression tries to fit a straight line, but the -ve result indicates that the relation between the 'Value' column and the 'Year' is complex and non-linear.

In [161]:
```
from sklearn import linear_model
from sklearn.metrics import mean_squared_error

regression = linear_model.LinearRegression()
regression.fit(X_train, y_train)

prediction = regression.predict(X_test)

mean_squared_score = mean_squared_error(y_test, prediction)

print("MEAN SQUARED SCORE", mean_squared_score)
```

```
MEAN SQUARED SCORE 345654.72371465917
```

Root mean squared error of the prediction is: 320041.277773838

Ridge Regression

In [162]:
```
X = df_Ireland_melted[['Year']]                          # features column'Year' &'Trade'
y = df_Ireland_melted['Value $M']                                  # Target column 'Value'

# Split the data into train set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, random_state = 0)

# Scaling the numeric values of the data
# sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

```

In [ ]:
```

```

In [163]:
```
# Using GridSearch for parameter optimization
ridgeregr = GridSearchCV(Ridge(),
                     param_grid={
                         'alpha': [0.01, 0.1, 1]
                     }, verbose=1)
#  Fit the model
ridgeregr.fit(X_train, y_train)
ridge = ridgeregr.best_estimator_
```

```
Fitting 5 folds for each of 3 candidates, totalling 15 fits
```

In [164]:
```
# Making predictions here
y_preds_train = ridge.predict(X_train)
y_preds_test_ridge = ridge.predict(X_test)

print("R-squared of the model in training set is: {}".format(ridge.score(X_train, y_train)))
print("-----Test set statistics-----")
print("R-squared of the model in test set is: {}".format(ridge.score(X_test, y_test)))
print("Root mean squared error of the prediction is: {}".format(mse(y_test, y_preds_test_ridge)**(1/2)))
print("Mean absolute percentage error of the prediction is: {}".format(np.mean(np.abs((y_test - y_preds_test_ridge) / y_test
```

```
R-squared of the model in training set is: 0.015849709943319468
-----Test set statistics-----
R-squared of the model in test set is: -0.13290921570790526
Root mean squared error of the prediction is: 587.6250189184932
Mean absolute percentage error of the prediction is: 703.9143766690495
```

In [165]:
```
# Calculate the train Forecasting
y_preds_train = ridge.predict(X_train)
y_preds_test_ridge = ridge.predict(X_test)

# Calculate teh r2 score for train and test
Rtrain_r2 = r2_score(y_train, y_preds_train)
Rtest_r2 = r2_score(y_test, y_preds_test_ridge)

# Display the results for train and test
print(Rtrain_r2, Rtest_r2)
```

```
0.015849709943319468 -0.13290921570790526
```

The R-squared of the model in training set is: 0.009696017495205767 and the R-squared of the model in test set is: -0.15062488725977974. Ridge regression does not appear any performnce as the result Same as the linear regression.

We try to use another model to can deal with the non linearity like a DecisionTreeRegressor

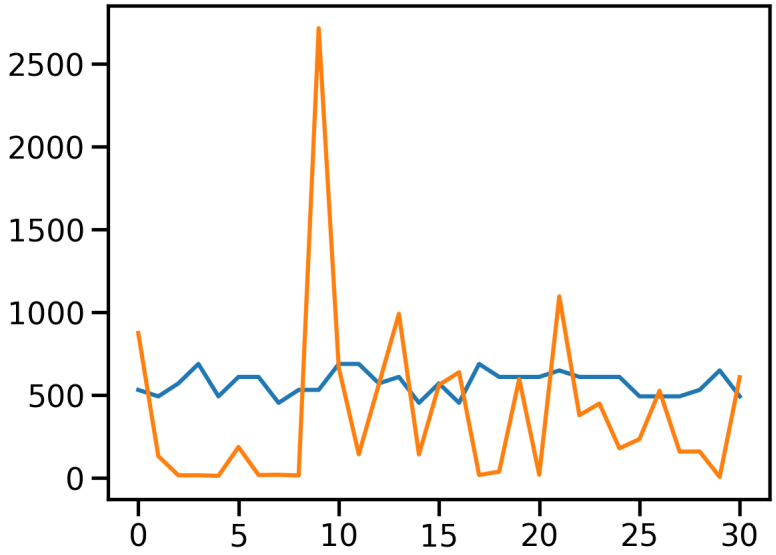
Decision Tree Regressor:

In [166]:
```
X = df_Ireland_melted[['Year']]                          # features column'Year' &'Trade'
y = df_Ireland_melted['Value $M']                                  # Target column 'Value'

# Split the data into train set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)

# Scaling the numeric values of the data
# sc = StandardScaler()
# X_train = sc.fit_transform(X_train)
# X_test = sc.transform(X_test)
# Split the data into train set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, random_state = 1)
```

In [167]:
```
y_lm = LinearRegression()
my_lm.fit(X = X_train, y = y_train)

# Calculate the train Forecasting
train_fcst = my_lm.predict(X_train)
test_fcst = my_lm.predict(X_test)

# Calculate the r2 score for train and test
train_r2 = r2_score(y_train, train_fcst)
test_r2 = r2_score(y_test, test_fcst)

# Display the results for train and test
print(train_r2, test_r2)

# Plot result
plt.plot(list(test_fcst))
plt.plot(list(y_test))
```

```
0.009696054920007247 -0.15073472276653788
```

Out[167]:
```
[<matplotlib.lines.Line2D object at 0x00000202BB2EDE80>]
```



In [168]:
```
# Fit the data
tree = DecisionTreeRegressor(max_depth=3).fit(X_train, y_train)
# Predict the results
target_predicted = tree.predict(X_test)
# Calculate the root mean squared error of the prediction
mean_squared_err = mse(y_test, target_predicted)

# Calculate the r2 score for train and test
train_r2 = r2_score(y_train, train_fcst)
test_r2 = r2_score(y_test, test_fcst)
print(train_r2,test_r2)
```

```
0.009696054920007247 -0.15073472276653788
```

changing the model to the Decision Tree Regressor didn't suit our dataset.

In [ ]:
```
1
```

In [ ]:
```
1
```

In [ ]:
```
1
```

Statistics

In [169]:
```
# We will study the exported crops and livestock products in the statistics section
# df_stat: is a data frame for the crops and livestock products exported by the European Union countries.
# df_stat_IRL: is a data farme for Ireland
df_stat = df.loc[df['Trade']=='Export']
```

In [170]:
```
# Rename the column 'Total Gross' -->'Total'
df_stat.rename(columns={'Total Gross': 'Total'}, inplace=True)
```

In [171]:
```
df_stat_IRL = df_stat.loc[df['Region']=='Ireland']
df_stat_IRL.reset_index(inplace=True, drop=True)
df_stat_IRL.head()
```

Out[171]:

	Domain	Region	Production	2015	2016	2017	2018	2019	2020	2021	Total	Trade
0	Crops and livestock products	Ireland	Bovine Meat	2454	2508	2716	2874	2601	2660	2838	18653.84379	Export
1	Crops and livestock products	Ireland	Cereals	40	18	21	22	36	45	64	249.10032	Export
2	Crops and livestock products	Ireland	Dairy Products	1869	1868	2627	3013	3270	3314	3682	19647.23284	Export
3	Crops and livestock products	Ireland	Eggs	18	13	15	14	17	20	41	141.71600	Export
4	Crops and livestock products	Ireland	Fodder and Feeding Stuff	306	290	339	375	377	416	505	2610.96716	Export

The dataset(s) contain different data types: Categorical data include Nominal and ordinal data. Nominal data is in the 'Domain', 'Region', 'Productions', and 'Trade' columns where the categories(labels) are unrelated and are not in order, unlike the ordinal type.

The columns from '2015' to '2021' contain numeric values (intger). The 'Total Gross' colum contain the continous value represt the export value in million $

In [172]:
```
df_stat.shape
```

Out[172]: (294, 12)

The sample size = 294

In [ ]:
```

```

In [173]:
```
# we filter the data frame to get the numeric features only to caluculate the descriptive Statistics
df_stat_Num = df.iloc[:,3:11]
df_stat_Num.head()
```

Out[173]:

	2015	2016	2017	2018	2019	2020	2021	Total Gross
0	543	500	550	561	546	526	589	3817.40904
1	413	416	451	433	461	527	592	3295.76317
2	1219	1196	1314	1423	1369	1483	1532	9540.37498
3	22	25	33	44	44	43	30	245.20825
4	756	748	838	961	949	1041	1194	6489.05085

Calculate the descriptive Statistics for the numeric features in our data frame like Min, Max, Mean, Standard Deviation, and Median

In [174]:
```
for i,val in enumerate(df_stat_Num):
    print(f'{val}:\nThe minimum of {val} is: {min(df_stat_Num[val])}')
    print(f'The maximum of {val} is: {max(df_stat_Num[val])}')
    print(f'The mean of {val} is: {(df_stat_Num[val]).mean():.3f}')
    print(f'The median of {val} is: {(df_stat_Num[val]).median():.3f}')
    print(f'The Standard deviation of {val} is: {df_stat_Num[val].std():.3f}\n')
```

```
2015:
The minimum of 2015 is: 0
The maximum of 2015 is: 9418
The mean of 2015 is: 688.003
The median of 2015 is: 172.000
The Standard deviation of 2015 is: 1316.897

2016:
The minimum of 2016 is: 0
The maximum of 2016 is: 9833
The mean of 2016 is: 691.514
The median of 2016 is: 174.000
The Standard deviation of 2016 is: 1328.884

2017:
The minimum of 2017 is: 0
The maximum of 2017 is: 10637
The mean of 2017 is: 770.225
The median of 2017 is: 188.000
The Standard deviation of 2017 is: 1493.527

2018:
The minimum of 2018 is: 0
The maximum of 2018 is: 11379
The mean of 2018 is: 814.963
The median of 2018 is: 214.000
The Standard deviation of 2018 is: 1573.844

2019:
The minimum of 2019 is: 0
The maximum of 2019 is: 10322
The mean of 2019 is: 799.897
The median of 2019 is: 214.000
The Standard deviation of 2019 is: 1533.525

2020:
The minimum of 2020 is: 0
The maximum of 2020 is: 11761
The mean of 2020 is: 836.181
The median of 2020 is: 213.000
The Standard deviation of 2020 is: 1635.637

2021:
The minimum of 2021 is: 0
The maximum of 2021 is: 12043
The mean of 2021 is: 919.134
The median of 2021 is: 244.000
The Standard deviation of 2021 is: 1768.002

Total Gross:
The minimum of Total Gross is: 0.04834
The maximum of Total Gross is: 75396.7903
The mean of Total Gross is: 5523.347
The median of Total Gross is: 1427.952
The Standard deviation of Total Gross is: 10616.430
```

We start to anlyse Ireland export dataset df_stat_IRL

In [175]:
```
df_stat_IRL
```

Out[175]:

	Domain	Region	Production	2015	2016	2017	2018	2019	2020	2021	Total	Trade
0	Crops and livestock products	Ireland	Bovine Meat	2454	2508	2716	2874	2601	2660	2838	18653.84379	Export
1	Crops and livestock products	Ireland	Cereals	40	18	21	22	36	45	64	249.10032	Export
2	Crops and livestock products	Ireland	Dairy Products	1869	1868	2627	3013	3270	3314	3682	19647.23284	Export
3	Crops and livestock products	Ireland	Eggs	18	13	15	14	17	20	41	141.71600	Export
4	Crops and livestock products	Ireland	Fodder and Feeding Stuff	306	290	339	375	377	416	505	2610.96716	Export
5	Crops and livestock products	Ireland	Fruit	140	139	162	197	177	185	187	1189.91805	Export
6	Crops and livestock products	Ireland	Nuts	5	3	3	5	7	4	5	34.13922	Export
7	Crops and livestock products	Ireland	Pigmeat (meat equivalent)	460	525	554	570	596	663	675	4045.17407	Export
8	Crops and livestock products	Ireland	Poultry Meat	352	280	306	347	307	281	279	2155.91462	Export
9	Crops and livestock products	Ireland	Roots and Tubers	10	11	13	12	16	15	16	94.93483	Export
10	Crops and livestock products	Ireland	Vegetables	162	152	158	161	148	165	256	1204.72782	Export

In [176]:
```
df_stat_IRL.shape
```

Out[176]: (11, 12)

Calculate the yearly average value for crops and livestock product exports from Ireland.

In [177]:
```
IRL_MeanExp = df_stat.iloc[:,3:10].sum(0)
IRL_MeanExp
```

Out[177]:
```
2015    211734
2016    212833
2017    235854
2018    248041
2019    246320
2020    260563
2021    286793
dtype: int64
```

One Sample T-test: The one-sample t-test is a statistical hypothesis test used to test if the unknown population mean is different from a specific value.

In [178]:
```
# Calculate the actual mean of the export yearly over 2015-2021
IRL_MeanExp.mean()
```

Out[178]: 243162.57142857142

We need to set a hypothesized mean(the mean we'd like to test, or the mean we'd expect in the population). Here, I'd like to test if the export price for all comidities exported by Ireland in million $ in the population would be 250000.

Null Hypothesis: --> H0 = μ, Population means
Alternative hypothesis: --> H1 ≠ μ, Population means

Suppose: μ = 250000 K$

In [179]:
```
# Define the variable
#x = The total trade(in Millioneuros)
X = IRL_MeanExp
```

The ttest_1samp function used to get the results:

In [180]:
```
# The mean of Total Gross is: 5523.347
stats.ttest_1samp(X,250000)
```

Out[180]: Ttest_1sampResult(statistic=-0.6836443174277725, pvalue=0.5197138596447316)

Let's describe the result, we got two values the first is the statistic=-0.68364431,it is the t-value and, the p-value which is 0.519, which is greater than 0.05, so we accept the null hypothesis and the alternative hypothesis is rejected. There is enough evidence to say that the average of exported crops is 250000 yearly.

If we want to test if the yearly export cost in $Million is less than €250000 M. We calculate the test at alpha = 5% significance level.

In [181]:
```
#H1 : u < 5000
stats.t.sf(-0.6836443174277725, 294)
```

Out[181]:
```
0.7526308827750456
```

Again, the p-value = 0.75> 0.05. We accept the null hypothesis H0. Thus, there is enough evidence to say that the yearly export price in average greater than $ Million 250000.

T-Test, two populations

Suppose we want to test if there any difference in the average of the 'Total Gross'between import and export crops and livestock in Ireland at a 5% significante level.

In [182]:
```
# Have a look to df_melted
df_melted
```

Out[182]:

	Domain	Region	Production	Trade	Year	Value
0	Crops and livestock products	Austria	Bovine Meat	Export	2015	543
1	Crops and livestock products	Austria	Cereals	Export	2015	413
2	Crops and livestock products	Austria	Dairy Products	Export	2015	1219
3	Crops and livestock products	Austria	Eggs	Export	2015	22
4	Crops and livestock products	Austria	Fodder and Feeding Stuff	Export	2015	756
...	...	...	...	...	...	...
4132	Crops and livestock products	Sweden	Nuts	Import	2021	207
4133	Crops and livestock products	Sweden	Pigmeat (meat equivalent)	Import	2021	343
4134	Crops and livestock products	Sweden	Poultry Meat	Import	2021	323
4135	Crops and livestock products	Sweden	Roots and Tubers	Import	2021	126
4136	Crops and livestock products	Sweden	Vegetables	Import	2021	1154

4137 rows × 6 columns

In [183]:
```
# df_stat_IRL['Total'] = df_stat_IRL['Total'].astype(int)
```

In [184]:
```
# Filter the dataframe to get Ireland only
IRL = df_melted[df_melted['Region'] == 'Ireland']
IRL.head()
```

Out[184]:

	Domain	Region	Production	Trade	Year	Value
285	Crops and livestock products	Ireland	Bovine Meat	Export	2015	2454
286	Crops and livestock products	Ireland	Cereals	Export	2015	40
287	Crops and livestock products	Ireland	Dairy Products	Export	2015	1869
288	Crops and livestock products	Ireland	Eggs	Export	2015	18
289	Crops and livestock products	Ireland	Fodder and Feeding Stuff	Export	2015	306

In [185]:
```
# We group the data according to import and export trade values
importCrops = IRL[IRL['Trade'] == 'Import']['Value']
exportCrops = IRL[IRL['Trade'] == 'Export']['Value']
```

In [186]:
```
# H0 => μ1 = μ2 (population mean of importCrops is equal to exportCrops)
# HA => μ1 ≠μ2 (population mean of importCrops is different from exportCrops)
```

In [187]:
```
# We perform the test assuming as H0 that mu1 = mu2 (importCrops = exportCrops)
# equal_var=True means that we take in consideration the equal population variances.
test = stats.ttest_ind(importCrops, exportCrops,
                       equal_var=True)

print (test)
```

```
Ttest_indResult(statistic=-1.8883506807233879, pvalue=0.06088428027866394)
```

In [188]:
```
# We perform the test assuming as H0 that mu1 = mu2 (importCrops = exportCrops)
# equal_var=False means the population variances are not equal.
test = stats.ttest_ind(importCrops, exportCrops,
                       equal_var=False)

print (test)
```

```
Ttest_indResult(statistic=-1.888350680723388, pvalue=0.062178394159737846)
```

pvalue = 0.06 >0.05 We cannot reject the null hypothesis H0. There is enough evidence at 5% significance level to say that the population mean of importCrops is equal to exportCrops.

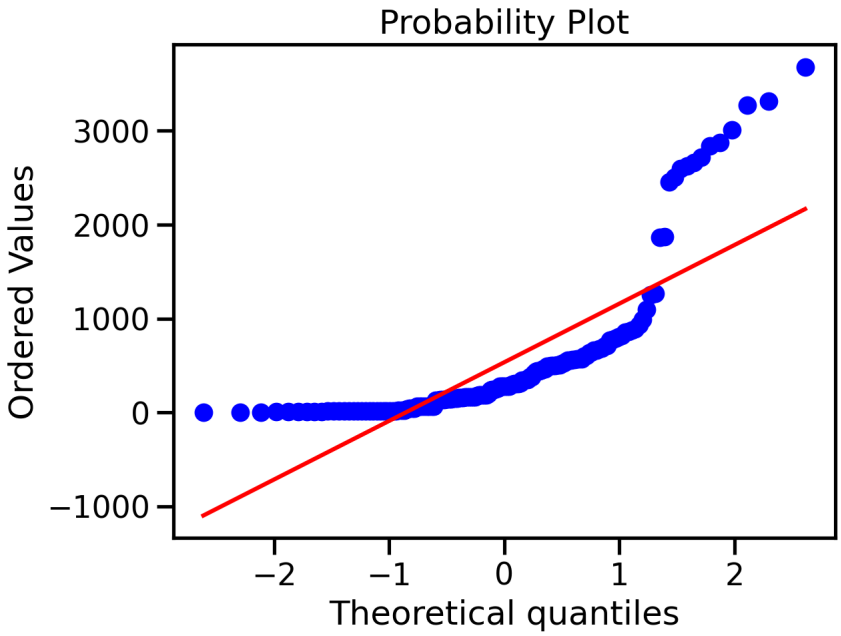
Compare the values of Import and export products in Ireland:

ANOVA(Analysis of Variance)

Checking the ANOVA conditions:

- **Independency:** The k populations are independent. In other words, their outcomes do not affect each other.
- **Normality:** The k populations have a normal distribution.
- **Variance Equality:** The variances of the k normal distributions are equal.

In [189]:
```
# Normality plot
stats.probplot(IRL['Value'], plot=plt);
plt.figure();
```




```
<Figure size 640x480 with 0 Axes>
```

In [190]:
```
The figure shows that the data is not normally distributed
```

```
  Cell In[190], line 1
    The figure shows that the data is not normally distributed
        ^
SyntaxError: invalid syntax
```

Shapiro

We apply the Shapiro wilk test to check if the sample data came from a normal distribution or not.

- H0 : The data narmally distributed
- H1 :The data is not normally distributed

In [ ]:
```
#Shapiro wilk test
stats.shapiro(IRL.Value)
```

In [ ]:
```
the p-value < 0.05, We reject the Null hypothesis. This enough evidence to say that the data is not normally distributed.
```

Comparing Ireland crops and livestock products exports with Netherlands(the highest export country in EU).

In [ ]:
```

```

In [ ]:
```
df_melted
```

Compare Ireland exported crops and livestock product with Franc and Spain

In [ ]:
```
# Filter data to extract the dataset for Ireland, France, and Spain
# List for the three regions selected
NewRegion = ['Ireland', 'France','Spain']

# Get the dataset for thev New_region
df_NewRegion = df_melted[df_melted['Region'].isin(NewRegion)]

# Reset the index of the filtered data
df_NewRegion.reset_index(drop= True,inplace=True)

# new dataset
data = df_NewRegion[df_NewRegion['Trade']=='Export']
```

In [ ]:
```
data.head()
```

We want to check if the average value(prices in $M) for the exported crops and livestock products for the three regions are the same or not. Let's check our randam sample stored in 'data'

ANOVA

In [ ]:
```
#Normality plot. Our variable is "Value"
stats.probplot(data['Value'], plot=plt);
plt.figure();
```

The figures display the 'Value' data points which form a curve rather than a straight line which confirms a skewness in the dataset sample.

Shapiro

We apply the Shapiro wilk test to check if the sample data came from a normal distribution or not.

- H0 : The data narmally distributed
- H1 :The data is not normally distributed

In [ ]:
```
#Shapiro wilk test
stats.shapiro(data.Value)
```

the p-value < 0.05, We reject the Null hypothesis. This enough evidence to say that the data is not normally distributed.

In [ ]:
```
Apply shapiro test for the three region seperately:
```

In [ ]:
```
#Shapiro wilk test
stats.shapiro(data.Value[data.Region == 'Ireland'])
```

In [ ]:
```
#Shapiro wilk test
stats.shapiro(data.Value[data.Region == 'France'])
```

In [ ]:
```
#Shapiro wilk test
stats.shapiro(data.Value[data.Region == 'Spain'])
```

In [ ]:
```
stats.t.interval(alpha=0.95, df_stat=len(data)-1, loc=np.mean(data), scale=st.sem(data))

```

The Pvalue < 0.05 in the three regions, that's confirm that the data is not normally distributed

Calculate the variane for each reion sample

In [ ]:
```
Ireland = data.Value[data.Region == 'Ireland']
sd1 = Ireland.std()
sd1
```

In [ ]:
```
France = data.Value[data.Region == 'France']
sd2 = France.std()
sd2
```

In [ ]:
```
Spain = data.Value[data.Region == 'Spain']
sd3 = Spain.std()
sd3
```

Levenes test

consider alpha = 0.05

In [ ]:
```
#Homogeinity of variance:
from scipy.stats import levene
levene(Ireland, Spain, France, center = 'mean')
```

In [ ]:
```
p-value is less than alpha, then we reject the null hypothesis, there is no enough evidence to say the variances are equal.
```

In [ ]:
```

```

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[10]

In [ ]:
```

```

In [ ]:
```

```

In [ ]:
```

```