Brazilian exportations

1.0 Background

Comex Stat is a system for consulting and extracting data from Brazilian foreign trade. Detailed data on Brazilian exports and imports are released monthly, extracted from SISCOMEX and based on the declaration of exporters and importers. The system database is also available for download.

Comex Stat will be constantly evolving, seeking to improve usability and create new features for data exploration. In this sense, your opinion, criticism and suggestion will be very important for the improvement of the system. Please contact Comex Responde and send us your impression.

The dataset contains all trackings of monthly imports and exports of a range of products (soybeans, soybean meal, soybean oil, corn, wheat and sugar), by brazilian states, by routes (air, sea, ground, etc) e from/to which country;

Questions to be answered and tasks to be done

- Task 1: Show the evolution of total monthly and total annual exports from Brazil (all states and to everywhere) of ‘soybeans’, ‘soybean oil’ and ‘soybean meal’;
- Task 2: What are the 3 most important products exported by Brazil in the last 5 years?
- Task 3: What are the main routes through which Brazil have been exporting ‘corn’ in the last few years? Are there differences in the relative importancem of routes depending on the product?
- Task 4: Which countries have been the most important trade partners for Brazil in terms of ‘corn’ and ‘sugar’ in the last 3 years?

- Task 5: For each of the products in the dataset, show the 5 most important states in terms of exports?
- Task 6: Now, we ask you to show your modelling skills. Feel free to use any type of modelling approach, but bear in mind that the modelling approach depends on the nature of your data, and so different models yield different estimates and forecasts. To help you out in this task we also provide you with a dataset of possible covariates (.xlsx). They all come from public sources (IMF, World Bank) and are presented in index number format. Question: What should be the total brazilian soybeans, soybean_meal, and corn export forecasts, in tons, for the next 11 years (2020-2030)? We're mostly interested in the annual forecast.

2.0 Importing libraries

In [333]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats


# Disabling warnings
import warnings
warnings.filterwarnings('ignore')

%matplotlib inline
```

In [334]:
```
train = pd.read_csv('data_comexstat.csv', encoding = "ISO-8859-1")
```

In [335]:
```
train.head()
```

Out[335]:

	date	product	state	country	type	route	tons	usd
0	1997-01-01	corn	ES	United States	Import	Sea	44.045	113029.0
1	1997-01-01	corn	GO	Argentina	Import	Ground	54.000	36720.0
2	1997-01-01	corn	GO	Bolivia	Export	Ground	0.200	180.0
3	1997-01-01	corn	GO	United States	Export	Sea	3.488	5688.0
4	1997-01-01	corn	MG	Argentina	Import	Ground	27.000	18630.0

3.0 Functions

In [336]:
```
def boxplot(df,x,y,x_text=None,y_text=None,title=None, x_lim=None, y_lim=None, pa

  plt.style.use("ggplot")
  ax = sns.boxplot(x=x, y=y, data=df, palette=palette)
  ax.set_xlabel(x_text, fontsize=16)
  ax.set_ylabel(y_text, fontsize=16)
  ax.set_xlim(x_lim)
  ax.set_ylim(y_lim)
  plt.title(title, fontsize=18)
```

4.0 Descriptive data analysis

- Variables types

In [337]:
```
train.dtypes
```

Out[337]:
```
date        object
product     object
state       object
country     object
type        object
route       object
tons       float64
usd        float64
dtype: object
```

- Variables summary

Feature	Type	Feature Name	Data Type
date	Objective Feature	Date the product was imported or exported	object
product	Objective Feature	product	object
state	Objective Feature	source state	object
country	Objective Feature	country that negotiated a product with brazil	object
type	Objective Feature	type of the commercial transaction	object
route	Objective Feature	type of the transportation	object
tons	Target variable	weight in tons	float
usd	Objective Feature	currency	float

- Dimension of the training dataset

In [338]:
```
train.shape
```

Out[338]:
```
(117965, 8)
```

- There is no null values

In [339]:
```
train.isna().sum()
```

Out[339]:
```
date       0
product    0
state      0
country    0
type       0
route      0
tons       0
usd        0
dtype: int64
```

In [340]:
```
print("Some transactions have the variables tons and usd equal to zero, that's so

train.describe()
```

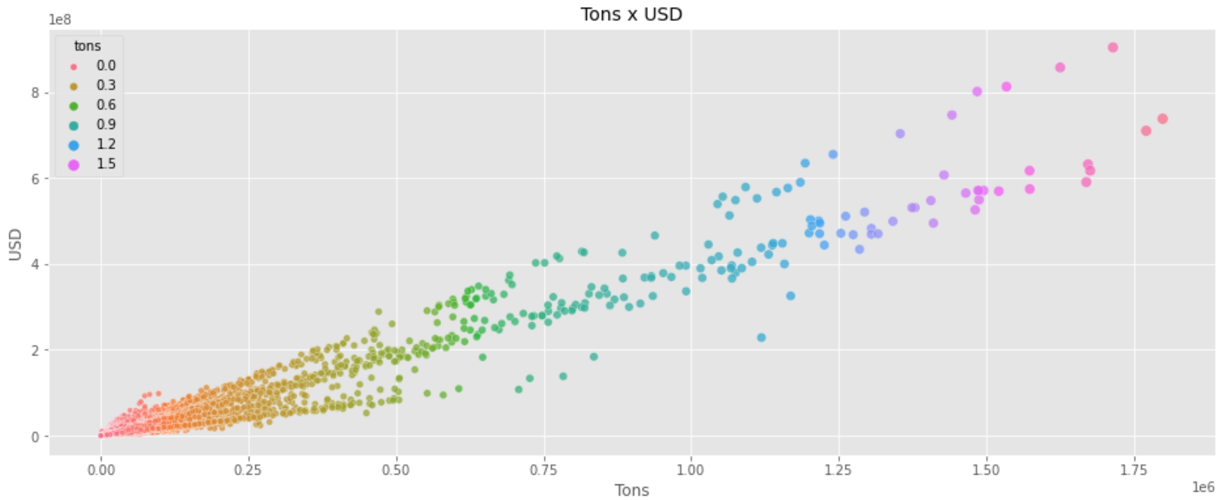
```
Some transactions have the variables tons and usd equal to zero, that's somethi
ng to be checked over the EDA
```

Out[340]:

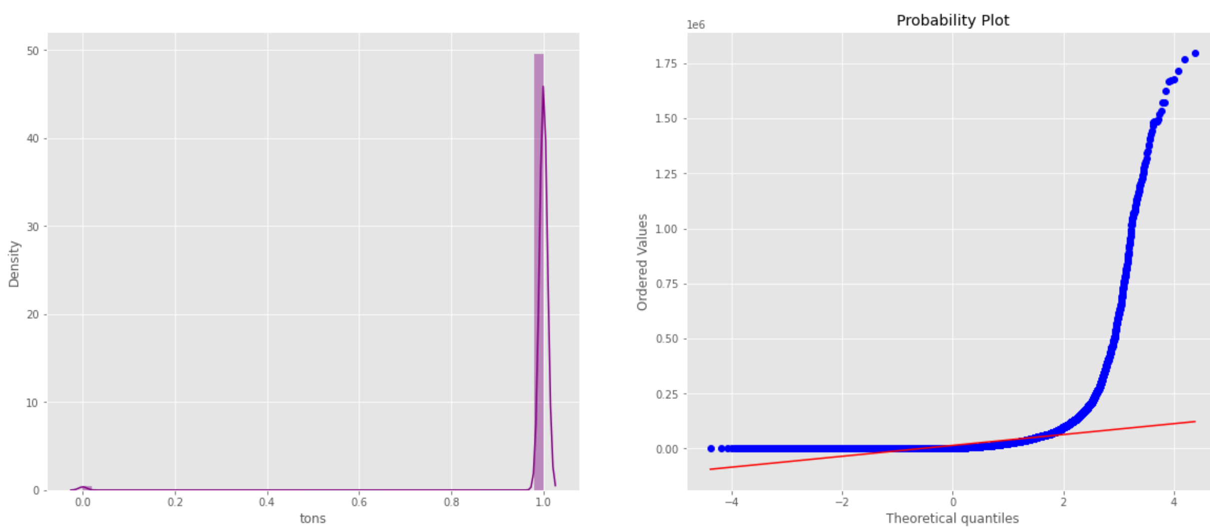
	tons	usd
count	1.179650e+05	1.179650e+05
mean	1.453681e+04	4.813150e+06
std	4.977926e+04	1.949412e+07
min	0.000000e+00	0.000000e+00
25%	1.249000e+02	7.155200e+04
50%	2.000000e+03	7.250000e+05
75%	1.353403e+04	3.895943e+06
max	1.798446e+06	9.039304e+08

- Distributions of the tons and usd variables

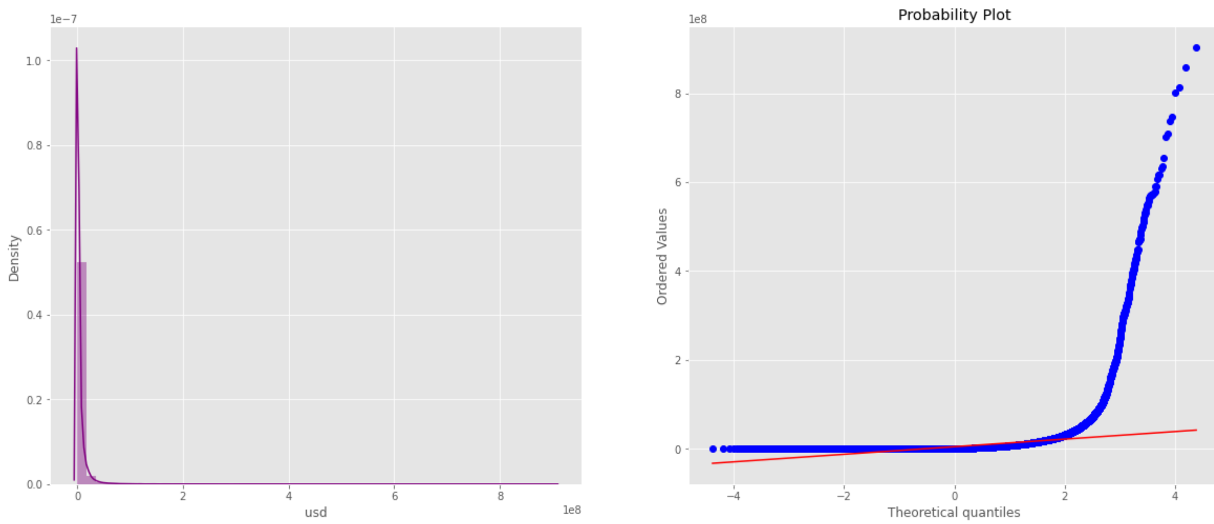
In [341]:
```python
# sets plot size
plt.figure(figsize=(16,6))
sns.scatterplot(x='tons', y='usd', data=train, hue='tons', size='tons', palette='
plt.xlabel("Tons")
plt.ylabel("USD")
plt.title("Tons x USD", fontsize=14)

# displays the plot
plt.show()
```



In [342]:
```python
# sets the figure size in inches
plt.figure(figsize=(20,8))

plt.subplot(1,2,1)
sns.distplot(train['tons']>0, color="purple")


plt.subplot(1,2,2)
# Probability plot
stats.probplot(train['tons'], plot=plt)

plt.show()
```



In [343]:
```
# sets the figure size in inches
plt.figure(figsize=(20,8))

plt.subplot(1,2,1)
sns.distplot(train['usd'], color="purple")


plt.subplot(1,2,2)
# Probability plot
stats.probplot(train['usd'], plot=plt)

plt.show()
```



In [ ]:

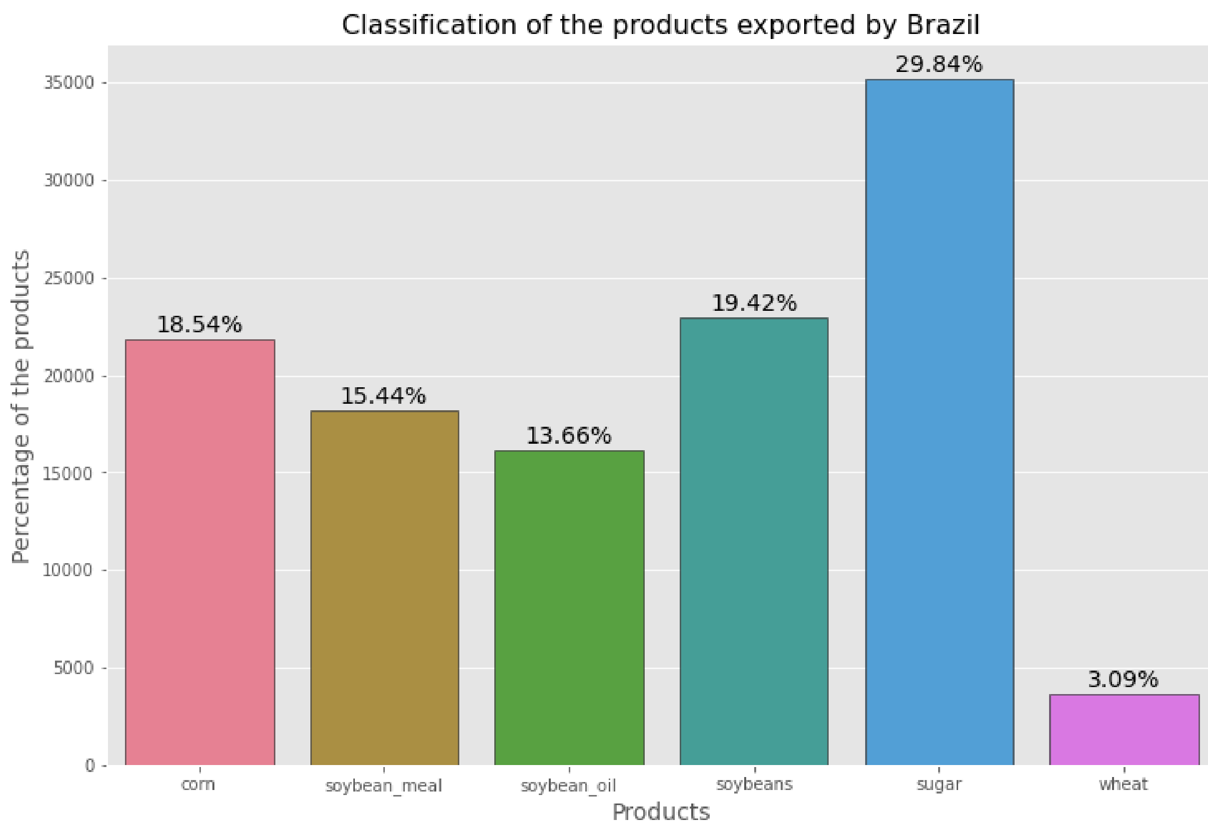
5.0 Feature engineering

In [344]:
```
train['date'] = pd.to_datetime(train['date'])
train['year'] = pd.to_datetime(train['date']).dt.year
train['month'] = pd.to_datetime(train['date']).dt.month
```

6.0 EDA - Exploratory data analysis

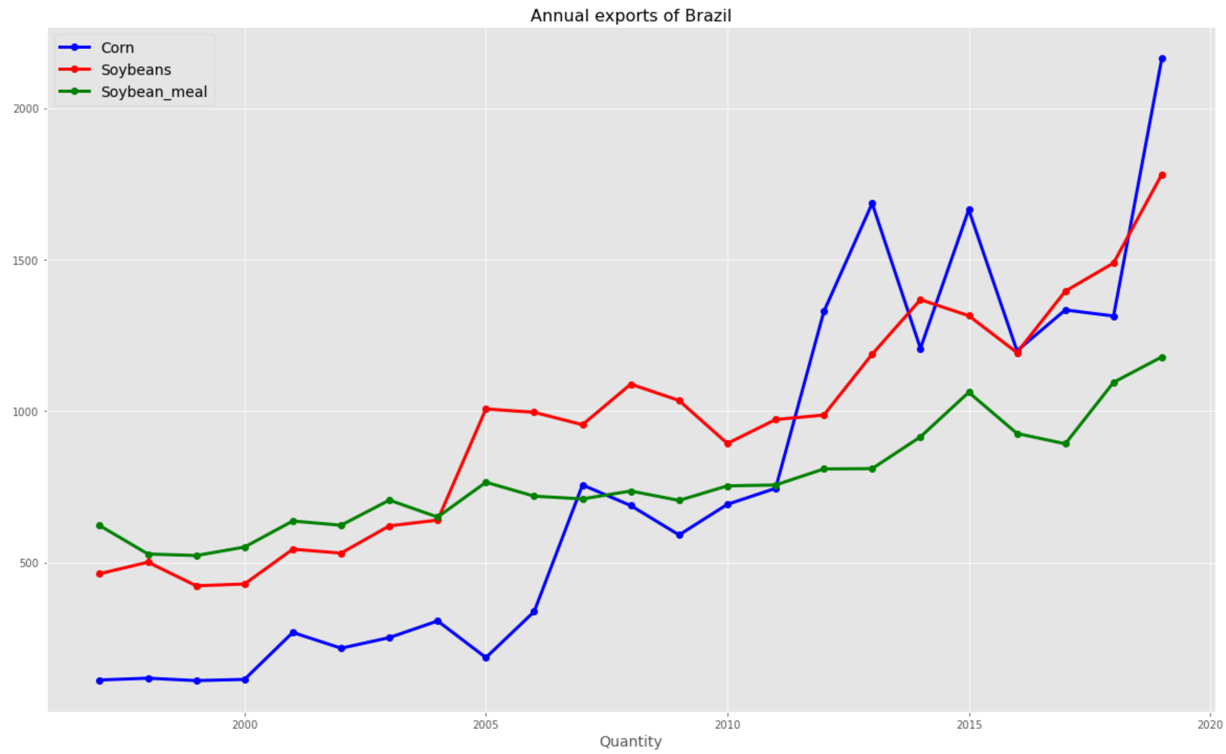
Univariate analysis

In [345]:
```
plt.figure(figsize=(12,8))
plt.style.use("ggplot")
count=sns.countplot(train['product'].sort_values(ascending=True), edgecolor='blac
dist_sum=sum([patch.get_height() for patch in  count.patches])
for patch in count.patches:
    count.annotate("{}%".format(np.round((patch.get_height()/dist_sum)*100,2)), (
                    xytext = (0, 8), textcoords ='offset points', ha='center', va

plt.xlabel('Products', fontsize=14)
plt.ylabel('Percentage of the products', fontsize=14)
plt.title('Classification of the products exported by Brazil', fontsize=16)
plt.show()
```

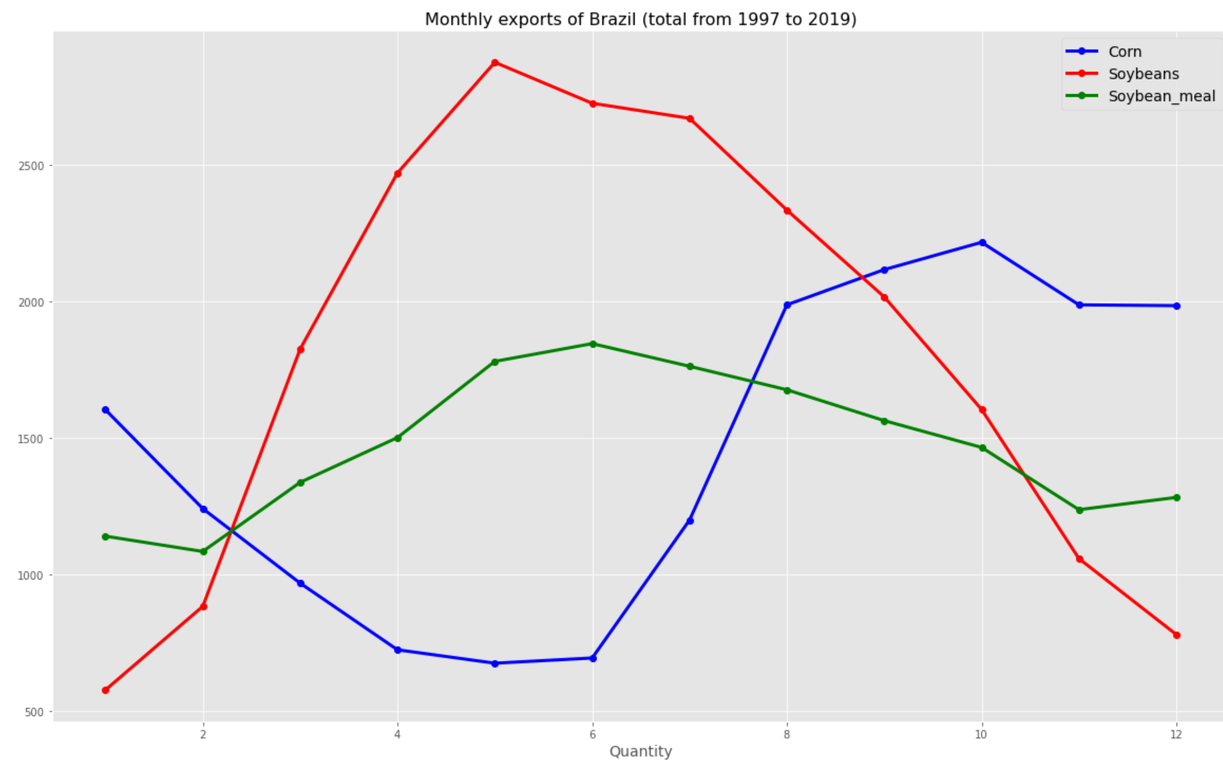


- Task 1: Show the evolution of total monthly and total annual exports from Brazil (all states and to everywhere) of ‘soybeans’, ‘soybean oil’ and ‘soybean meal’;

In [468]:
```
exports_brazil_corn = train[train['type'] =='Export'][train['product'] == 'corn']
exports_brazil_corn.groupby(['year']).count()['date'].plot(figsize=(20,12), linew

exports_brazil_soybeans = train[train['type'] =='Export'][train['product'] == 'sc
exports_brazil_soybeans.groupby(['year']).count()['date'].plot(figsize=(20,12), l

exports_brazil_soybean_meal = train[train['type'] =='Export'][train['product'] ==
exports_brazil_soybean_meal.groupby(['year']).count()['date'].plot(figsize=(20,12


plt.title("Annual exports of Brazil", fontsize=16)
plt.xlabel("Year", fontsize=14)
plt.xlabel("Quantity", fontsize=14)
plt.legend(['Corn', 'Soybeans', 'Soybean_meal'], fontsize=14)

plt.show()
```



In [471]:
```
exports_brazil_corn = train[train['type'] =='Export'][train['product'] == 'corn']
exports_brazil_corn.groupby(['month']).count()['date'].plot(figsize=(20,12), line

exports_brazil_soybeans = train[train['type'] =='Export'][train['product'] == 'so
exports_brazil_soybeans.groupby(['month']).count()['date'].plot(figsize=(20,12),

exports_brazil_soybean_meal = train[train['type'] =='Export'][train['product'] ==
exports_brazil_soybean_meal.groupby(['month']).count()['date'].plot(figsize=(20,1


plt.title("Monthly exports of Brazil (total from 1997 to 2019)", fontsize=16)
plt.xlabel("Year", fontsize=14)
plt.xlabel("Quantity", fontsize=14)
plt.legend(['Corn', 'Soybeans', 'Soybean_meal'], fontsize=14)

plt.show()
```

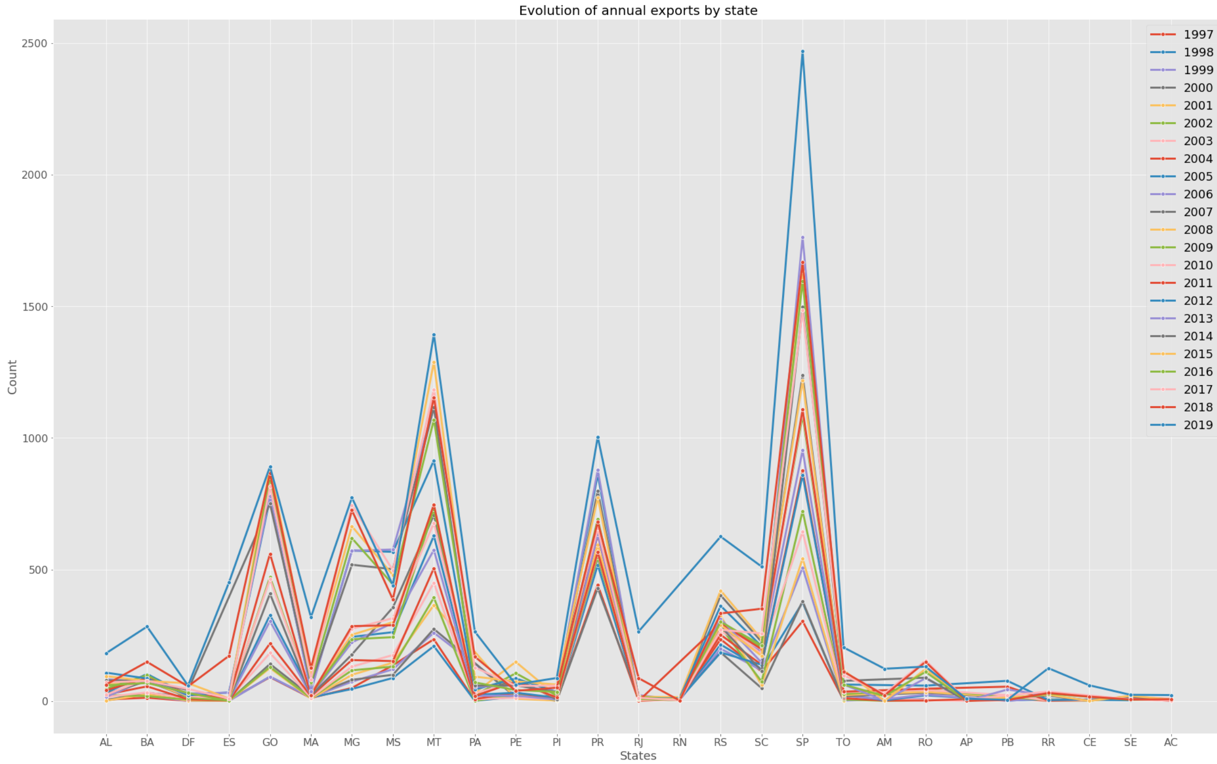


Type *Markdown* and LaTeX: α^2

In [346]:
```
df_1997_ = train[train['type'] =='Export']
df_1997 = pd.DataFrame(df_1997_[df_1997_['year'] == 1997][['state','year']])
df_1997 = df_1997.groupby('state').count().reset_index()

df_1998_ = train[train['type'] =='Export']
df_1998 = pd.DataFrame(df_1998_[df_1998_['year'] == 1998][['state','year']])
df_1998 = df_1998.groupby('state').count().reset_index()

df_1999_ = train[train['type'] =='Export']
df_1999 = pd.DataFrame(df_1999_[df_1999_['year'] == 1999][['state','year']])
df_1999 = df_1999.groupby('state').count().reset_index()

df_2000_ = train[train['type'] =='Export']
df_2000 = pd.DataFrame(df_2000_[df_2000_['year'] == 2000][['state','year']])
df_2000 = df_2000.groupby('state').count().reset_index()

df_2001_ = train[train['type'] =='Export']
df_2001 = pd.DataFrame(df_2001_[df_2001_['year'] == 2001][['state','year']])
df_2001 = df_2001.groupby('state').count().reset_index()

df_2002_ = train[train['type'] =='Export']
df_2002 = pd.DataFrame(df_2002_[df_2002_['year'] == 2002][['state','year']])
df_2002 = df_2002.groupby('state').count().reset_index()

df_2003_ = train[train['type'] =='Export']
df_2003 = pd.DataFrame(df_2003_[df_2003_['year'] == 2003][['state','year']])
df_2003 = df_2003.groupby('state').count().reset_index()

df_2004_ = train[train['type'] =='Export']
df_2004 = pd.DataFrame(df_2004_[df_2004_['year'] == 2004][['state','year']])
df_2004 = df_2004.groupby('state').count().reset_index()

df_2005_ = train[train['type'] =='Export']
df_2005 = pd.DataFrame(df_2005_[df_2005_['year'] == 2005][['state','year']])
df_2005 = df_2005.groupby('state').count().reset_index()

df_2006_ = train[train['type'] =='Export']
df_2006 = pd.DataFrame(df_2006_[df_2006_['year'] == 2006][['state','year']])
df_2006 = df_2006.groupby('state').count().reset_index()

df_2007_ = train[train['type'] =='Export']
df_2007 = pd.DataFrame(df_2007_[df_2007_['year'] == 2007][['state','year']])
df_2007 = df_2007.groupby('state').count().reset_index()

df_2008_ = train[train['type'] =='Export']
df_2008 = pd.DataFrame(df_2008_[df_2008_['year'] == 2008][['state','year']])
df_2008 = df_2008.groupby('state').count().reset_index()

df_2009_ = train[train['type'] =='Export']
df_2009 = pd.DataFrame(df_2009_[df_2009_['year'] == 2009][['state','year']])
df_2009 = df_2009.groupby('state').count().reset_index()

df_2010_ = train[train['type'] =='Export']
df_2010 = pd.DataFrame(df_2010_[df_2010_['year'] == 2010][['state','year']])
df_2010 = df_2010.groupby('state').count().reset_index()
```

```
df_2011_ = train[train['type'] =='Export']
df_2011 = pd.DataFrame(df_2011_[df_2011_['year'] == 2011][['state','year']])
df_2011 = df_2011.groupby('state').count().reset_index()

df_2012_ = train[train['type'] =='Export']
df_2012 = pd.DataFrame(df_2012_[df_2012_['year'] == 2012][['state','year']])
df_2012 = df_2012.groupby('state').count().reset_index()

df_2013_ = train[train['type'] =='Export']
df_2013 = pd.DataFrame(df_2013_[df_2013_['year'] == 2013][['state','year']])
df_2013 = df_2013.groupby('state').count().reset_index()

df_2014_ = train[train['type'] =='Export']
df_2014 = pd.DataFrame(df_2014_[df_2014_['year'] == 2014][['state','year']])
df_2014 = df_2014.groupby('state').count().reset_index()

df_2015_ = train[train['type'] =='Export']
df_2015 = pd.DataFrame(df_2015_[df_2015_['year'] == 2015][['state','year']])
df_2015 = df_2015.groupby('state').count().reset_index()

df_2016_ = train[train['type'] =='Export']
df_2016 = pd.DataFrame(df_2016_[df_2016_['year'] == 2016][['state','year']])
df_2016 = df_2016.groupby('state').count().reset_index()

df_2017_ = train[train['type'] =='Export']
df_2017 = pd.DataFrame(df_2017_[df_2017_['year'] == 2017][['state','year']])
df_2017 = df_2017.groupby('state').count().reset_index()

df_2018_ = train[train['type'] =='Export']
df_2018 = pd.DataFrame(df_2018_[df_2018_['year'] == 2018][['state','year']])
df_2018 = df_2018.groupby('state').count().reset_index()

df_2019_ = train[train['type'] =='Export']
df_2019 = pd.DataFrame(df_2019_[df_2019_['year'] == 2019][['state','year']])
df_2019 = df_2019.groupby('state').count().reset_index()
```

In [347]:
```
plt.figure(figsize=(32,20))
sns.lineplot(data=df_1997, x="state", y="year", marker='o', linewidth=3)
sns.lineplot(data=df_1998, x="state", y="year", marker='o', linewidth=3)
sns.lineplot(data=df_1999, x="state", y="year", marker='o', linewidth=3)
sns.lineplot(data=df_2000, x="state", y="year", marker='o', linewidth=3)
sns.lineplot(data=df_2001, x="state", y="year", marker='o', linewidth=3)
sns.lineplot(data=df_2002, x="state", y="year", marker='o', linewidth=3)
sns.lineplot(data=df_2003, x="state", y="year", marker='o', linewidth=3)
sns.lineplot(data=df_2004, x="state", y="year", marker='o', linewidth=3)
sns.lineplot(data=df_2005, x="state", y="year", marker='o', linewidth=3)
sns.lineplot(data=df_2006, x="state", y="year", marker='o', linewidth=3)
sns.lineplot(data=df_2007, x="state", y="year", marker='o', linewidth=3)
sns.lineplot(data=df_2008, x="state", y="year", marker='o', linewidth=3)
sns.lineplot(data=df_2009, x="state", y="year", marker='o', linewidth=3)
sns.lineplot(data=df_2010, x="state", y="year", marker='o', linewidth=3)
sns.lineplot(data=df_2011, x="state", y="year", marker='o', linewidth=3)
sns.lineplot(data=df_2012, x="state", y="year", marker='o', linewidth=3)
sns.lineplot(data=df_2013, x="state", y="year", marker='o', linewidth=3)
sns.lineplot(data=df_2014, x="state", y="year", marker='o', linewidth=3)
sns.lineplot(data=df_2015, x="state", y="year", marker='o', linewidth=3)
sns.lineplot(data=df_2016, x="state", y="year", marker='o', linewidth=3)
sns.lineplot(data=df_2017, x="state", y="year", marker='o', linewidth=3)
sns.lineplot(data=df_2018, x="state", y="year", marker='o', linewidth=3)
sns.lineplot(data=df_2019, x="state", y="year", marker='o', linewidth=3)



plt.legend(['1997','1998','1999','2000','2001','2002','2003','2004','2005','2006'
plt.title('Evolution of annual exports by state', fontsize=20)
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)
plt.xlabel('States', fontsize=18)
plt.ylabel('Count', fontsize=18)
plt.show()
```



In [ ]:

- Task 2: What are the 3 most important products exported by Brazil in the last 5 years?

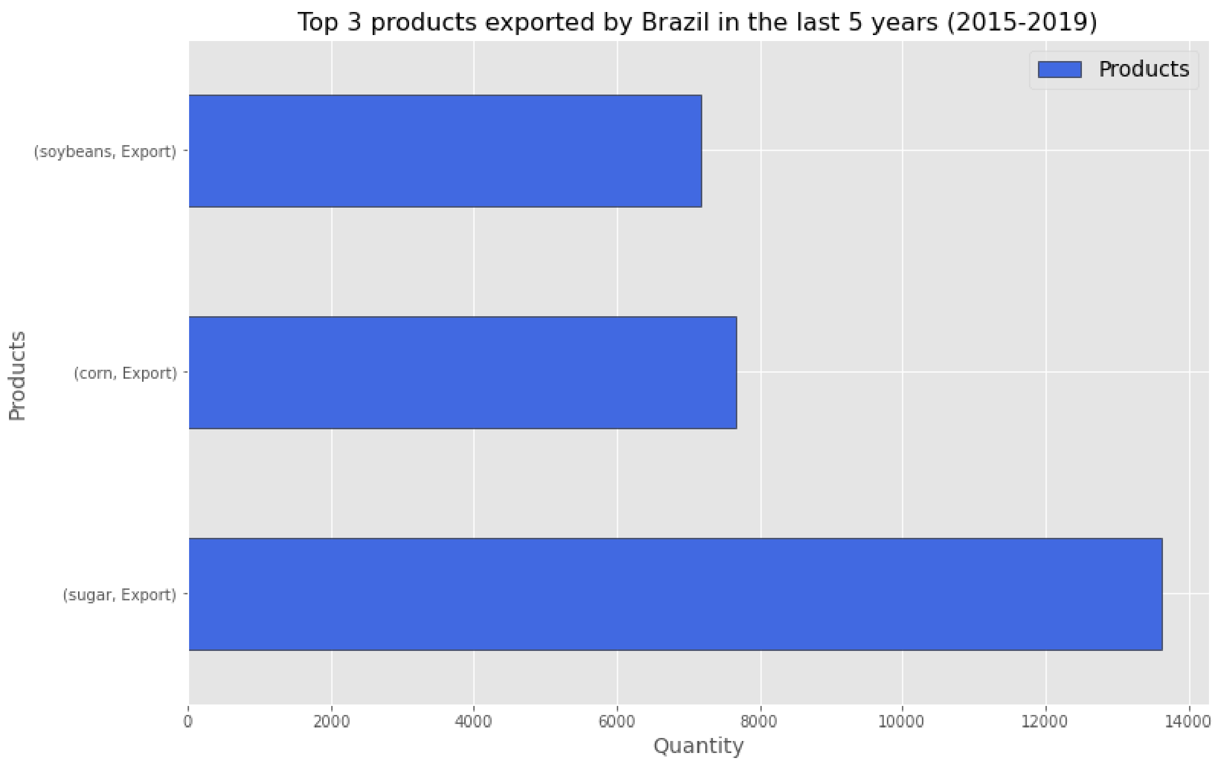
In [348]:

```
top_product = train[train['year']>2014][['product','type']]
top_product_exported = pd.DataFrame(top_product[top_product['type'] == 'Export'].
top_3_product = top_product_exported.nlargest(3, 'count')
top_3_product
```

Out[348]:

		count
product	**type**	
sugar	**Export**	13614
corn	**Export**	7677
soybeans	**Export**	7175

In [349]:
```
ax = top_3_product
ax.plot(kind='barh', color='royalblue', edgecolor='black', figsize=(12,8))

plt.title('Top 3 products exported by Brazil in the last 5 years (2015-2019)', fo
plt.ylabel('Products', fontsize=14)
plt.xlabel('Quantity', fontsize=14)
plt.legend(['Products'], fontsize=14)
plt.show()
```



The most 3 important products exported by Brazil are Sugar, Corn and Soybeans

---

- Task 3: What are the main routes through which Brazil have been exporting ‘corn’ in the last few years? Are there differences in the relative importance of routes depending on the product?

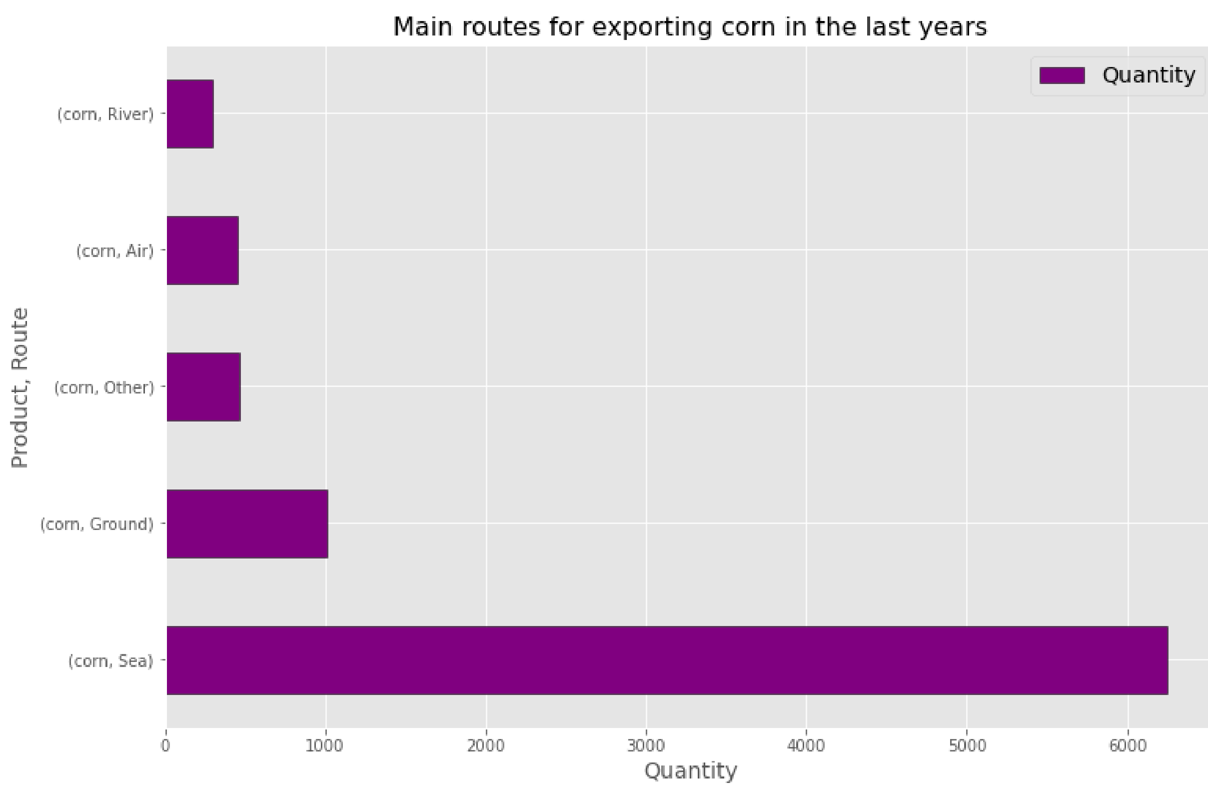
In [350]:
```
greater_2014 = train[train['year']>2014][['product','route']]
```

In [351]:
```
route_corn = pd.DataFrame(greater_2014[greater_2014['product'] =='corn'].value_co
route_corn
```

Out[351]:

product	route	count
corn	Sea	6244
	Ground	1006
	Other	460
	Air	455
	River	293

In [352]:
```
route_corn.plot(kind='barh', edgecolor='black', color='purple', figsize=(12,8))
plt.title('Main routes for exporting corn in the last years', fontsize=16)
plt.xlabel('Quantity', fontsize=14)
plt.ylabel('Product, Route', fontsize=14)
plt.legend(['Quantity'], fontsize=14)
plt.show()
```



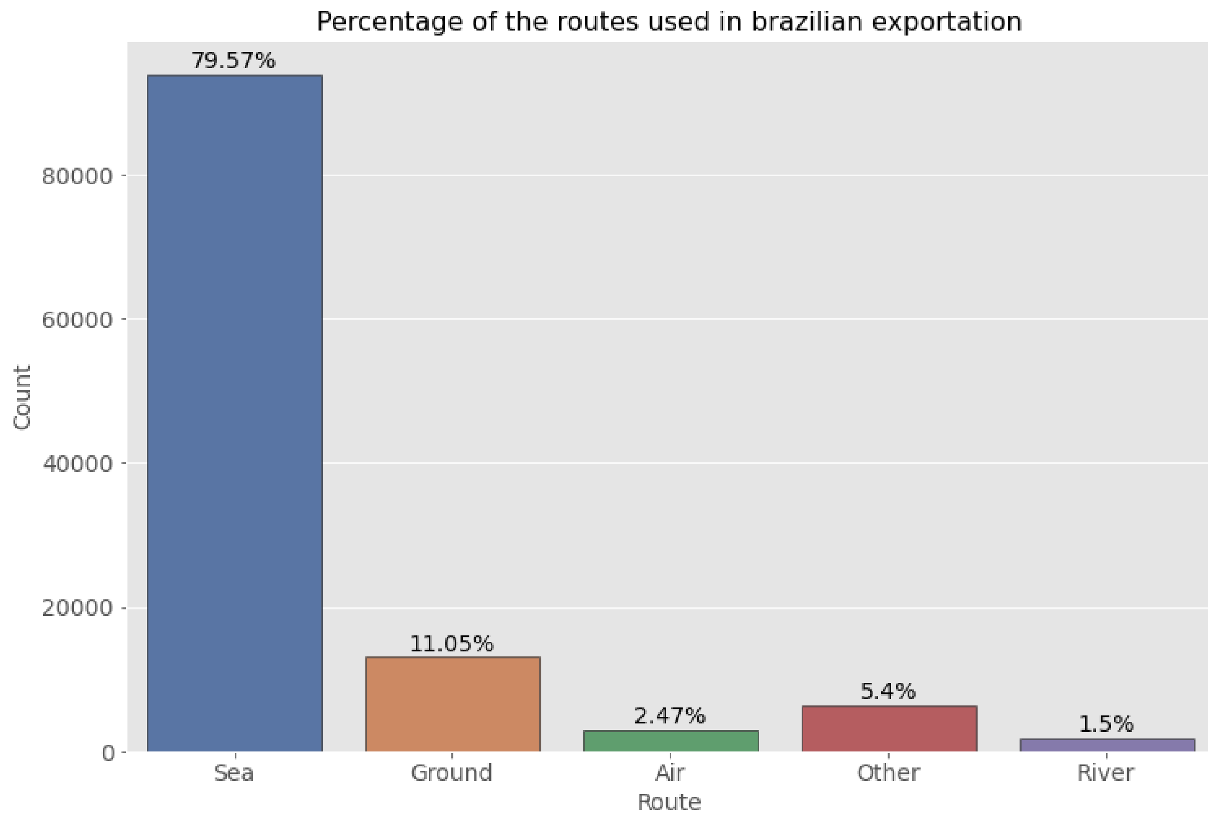
- Are there differences in the relative importance of routes depending on the product?

In [353]:
```
product_route = pd.DataFrame(train[['product','route']].value_counts(normalize=Tr
product_route
```

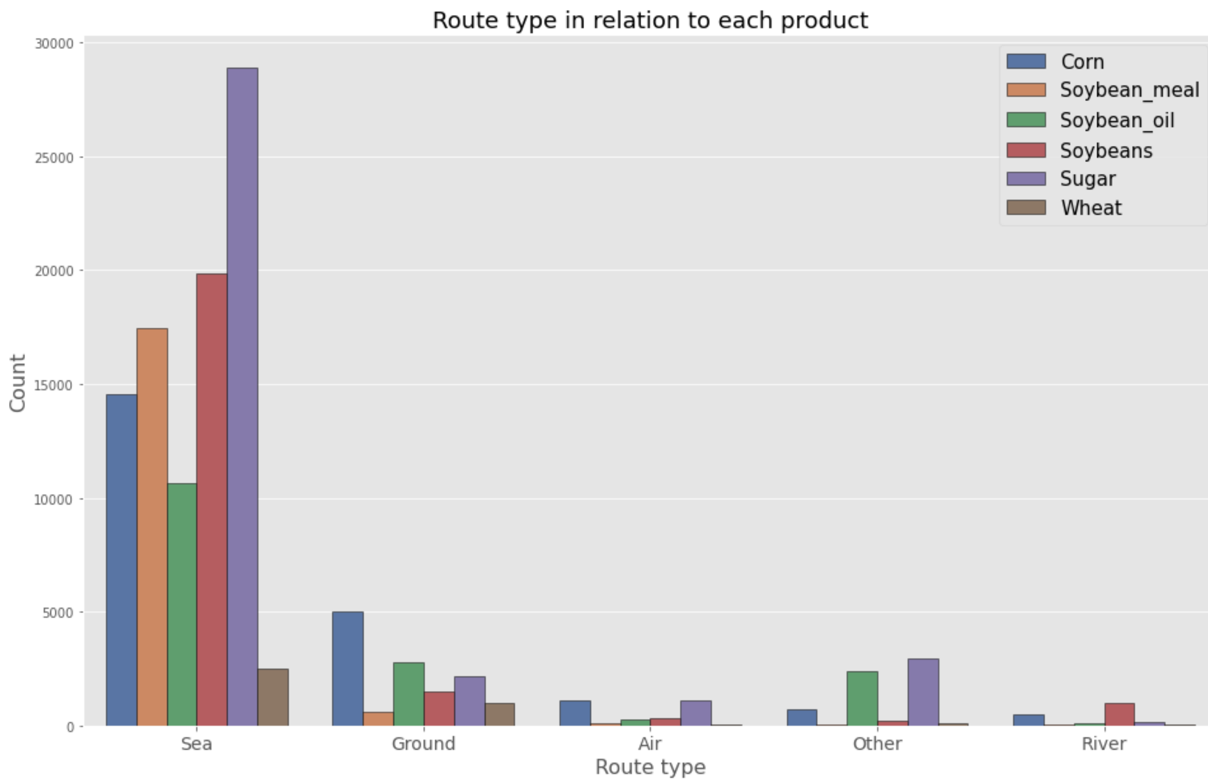
Out[353]:

product	route	count (%)
sugar	Sea	24.477599
soybeans	Sea	16.833807
soybean_meal	Sea	14.801000
corn	Sea	12.335862
soybean_oil	Sea	9.000127
corn	Ground	4.262281
sugar	Other	2.479549
soybean_oil	Ground	2.341372
wheat	Sea	2.126054
soybean_oil	Other	2.015004
sugar	Ground	1.840376
soybeans	Ground	1.286822
sugar	Air	0.930785
corn	Air	0.924003
soybeans	River	0.858729
wheat	Ground	0.821430
corn	Other	0.622218
soybean_meal	Ground	0.500148
corn	River	0.396728
soybeans	Air	0.277201
soybean_oil	Air	0.233120
soybeans	Other	0.167846
sugar	River	0.112745
wheat	Other	0.086466
soybean_oil	River	0.072055
soybean_meal	Air	0.066969
wheat	Air	0.041538
soybean_meal	River	0.040690
	Other	0.032213
wheat	River	0.015259

In [354]:
```
plt.figure(figsize=(12,8))
plt.style.use("ggplot")
count=sns.countplot(train['route'], edgecolor='black', palette='deep')
dist_sum=sum([patch.get_height() for patch in  count.patches])
for patch in count.patches:
    count.annotate("{}%".format(np.round((patch.get_height()/dist_sum)*100,2)), (
                    xytext = (0, 8), textcoords ='offset points', ha='center', va

plt.title('Percentage of the routes used in brazilian exportation', fontsize=16)
plt.xlabel('Route', fontsize=14)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
plt.ylabel('Count', fontsize=14)
plt.show()
```



In [355]:
```
# sets plot size
plt.figure(figsize=(16,10))

# plots countplot
ax = sns.countplot(x='route', hue='product', data=train, edgecolor='black', palet

# sets plot features
plt.title("Route type in relation to each product", fontsize=18)
plt.xlabel("Route type", fontsize=16)
plt.ylabel("Count", fontsize=16)
plt.xticks(ticks=[0,1,2,3,4], labels=['Sea', 'Ground', 'Air', 'Other', 'River'],
plt.legend(['Corn', 'Soybean_meal', 'Soybean_oil', 'Soybeans', 'Sugar', 'Wheat'],


# display plot
plt.show()
```



The majority of Brazilian exports are made by sea and regardless of the product, maritime exports lead this classification.

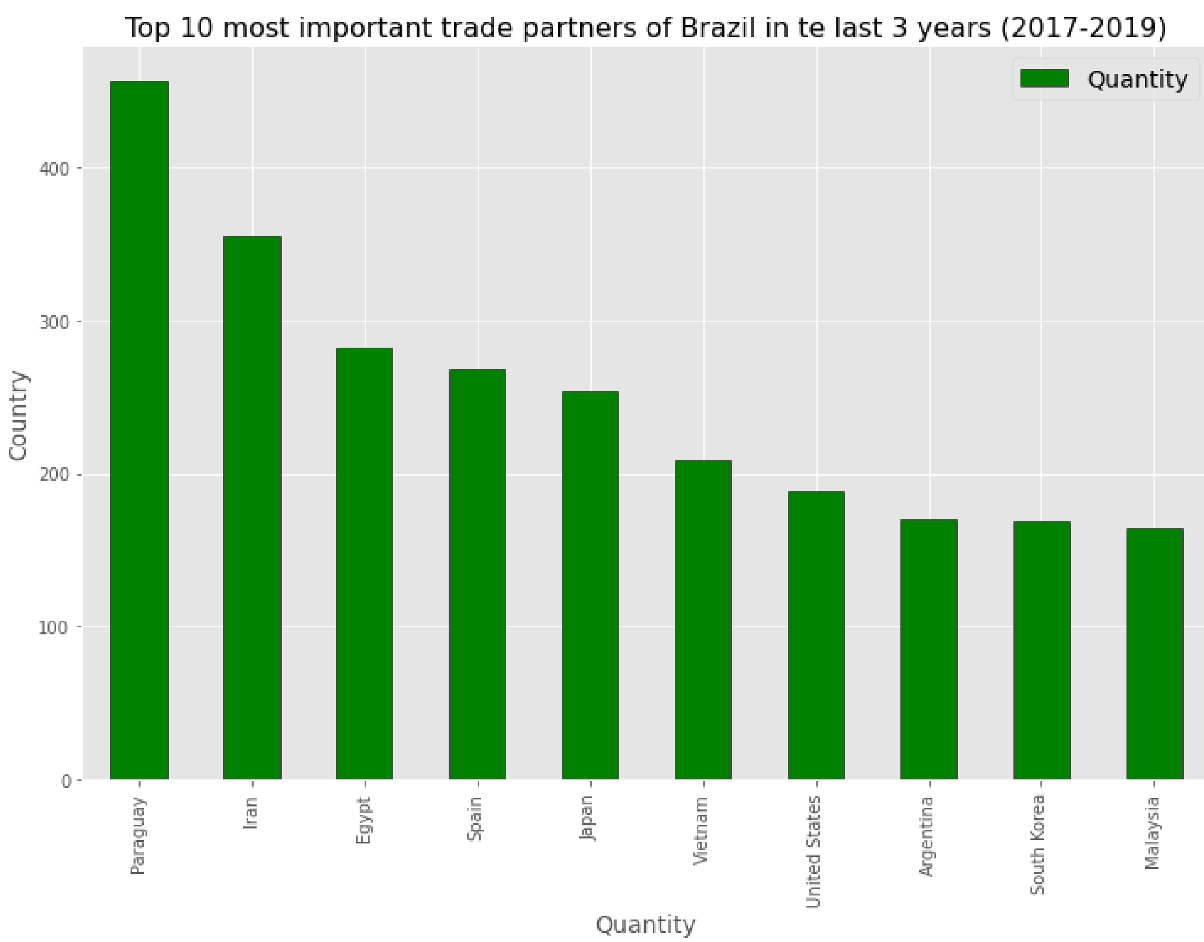
This is due to the fact of the transport cost since maritime transport makes it possible to transport products over long distances and is cheaper than air transport.

Ground and river transport have limitations related to being only possible for short distances.

- Task 4: Which countries have been the most important trade partners for Brazil in terms of ‘corn’ and ‘sugar’ in the last 3 years?

In [356]:
```
years_2016_2019 = train[train['year']>2016]
important_partners = pd.DataFrame(years_2016_2019[years_2016_2019['product']=='co
```

In [357]:
```
important_partners.nlargest(10, 'country').plot(kind='bar', edgecolor='black', co
plt.title('Top 10 most important trade partners of Brazil in te last 3 years (201
plt.ylabel('Country', fontsize=14)
plt.xlabel('Quantity', fontsize=14)
plt.legend(['Quantity'], fontsize=14)
plt.show()
```



- Task 5: For each of the products in the dataset, show the 5 most important states in terms of exports?

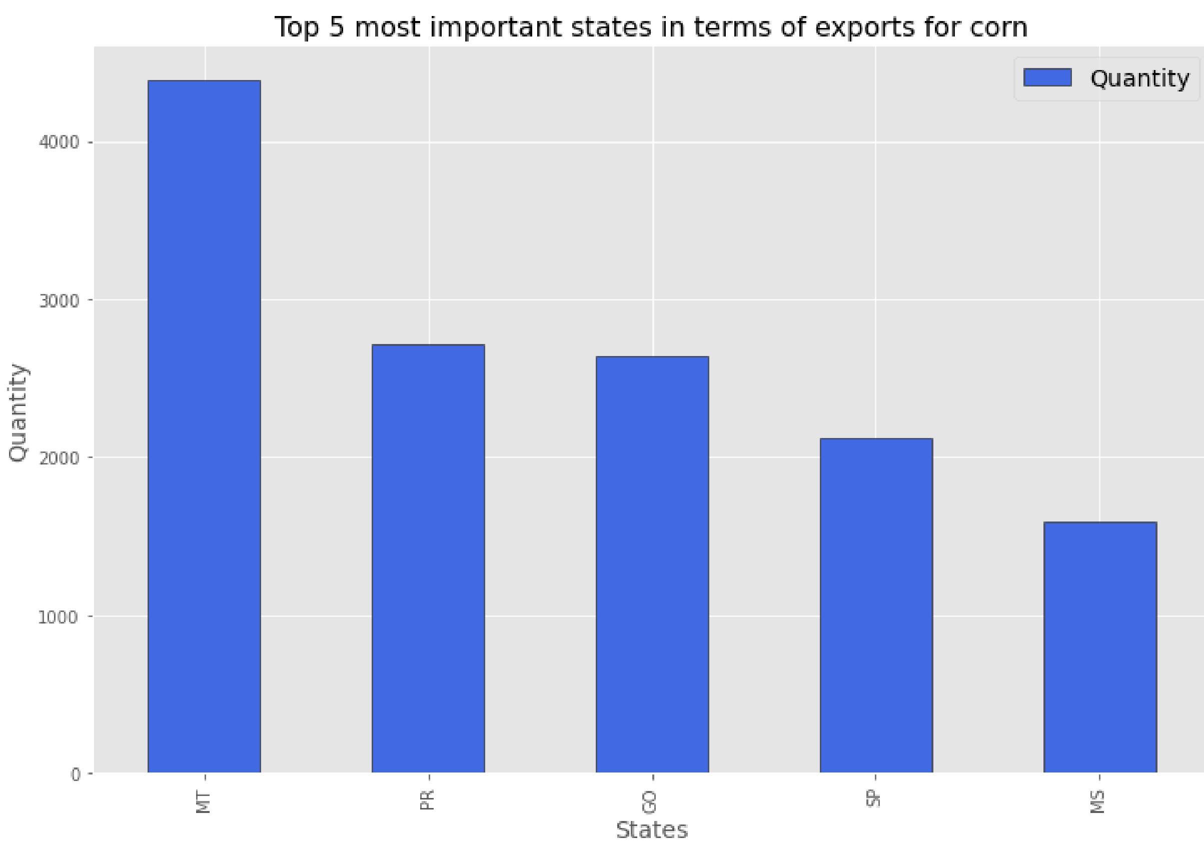
In [358]:
```
# - All products

products = list(train['product'].unique())

print('The products in the dataset are: {}'.format(products))
```

```
The products in the dataset are: ['corn', 'soybean_meal', 'soybean_oil', 'soybe
ans', 'sugar', 'wheat']
```

Corn

In [359]:
```
products_corn = train[train['type'] == 'Export'][['product','state']]
products_corn_state = pd.DataFrame(products_corn[products_corn['product']=='corn'
```

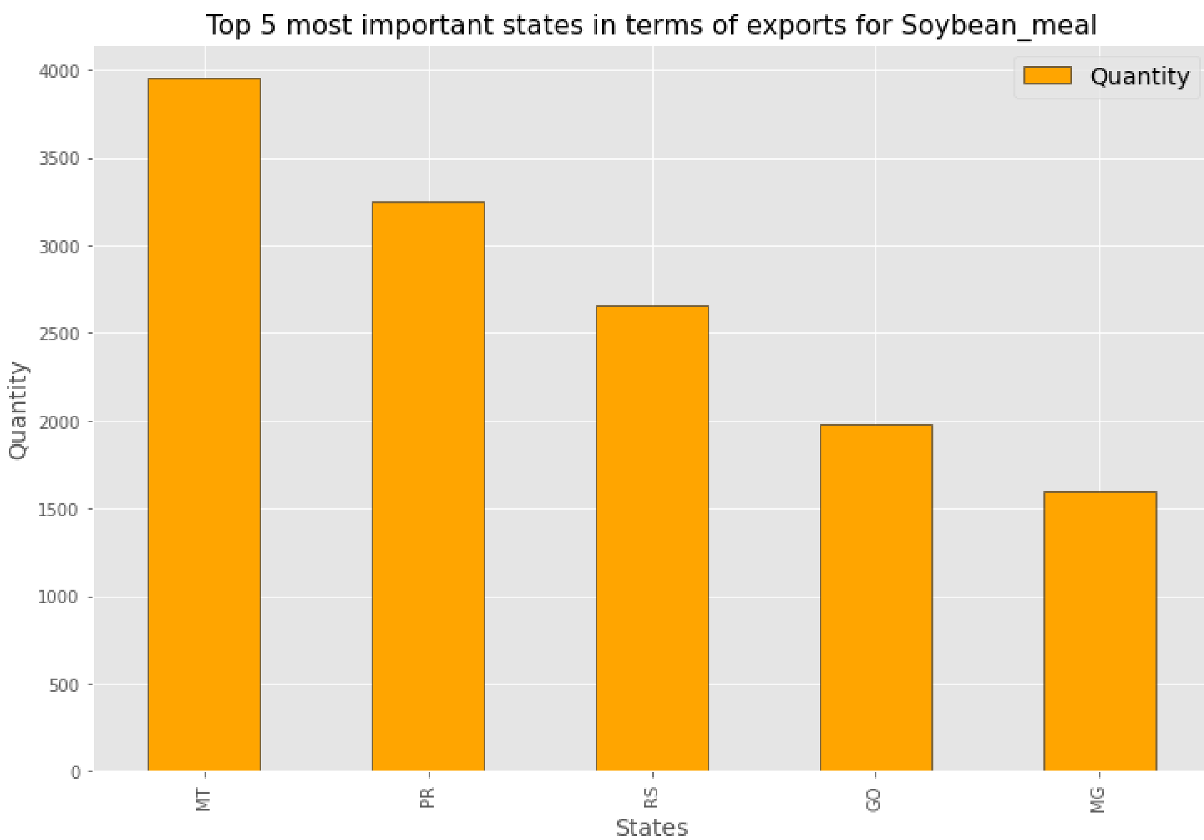
In [360]:
```
products_corn_state.nlargest(5, 'state').plot(kind='bar', edgecolor='black', colo
plt.title('Top 5 most important states in terms of exports for corn', fontsize=16
plt.ylabel('Quantity', fontsize=14)
plt.xlabel('States', fontsize=14)
plt.legend(['Quantity'], fontsize=14)
plt.show()
```



Soybean_meal

In [361]:
```
products_soybean_meal = train[train['type'] == 'Export'][['product','state']]
products_soybean_meal_state = pd.DataFrame(products_soybean_meal[products_soybean
```

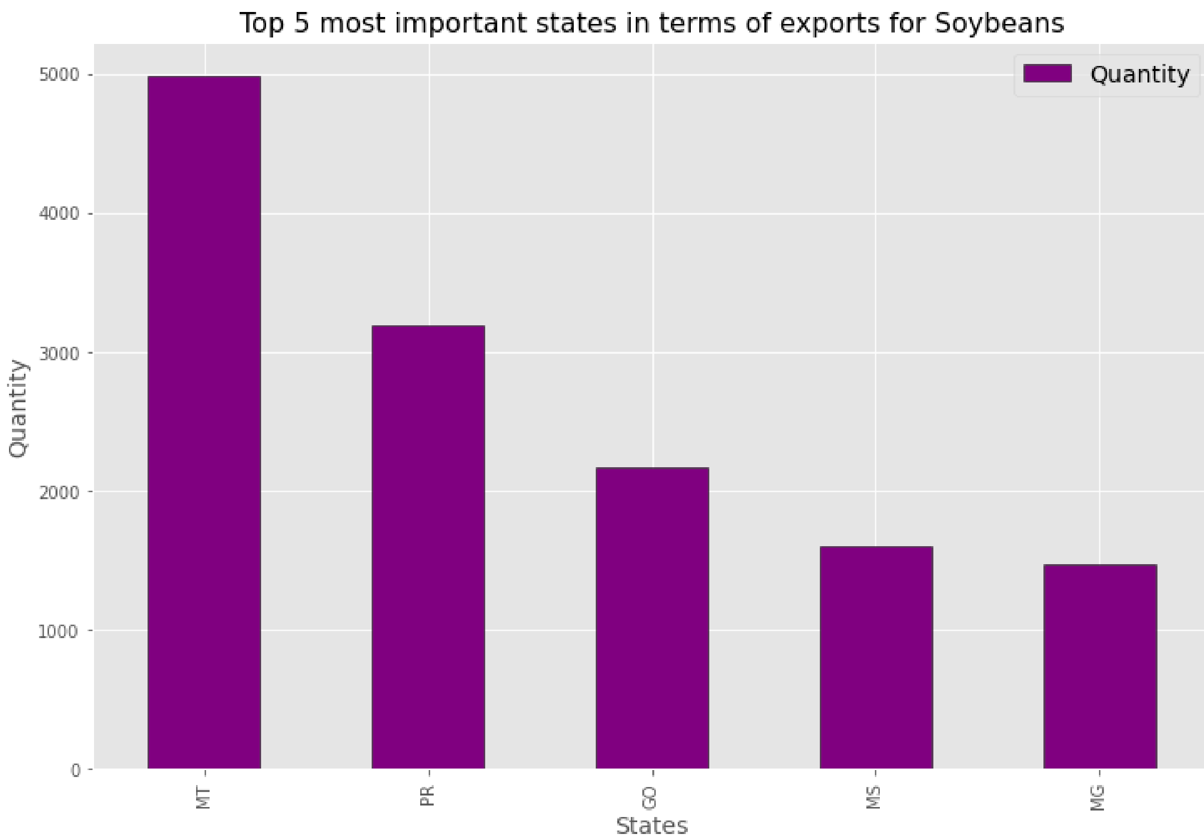
In [362]:
```
products_soybean_meal_state.nlargest(5, 'state').plot(kind='bar', edgecolor='blac
plt.title('Top 5 most important states in terms of exports for Soybean_meal', for
plt.ylabel('Quantity', fontsize=14)
plt.xlabel('States', fontsize=14)
plt.legend(['Quantity'], fontsize=14)
plt.show()
```



Soybeans

In [363]:
```
products_soybeans = train[train['type'] == 'Export'][['product','state']]
products_soybean_state = pd.DataFrame(products_soybeans[products_soybeans['produc
```

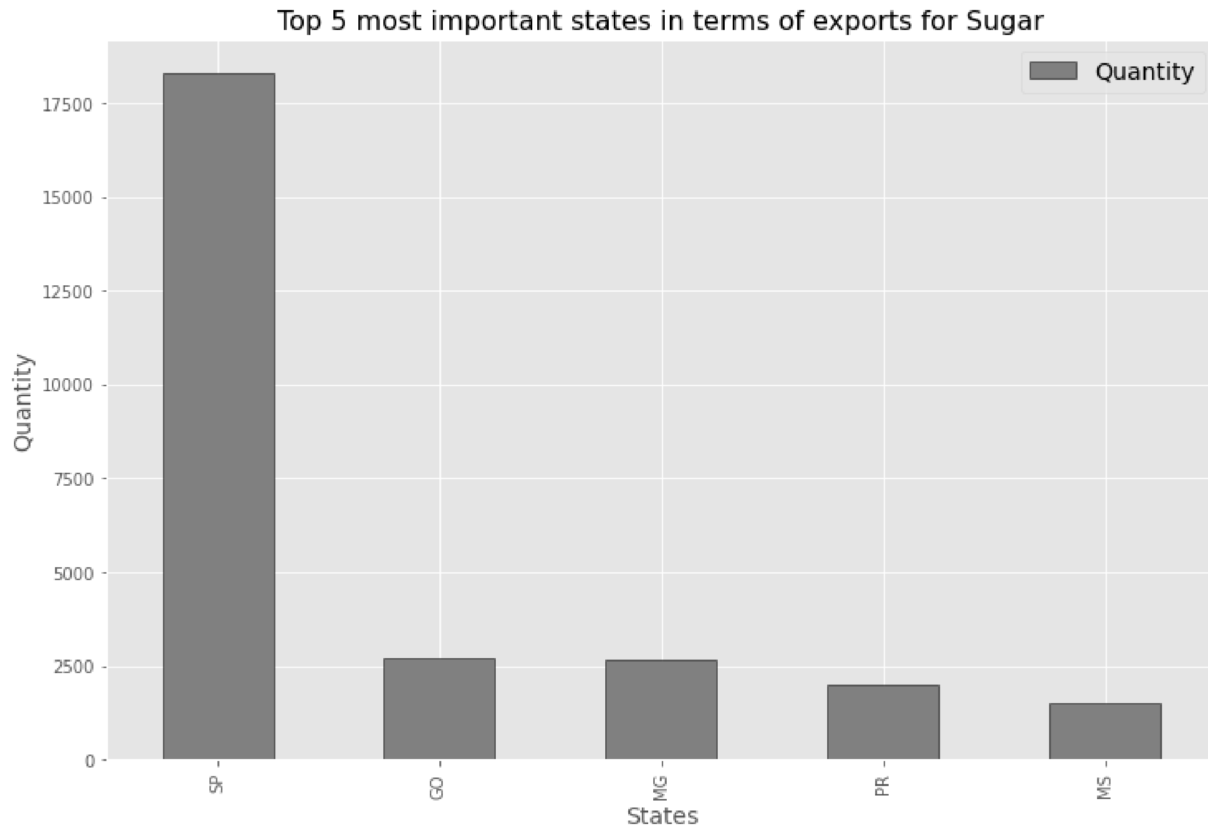
In [364]:
```
products_soybean_state.nlargest(5, 'state').plot(kind='bar', edgecolor='black', c
plt.title('Top 5 most important states in terms of exports for Soybeans', fontsiz
plt.ylabel('Quantity', fontsize=14)
plt.xlabel('States', fontsize=14)
plt.legend(['Quantity'], fontsize=14)
plt.show()
```



Sugar

In [365]:
```
products_sugar = train[train['type'] == 'Export'][['product','state']]
products_sugar_state = pd.DataFrame(products_sugar[products_sugar['product']=='su
```

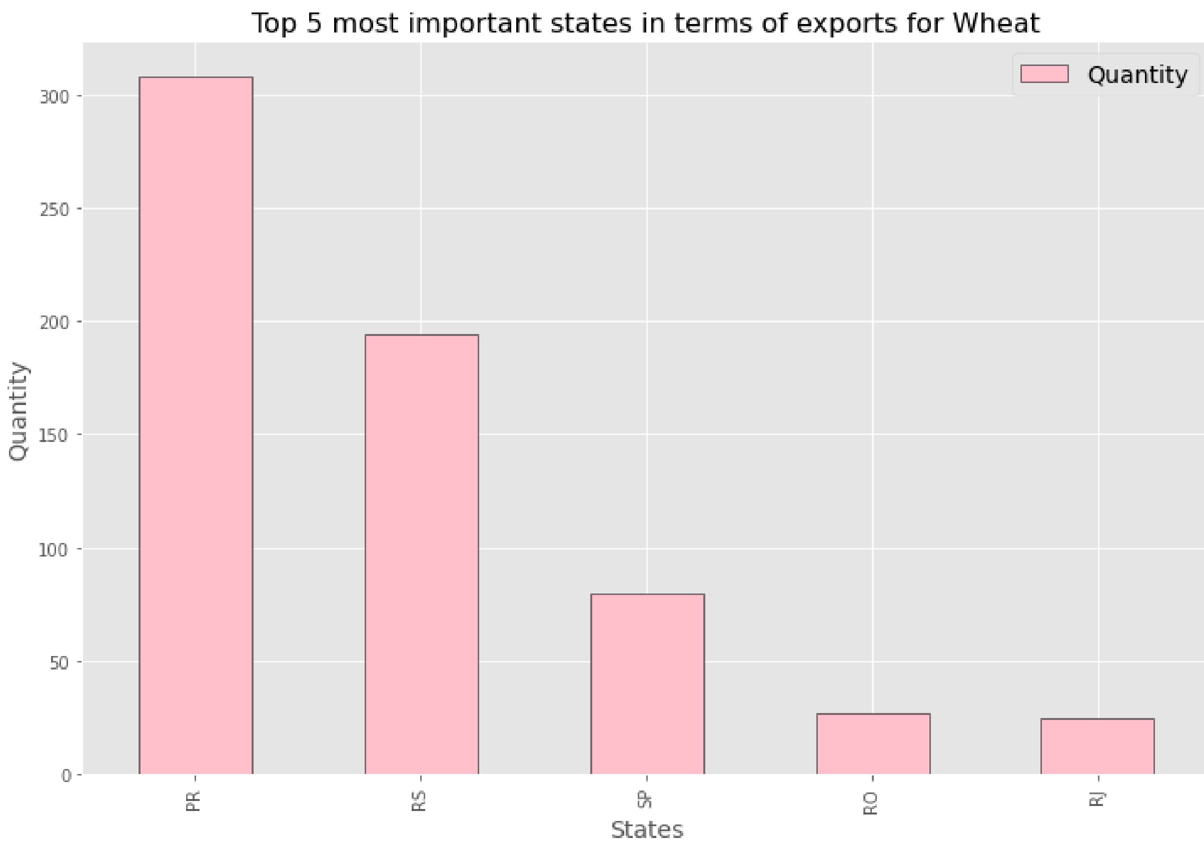
In [366]:
```
products_sugar_state.nlargest(5, 'state').plot(kind='bar', edgecolor='black', col
plt.title('Top 5 most important states in terms of exports for Sugar', fontsize=1
plt.ylabel('Quantity', fontsize=14)
plt.xlabel('States', fontsize=14)
plt.legend(['Quantity'], fontsize=14)
plt.show()
```



Wheat

In [367]:
```
products_wheat = train[train['type'] == 'Export'][['product','state']]
products_wheat_state = pd.DataFrame(products_wheat[products_wheat['product']=='wh
```

In [368]:
```
products_wheat_state.nlargest(5, 'state').plot(kind='bar', edgecolor='black', col
plt.title('Top 5 most important states in terms of exports for Wheat', fontsize=1
plt.ylabel('Quantity', fontsize=14)
plt.xlabel('States', fontsize=14)
plt.legend(['Quantity'], fontsize=14)
plt.show()
```



Multivariate analysis

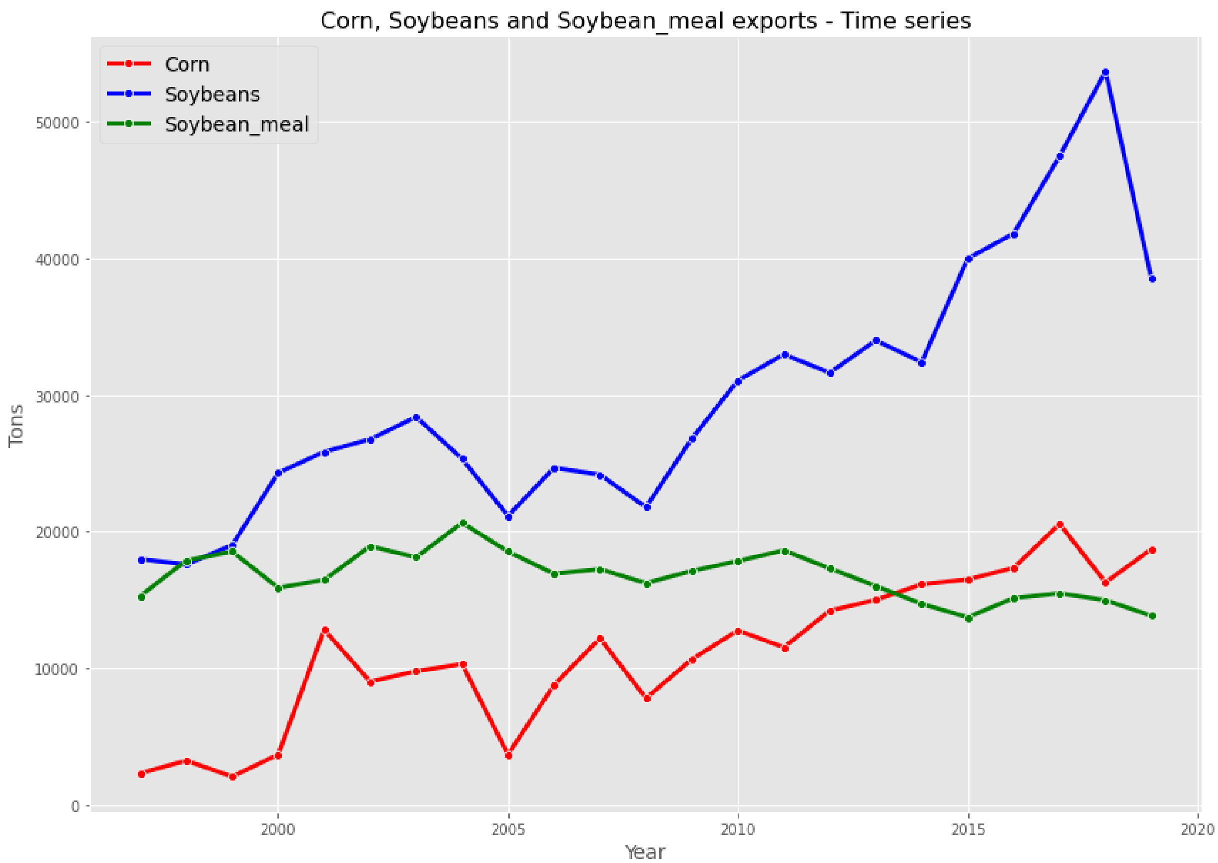
In [369]:
```
numeric_variables = train.select_dtypes(include = [np.number])
```

In [370]:
```
# calculates the correlations
correlations = numeric_variables.corr(method='pearson')

# uses the variable ax for single a Axes
fig, ax = plt.subplots()

# sets the figure size in inches
ax.figure.set_size_inches(12, 10)

# generates a mask for the upper triangle
mask = np.triu(np.ones_like(correlations, dtype=np.bool))

# generates a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# plots the heatmap
sns.heatmap(correlations, cmap="crest", mask=mask, linewidths=.5, annot=True)
plt.title('Correlations', fontsize=16)

# displays the plot
plt.show()
```

In [ ]:

In [371]:
```
corn = train[train['product'] == 'corn'][['year', 'tons']]
soybeans = train[train['product'] == 'soybeans'][['year', 'tons']]
soybean_meal = train[train['product'] == 'soybean_meal'][['year', 'tons']]
```

In [372]:
```
plt.figure(figsize=(14,10))
sns.lineplot(x='year', y='tons', data=corn, marker='o', linewidth=3, ci=None, col
sns.lineplot(x='year', y='tons', data=soybeans, marker='o', linewidth=3, ci=None,
sns.lineplot(x='year', y='tons', data=soybean_meal, marker='o', linewidth=3, ci=N
plt.title('Corn, Soybeans and Soybean_meal exports - Time series', fontsize=16)
plt.legend(['Corn', 'Soybeans', 'Soybean_meal'], fontsize=14)
plt.xlabel('Year', fontsize=14)
plt.ylabel('Tons', fontsize=14)
plt.grid(True)
plt.show()
```

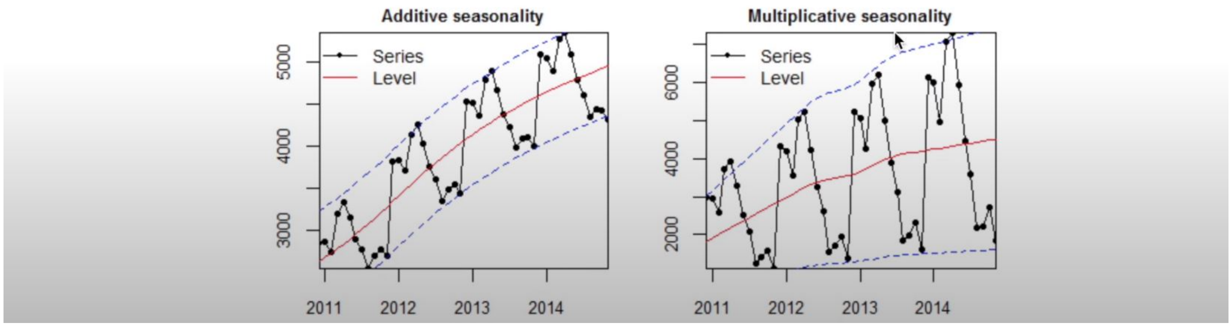


- Checking trend and seasonality

In [ ]:

Additive or Multiplicative Decomposition?

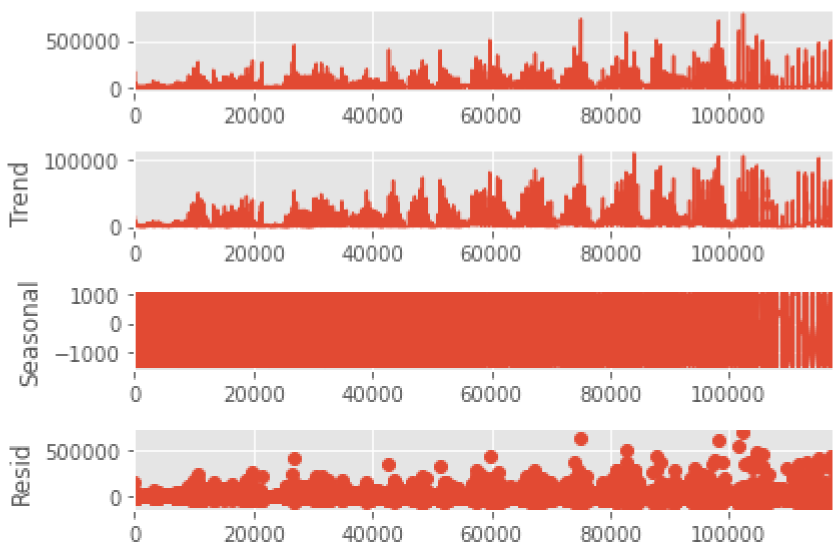
To achieve successful decomposition, it is important to choose between the additive and multiplicative models, which requires analyzing the series. For example, does the magnitude of the seasonality increase when the time series increases?



Corn

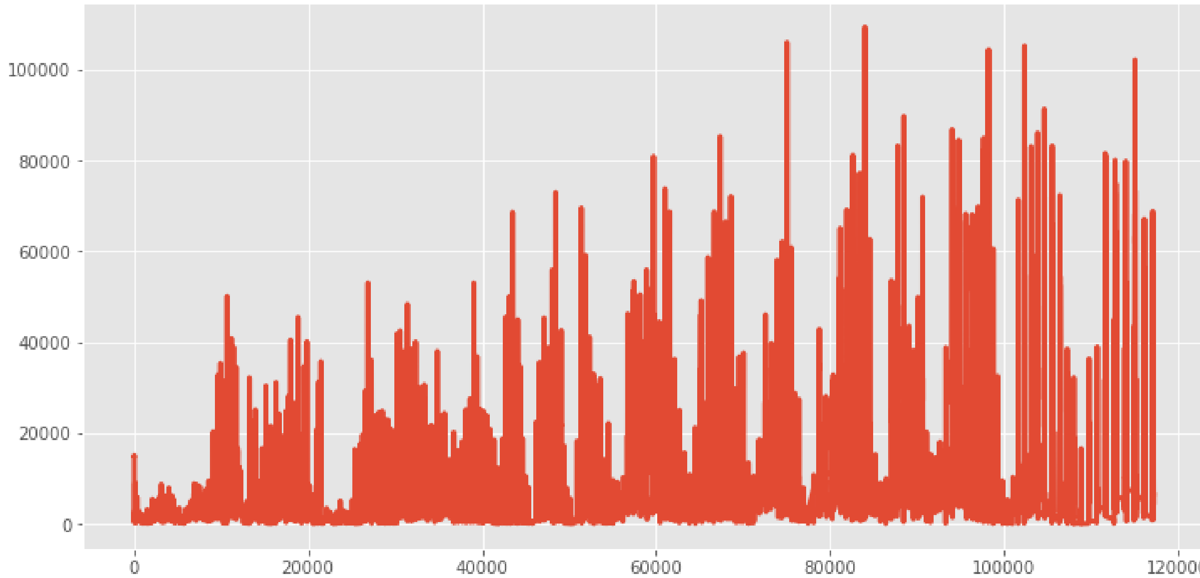
In [373]:
```python
from statsmodels.tsa.seasonal import seasonal_decompose
```

In [374]:
```python
corn_ts = seasonal_decompose(train[train['product'] == 'corn'][['tons']], model='
corn_ts.plot()
plt.show()
```



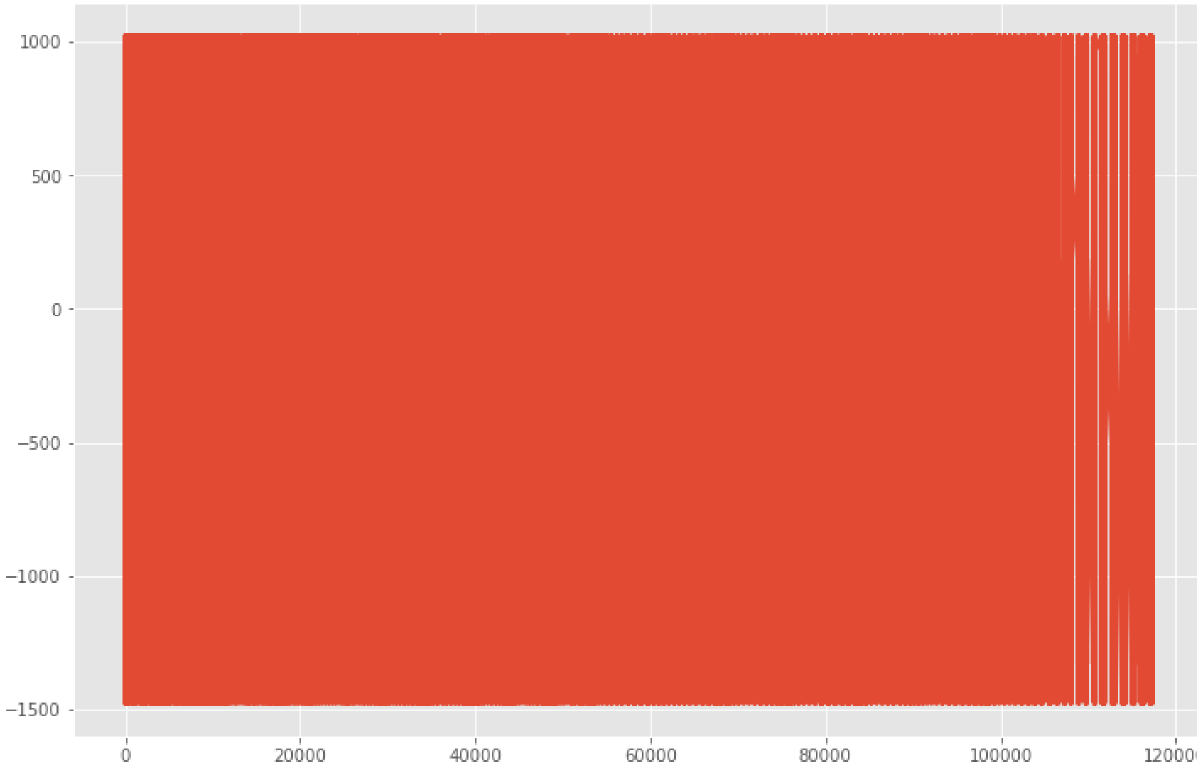
In [375]:
```
corn_ts.trend.plot(figsize=(12,6), linewidth=3)
```

Out[375]: <AxesSubplot:>



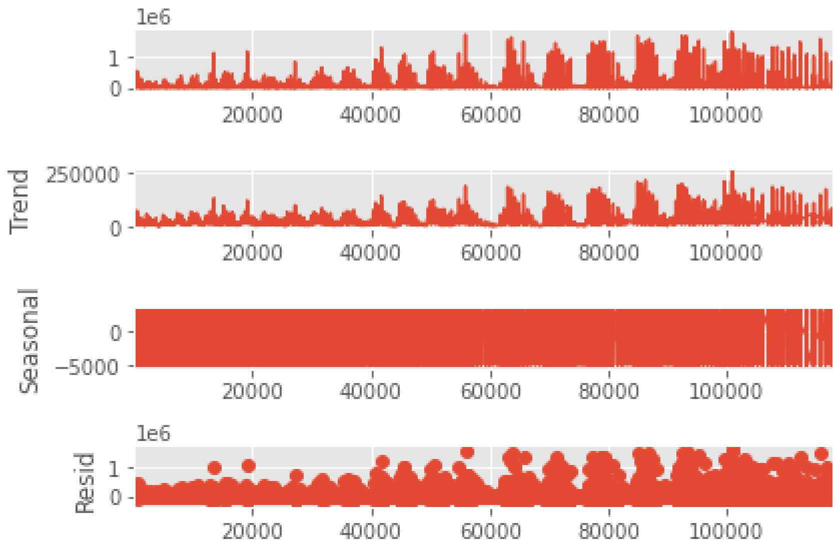
In [376]:
```
corn_ts.seasonal.plot(figsize=(12,8), linewidth=3)
```

Out[376]: <AxesSubplot:>



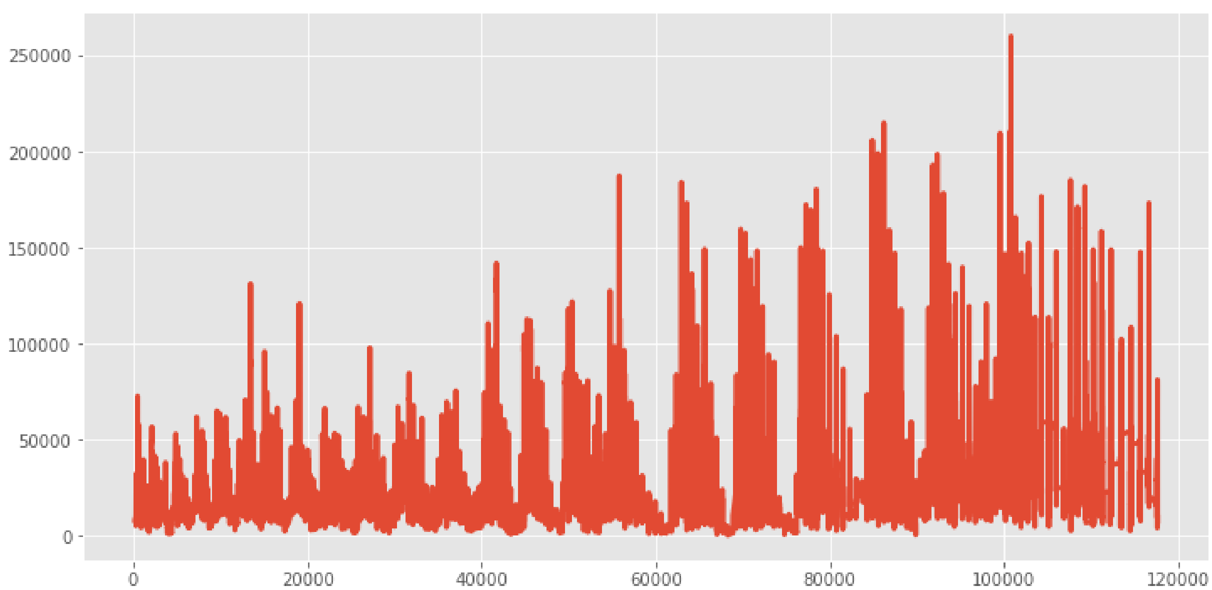
Soybeans

In [377]:
```
soybeans_ts = seasonal_decompose(train[train['product'] == 'soybeans'][['tons']],
soybeans_ts.plot()
plt.show()
```



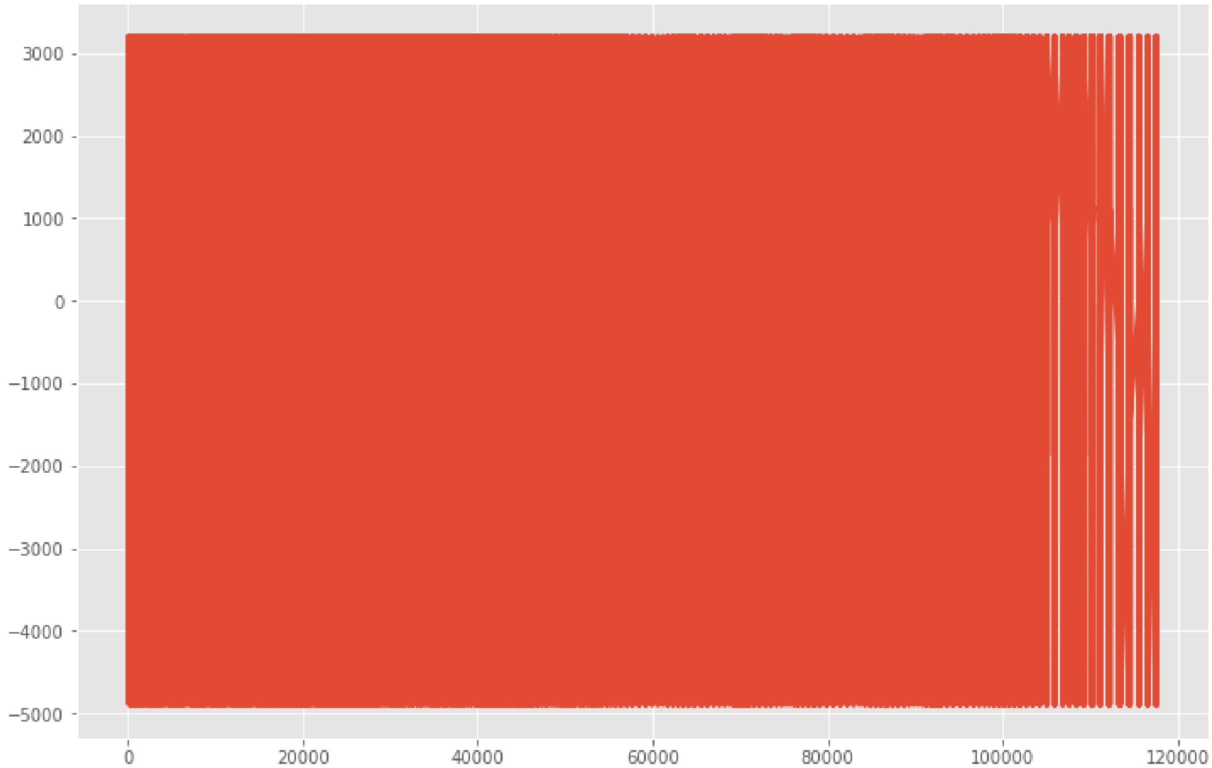
In [378]:
```
soybeans_ts.trend.plot(figsize=(12,6), linewidth=3)
```

Out[378]: <AxesSubplot:>



In [379]:
```
soybeans_ts.seasonal.plot(figsize=(12,8), linewidth=3)
```

Out[379]: <AxesSubplot:>

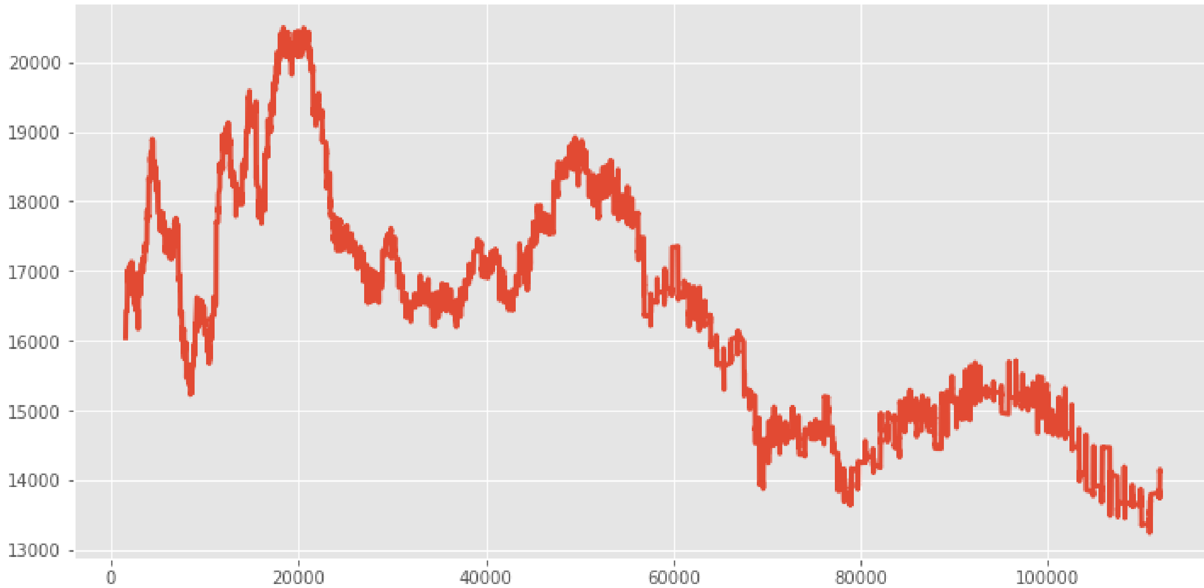


Soybean_meal

In [380]:
```
soybean_meal_ts = seasonal_decompose(train[train['product'] == 'soybean_meal'][['
soybean_meal_ts.plot()
plt.show()
```

In [381]:
```
soybean_meal_ts.trend.plot(figsize=(12,6), linewidth=3)
```

Out[381]: <AxesSubplot:>



In [382]:
```
soybean_meal_ts.seasonal.plot(figsize=(12,8), linewidth=3)
```

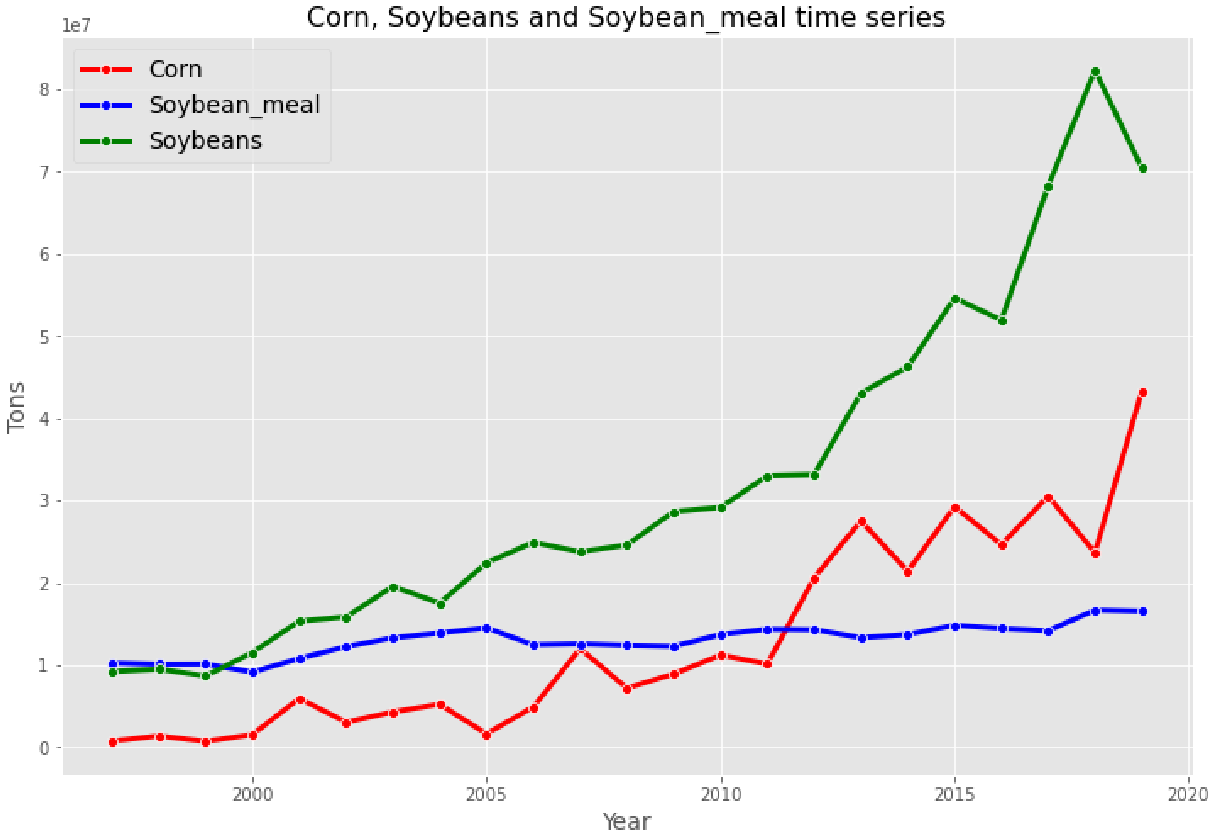
Out[382]: <AxesSubplot:>

There is no trend and seasonality

7.0 Data preparation

In [383]:
```
corn_year = corn.groupby('year').sum()
soybeans_year = soybeans.groupby('year').sum()
soybean_meal_year = soybean_meal.groupby('year').sum()
```

In [384]:
```
plt.figure(figsize=(12,8))

sns.lineplot(x='year', y='tons', data=corn_year, marker='o', linewidth=3, ci=None
sns.lineplot(x='year', y='tons', data=soybean_meal_year, marker='o', linewidth=3,
sns.lineplot(x='year', y='tons', data=soybeans_year, marker='o', linewidth=3, ci=


plt.title('Corn, Soybeans and Soybean_meal time series', fontsize=16)
plt.ylabel('Tons', fontsize=14)
plt.xlabel('Year', fontsize=14)
plt.legend(['Corn', 'Soybean_meal', 'Soybeans'], fontsize=14)
plt.show()
```



8.0 Data preprocessing

In [385]:
```
train_corn_year = corn_year[:12]
test_corn_year = corn_year[12:]
train_soybeans_year = soybeans_year[:12]
test_soybeans_year = soybeans_year[12:]
train_soybean_meal_year = soybean_meal_year[:12]
test_soybean_meal_year = soybean_meal_year[12:]
```

9.0 Machine learning modeling

Corn time series

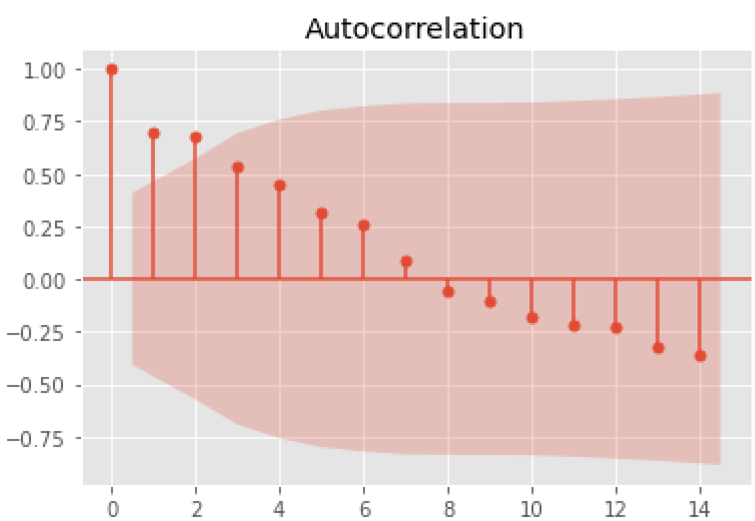
Arima

In [386]:
```
from statsmodels.tsa.stattools import adfuller
```

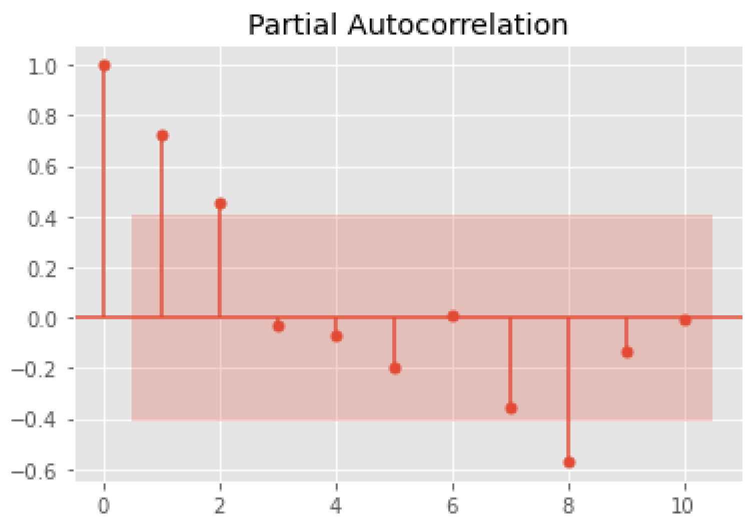
In [387]:
```
X = corn_year
result = adfuller(X)
result
print('ADF Statistics: %f' % result[0])
print('P value: %f' % result[1])
print('Critical values: ')

for key, value in result[4].items():
    print('\t%s: %.3f' % (key, value))

# If p>0.05 - Time series is not stationary
```

```
ADF Statistics: -0.728732
P value: 0.839166
Critical values:
	1%: -3.964
	5%: -3.085
	10%: -2.682
```

In [388]:
```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
plot_acf(corn_year)
plt.show()
```



In [389]:
```
plot_pacf(corn_year, lags=10)
plt.show()
```



In [390]:
```
from pmdarima.arima import auto_arima
```

In [391]:
```
stepwise_model = auto_arima(corn_year, start_p=1, start_q=1, max_p=40, max_q=40,
```

```
 ARIMA(0,1,0)(0,0,0)[1] intercept   : AIC=753.399, Time=0.01 sec
 ARIMA(0,1,1)(0,0,0)[1] intercept   : AIC=754.963, Time=0.01 sec
 ARIMA(0,1,2)(0,0,0)[1] intercept   : AIC=753.907, Time=0.02 sec
 ARIMA(0,1,3)(0,0,0)[1] intercept   : AIC=758.844, Time=0.07 sec
 ARIMA(0,1,4)(0,0,0)[1] intercept   : AIC=767.165, Time=0.04 sec
 ARIMA(0,1,5)(0,0,0)[1] intercept   : AIC=inf, Time=0.16 sec
 ARIMA(1,1,0)(0,0,0)[1] intercept   : AIC=746.306, Time=0.01 sec
 ARIMA(1,1,1)(0,0,0)[1] intercept   : AIC=748.687, Time=0.03 sec
 ARIMA(1,1,2)(0,0,0)[1] intercept   : AIC=751.043, Time=0.08 sec
 ARIMA(1,1,3)(0,0,0)[1] intercept   : AIC=754.510, Time=0.07 sec
 ARIMA(1,1,4)(0,0,0)[1] intercept   : AIC=inf, Time=0.17 sec
 ARIMA(2,1,0)(0,0,0)[1] intercept   : AIC=748.185, Time=0.02 sec
 ARIMA(2,1,1)(0,0,0)[1] intercept   : AIC=750.256, Time=0.08 sec
 ARIMA(2,1,2)(0,0,0)[1] intercept   : AIC=inf, Time=0.10 sec
 ARIMA(2,1,3)(0,0,0)[1] intercept   : AIC=753.526, Time=0.15 sec
 ARIMA(3,1,0)(0,0,0)[1] intercept   : AIC=749.882, Time=0.03 sec
 ARIMA(3,1,1)(0,0,0)[1] intercept   : AIC=751.516, Time=0.08 sec
 ARIMA(3,1,2)(0,0,0)[1] intercept   : AIC=755.366, Time=0.15 sec
 ARIMA(4,1,0)(0,0,0)[1] intercept   : AIC=751.744, Time=0.06 sec
 ARIMA(4,1,1)(0,0,0)[1] intercept   : AIC=753.298, Time=0.12 sec
 ARIMA(5,1,0)(0,0,0)[1] intercept   : AIC=inf, Time=0.13 sec

Best model:  ARIMA(1,1,0)(0,0,0)[1] intercept
Total fit time: 1.598 seconds
```

In [392]:
```
print(stepwise_model.aic())
```

```
746.3056290411395
```

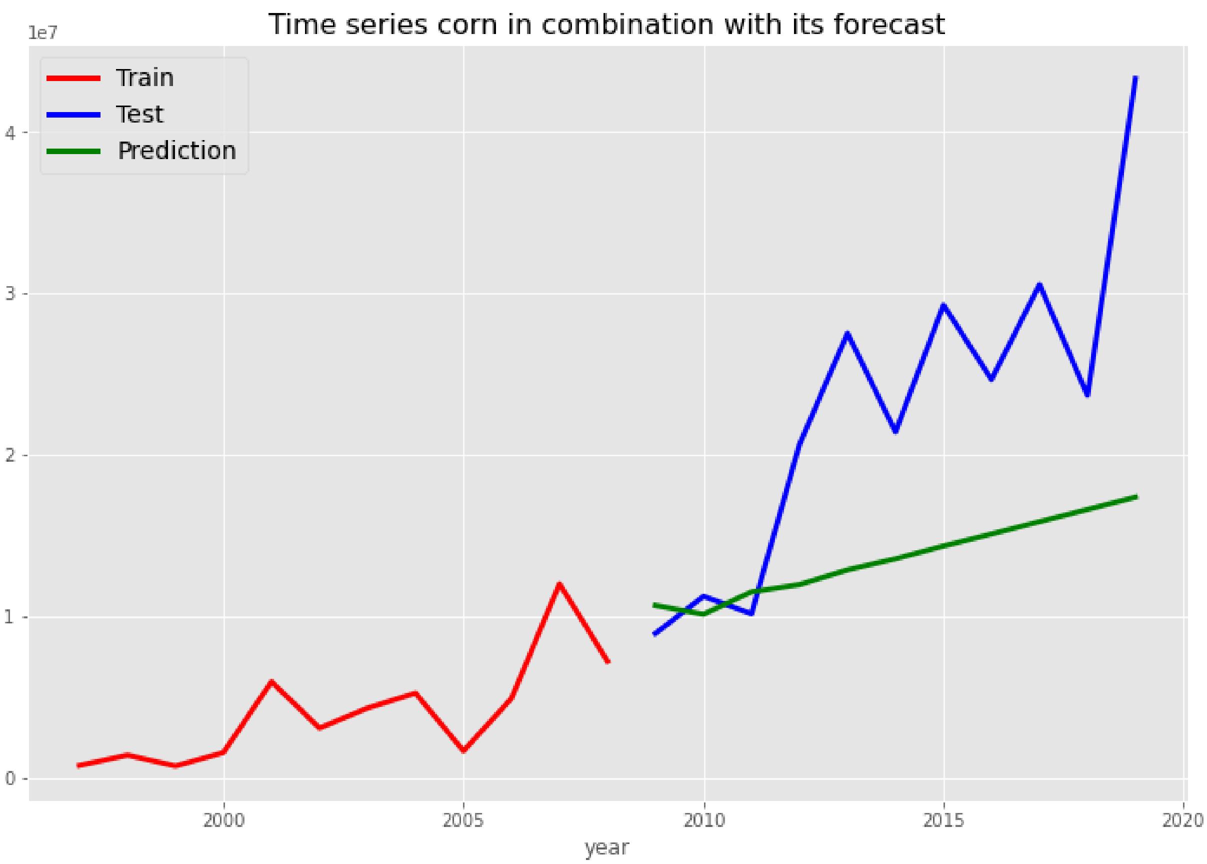
In [393]:
```
stepwise_model.fit(train_corn_year)
```

Out[393]:
```
ARIMA(order=(1, 1, 0), scoring_args={}, seasonal_order=(0, 0, 0, 1),
      suppress_warnings=True)
```

In [394]:
```
future_forecast = stepwise_model.predict(n_periods=11)
```

In [395]:
```
new_future_forecast = pd.DataFrame(future_forecast, index = test_corn_year.index,
```

In [396]:
```
plt.figure(figsize=(12,8))
train_corn_year['tons'].plot(linewidth=3, color='red')
test_corn_year['tons'].plot(linewidth=3, color='blue')
new_future_forecast['tons'].plot(linewidth=3, color='green')

plt.title('Time series corn in combination with its forecast', fontsize=16)
plt.legend(['Train', 'Test', 'Prediction'], fontsize=14)

plt.show()
```



In [397]:
```
years = range(2020,2031)
```

In [398]:
```
from sklearn.metrics import mean_squared_error, mean_absolute_error
```

In [399]:
```
mean_absolute_error(test_corn_year['tons'], new_future_forecast['tons'])
```

Out[399]:
```
9782996.104442842
```

In [400]:
```
np.sqrt(mean_squared_error(test_corn_year['tons'], new_future_forecast['tons']))
```

Out[400]:
```
12102143.314376611
```

In [401]:
```
stepwise_model.fit(corn_year)
```

Out[401]:
```
ARIMA(order=(1, 1, 0), scoring_args={}, seasonal_order=(0, 0, 0, 1),
      suppress_warnings=True)
```

In [402]:
```
future_forecast = stepwise_model.predict(n_periods=11)
```

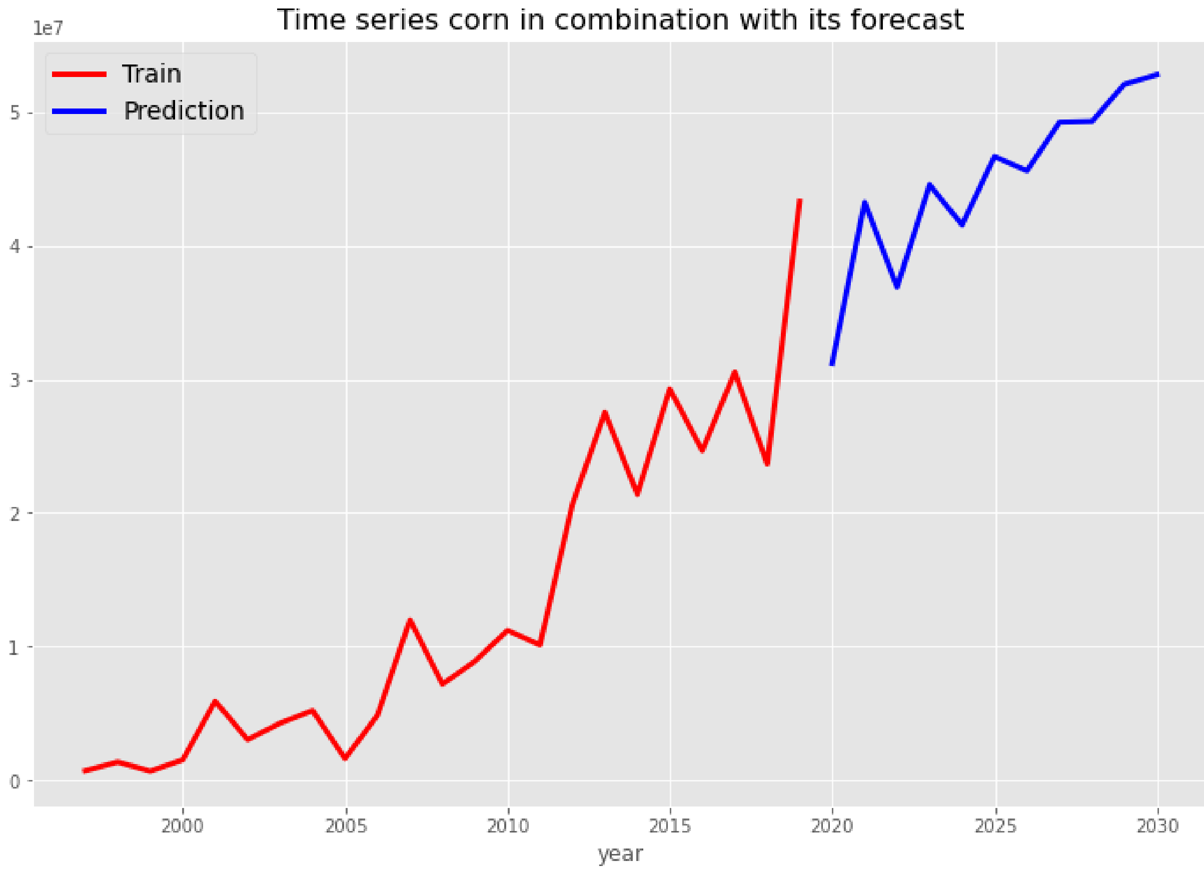
- Corn forecast for next 11 years

In [403]:
```
new_future_forecast_corn = pd.DataFrame(future_forecast, index = years, columns=[
new_future_forecast_corn
```

Out[403]:

	tons_corn
2020	3.118020e+07
2021	4.322437e+07
2022	3.688005e+07
2023	4.453387e+07
2024	4.153168e+07
2025	4.664132e+07
2026	4.557588e+07
2027	4.921118e+07
2028	4.926807e+07
2029	5.204901e+07
2030	5.275628e+07

In [404]:
```
plt.figure(figsize=(12,8))
corn_year['tons'].plot(linewidth=3, color='red')
new_future_forecast_corn['tons_corn'].plot(linewidth=3, color='blue')
plt.title('Time series corn in combination with its forecast', fontsize=16)
plt.legend(['Train', 'Prediction'], fontsize=14)

plt.show()
```

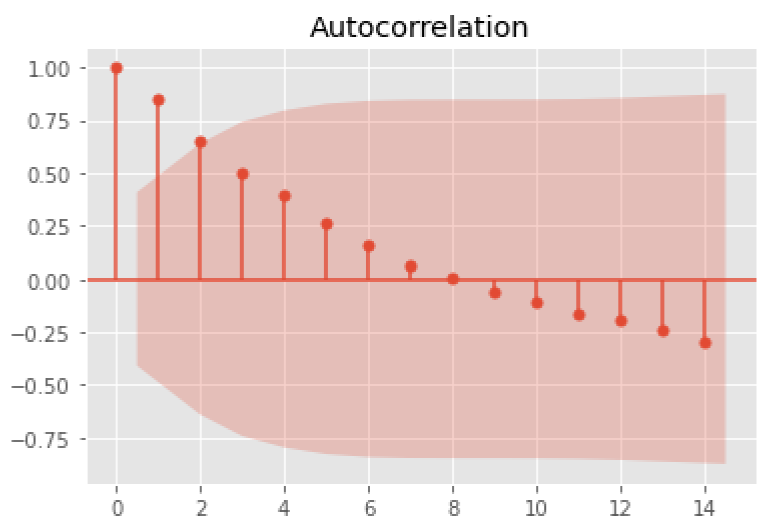


Soybeans time series

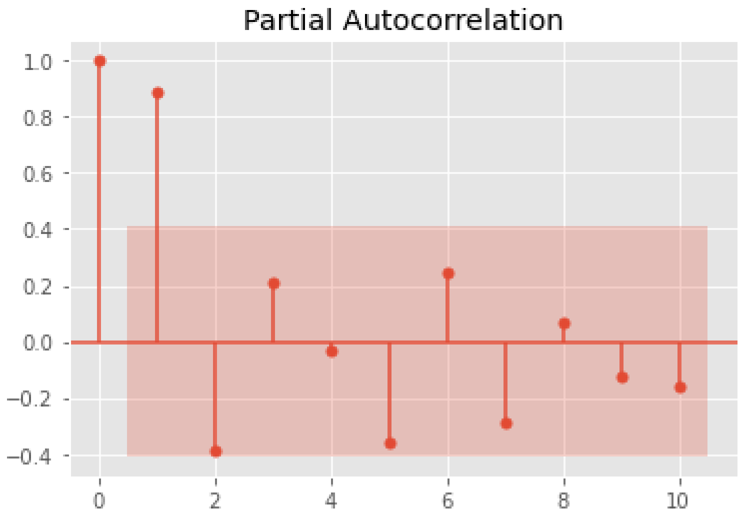
In [405]:
```
X_soybeans = soybeans_year
result = adfuller(X_soybeans)
result
print('ADF Statistics: %f' % result[0])
print('P value: %f' % result[1])
print('Critical values: ')

for key, value in result[4].items():
    print('\t%s: %.3f' % (key, value))

# If p>0.05 - Time series is not stationary
```

```
ADF Statistics: 1.221751
P value: 0.996133
Critical values:
	1%: -4.069
	5%: -3.127
	10%: -2.702
```

In [406]:
```
plot_acf(soybeans_year)
plt.show()
```



In [407]:
```
plot_pacf(soybeans_year, lags=10)
plt.show()
```



In [408]:
```
stepwise_model_soybeans = auto_arima(soybeans_year, start_p=1, start_q=1, max_p=4
```

```
 ARIMA(0,1,0)(0,0,0)[1] intercept   : AIC=751.239, Time=0.01 sec
 ARIMA(0,1,1)(0,0,0)[1] intercept   : AIC=753.510, Time=0.02 sec
 ARIMA(0,1,2)(0,0,0)[1] intercept   : AIC=751.045, Time=0.04 sec
 ARIMA(0,1,3)(0,0,0)[1] intercept   : AIC=inf, Time=0.06 sec
 ARIMA(0,1,4)(0,0,0)[1] intercept   : AIC=inf, Time=0.13 sec
 ARIMA(0,1,5)(0,0,0)[1] intercept   : AIC=inf, Time=0.24 sec
 ARIMA(1,1,0)(0,0,0)[1] intercept   : AIC=751.757, Time=0.01 sec
 ARIMA(1,1,1)(0,0,0)[1] intercept   : AIC=754.196, Time=0.06 sec
 ARIMA(1,1,2)(0,0,0)[1] intercept   : AIC=750.948, Time=0.06 sec
 ARIMA(1,1,3)(0,0,0)[1] intercept   : AIC=inf, Time=0.15 sec
 ARIMA(1,1,4)(0,0,0)[1] intercept   : AIC=inf, Time=0.13 sec
 ARIMA(2,1,0)(0,0,0)[1] intercept   : AIC=752.049, Time=0.02 sec
 ARIMA(2,1,1)(0,0,0)[1] intercept   : AIC=754.376, Time=0.03 sec
 ARIMA(2,1,2)(0,0,0)[1] intercept   : AIC=751.843, Time=0.05 sec
 ARIMA(2,1,3)(0,0,0)[1] intercept   : AIC=inf, Time=0.18 sec
 ARIMA(3,1,0)(0,0,0)[1] intercept   : AIC=753.507, Time=0.03 sec
 ARIMA(3,1,1)(0,0,0)[1] intercept   : AIC=755.432, Time=0.03 sec
 ARIMA(3,1,2)(0,0,0)[1] intercept   : AIC=749.643, Time=0.08 sec
 ARIMA(4,1,0)(0,0,0)[1] intercept   : AIC=753.182, Time=0.03 sec
 ARIMA(4,1,1)(0,0,0)[1] intercept   : AIC=754.688, Time=0.04 sec
 ARIMA(5,1,0)(0,0,0)[1] intercept   : AIC=753.741, Time=0.05 sec

Best model:  ARIMA(3,1,2)(0,0,0)[1] intercept
Total fit time: 1.492 seconds
```

In [409]:
```
print(stepwise_model_soybeans.aic())
```

```
749.6432949260573
```

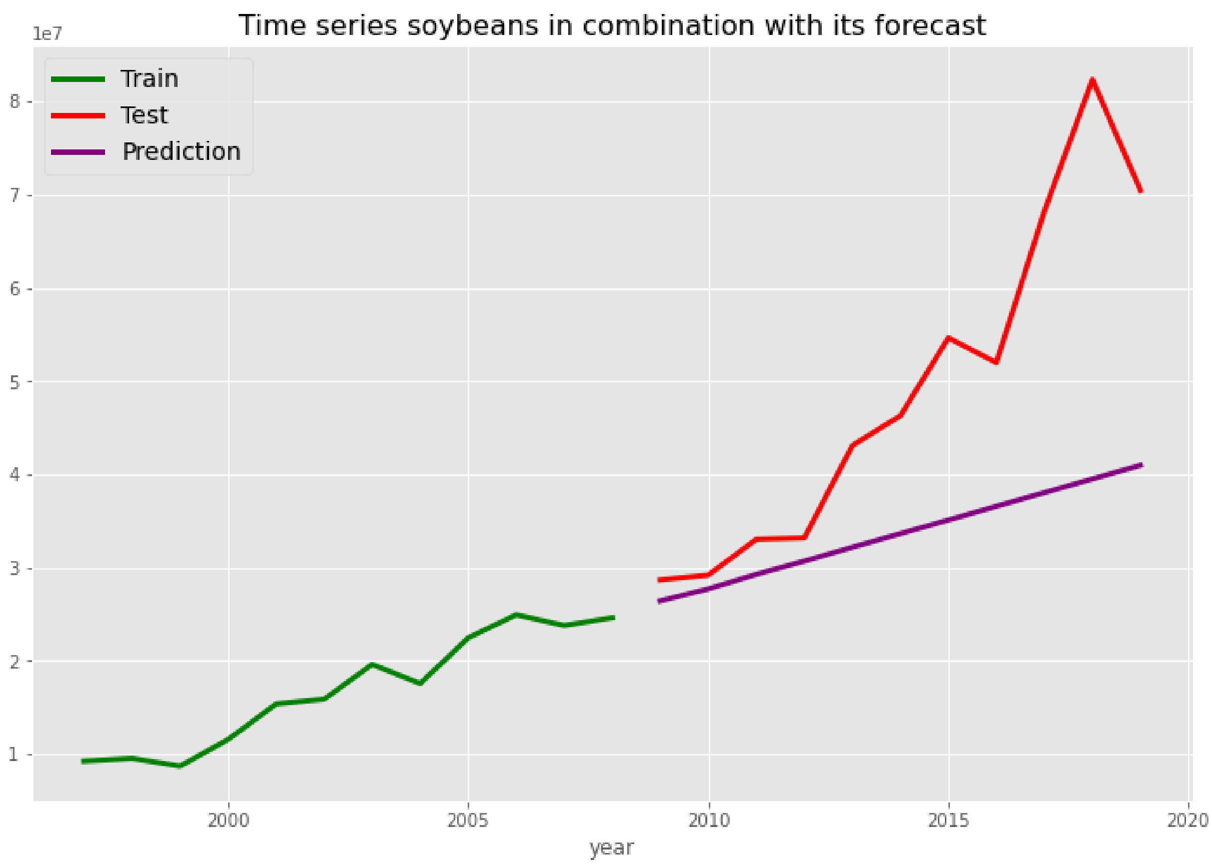
In [410]:
```
stepwise_model_soybeans.fit(train_soybeans_year)
```

Out[410]:
```
ARIMA(order=(3, 1, 2), scoring_args={}, seasonal_order=(0, 0, 0, 1),
      suppress_warnings=True)
```

In [411]:
```
future_forecast_soybeans = stepwise_model_soybeans.predict(n_periods=11)
```

In [412]:
```
new_future_forecast_soybeans = pd.DataFrame(future_forecast_soybeans, index = tes
```

In [413]:
```
plt.figure(figsize=(12,8))
train_soybeans_year['tons'].plot(linewidth=3, color='green')
test_soybeans_year['tons'].plot(linewidth=3, color='red')
new_future_forecast_soybeans['tons'].plot(linewidth=3, color='purple')

plt.title('Time series soybeans in combination with its forecast', fontsize=16)
plt.legend(['Train', 'Test', 'Prediction'], fontsize=14)

plt.show()
```



In [414]:
```
mean_absolute_error(test_soybeans_year['tons'], new_future_forecast_soybeans['tor
```

Out[414]:
```
15553525.600607552
```

In [415]:
```
np.sqrt(mean_squared_error(test_soybeans_year['tons'], new_future_forecast_soybea
```

Out[415]:
```
20329348.821357563
```

In [416]:
```
stepwise_model.fit(soybeans_year)
```

Out[416]:
```
ARIMA(order=(1, 1, 0), scoring_args={}, seasonal_order=(0, 0, 0, 1),
      suppress_warnings=True)
```

In [417]:
```
future_forecast_soybeans = stepwise_model.predict(n_periods=11)
```

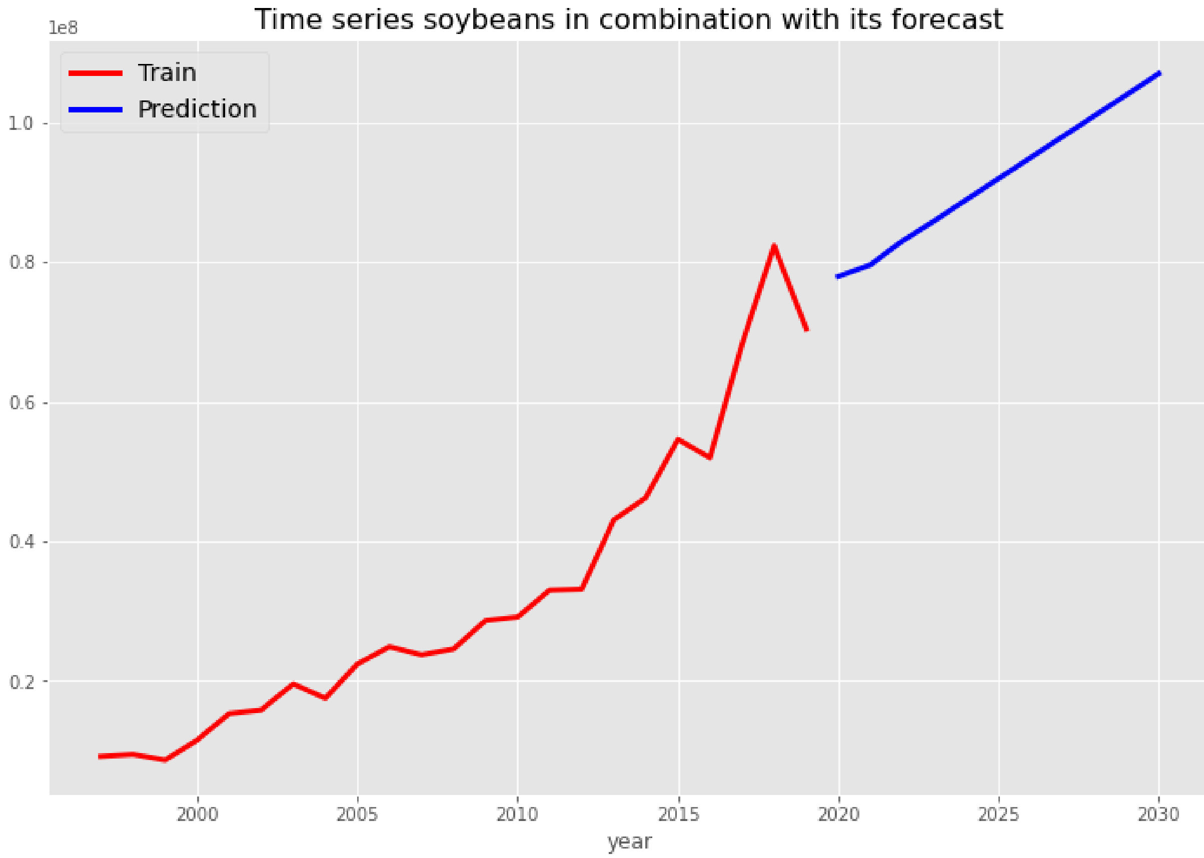
Soybeans forecast for next 11 years

In [418]:
```
new_future_forecast_soybeans = pd.DataFrame(future_forecast_soybeans, index = yea
new_future_forecast_soybeans
```

Out[418]:

	tons_soybeans
2020	7.793665e+07
2021	7.959537e+07
2022	8.300983e+07
2023	8.589586e+07
2024	8.894093e+07
2025	9.193813e+07
2026	9.494974e+07
2027	9.795702e+07
2028	1.009656e+08
2029	1.039738e+08
2030	1.069821e+08

In [419]:
```
plt.figure(figsize=(12,8))
soybeans_year['tons'].plot(linewidth=3, color='red')
new_future_forecast_soybeans['tons_soybeans'].plot(linewidth=3, color='blue')
plt.title('Time series soybeans in combination with its forecast', fontsize=16)
plt.legend(['Train', 'Prediction'], fontsize=14)

plt.show()
```

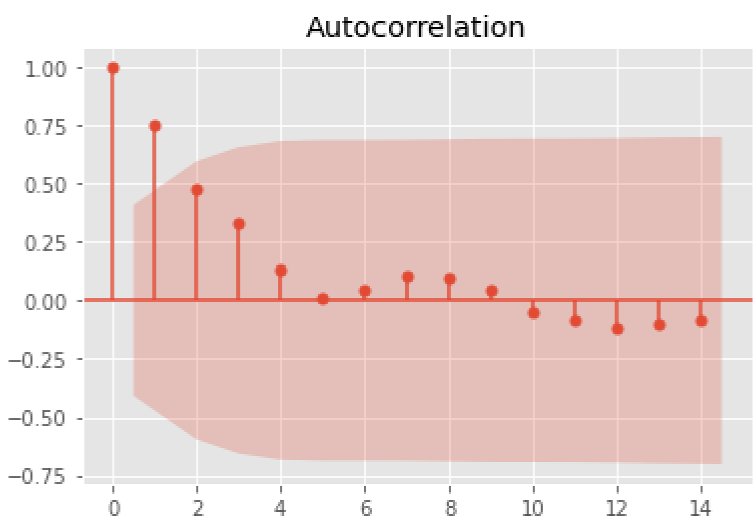


Soybean_meal

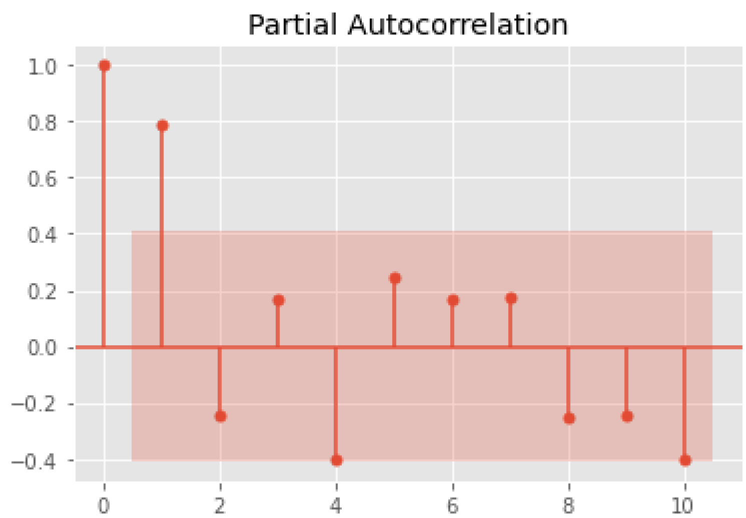
In [420]:
```
X_soybean_meal = soybean_meal_year
result = adfuller(X_soybean_meal)
result
print('ADF Statistics: %f' % result[0])
print('P value: %f' % result[1])
print('Critical values: ')

for key, value in result[4].items():
    print('\t%s: %.3f' % (key, value))

# If p>0.05 - Time series is not stationary
```

```
ADF Statistics: -0.969932
P value: 0.764072
Critical values:
        1%: -3.770
        5%: -3.005
        10%: -2.643
```

In [421]:
```
plot_acf(soybean_meal_year)
plt.show()
```



In [422]:
```
plot_pacf(soybean_meal_year, lags=10)
plt.show()
```



In [423]:
```
stepwise_model_soybean_meal = auto_arima(soybean_meal_year, start_p=1, start_q=1,
```

```
 ARIMA(0,1,0)(0,0,0)[1] intercept   : AIC=673.567, Time=0.01 sec
 ARIMA(0,1,1)(0,0,0)[1] intercept   : AIC=675.564, Time=0.01 sec
 ARIMA(0,1,2)(0,0,0)[1] intercept   : AIC=676.840, Time=0.02 sec
 ARIMA(0,1,3)(0,0,0)[1] intercept   : AIC=678.257, Time=0.02 sec
 ARIMA(0,1,4)(0,0,0)[1] intercept   : AIC=682.023, Time=0.03 sec
 ARIMA(0,1,5)(0,0,0)[1] intercept   : AIC=inf, Time=0.16 sec
 ARIMA(1,1,0)(0,0,0)[1] intercept   : AIC=675.369, Time=0.01 sec
 ARIMA(1,1,1)(0,0,0)[1] intercept   : AIC=676.955, Time=0.04 sec
 ARIMA(1,1,2)(0,0,0)[1] intercept   : AIC=680.219, Time=0.04 sec
 ARIMA(1,1,3)(0,0,0)[1] intercept   : AIC=680.069, Time=0.07 sec
 ARIMA(1,1,4)(0,0,0)[1] intercept   : AIC=683.282, Time=0.06 sec
 ARIMA(2,1,0)(0,0,0)[1] intercept   : AIC=677.011, Time=0.02 sec
 ARIMA(2,1,1)(0,0,0)[1] intercept   : AIC=679.214, Time=0.04 sec
 ARIMA(2,1,2)(0,0,0)[1] intercept   : AIC=inf, Time=0.16 sec
 ARIMA(2,1,3)(0,0,0)[1] intercept   : AIC=inf, Time=0.17 sec
 ARIMA(3,1,0)(0,0,0)[1] intercept   : AIC=676.899, Time=0.02 sec
 ARIMA(3,1,1)(0,0,0)[1] intercept   : AIC=678.651, Time=0.05 sec
 ARIMA(3,1,2)(0,0,0)[1] intercept   : AIC=680.902, Time=0.11 sec
 ARIMA(4,1,0)(0,0,0)[1] intercept   : AIC=678.383, Time=0.02 sec
 ARIMA(4,1,1)(0,0,0)[1] intercept   : AIC=680.371, Time=0.06 sec
 ARIMA(5,1,0)(0,0,0)[1] intercept   : AIC=682.409, Time=0.03 sec

Best model:  ARIMA(0,1,0)(0,0,0)[1] intercept
Total fit time: 1.187 seconds
```

In [424]:
```
print(stepwise_model_soybean_meal.aic())
```

```
673.5667975081539
```

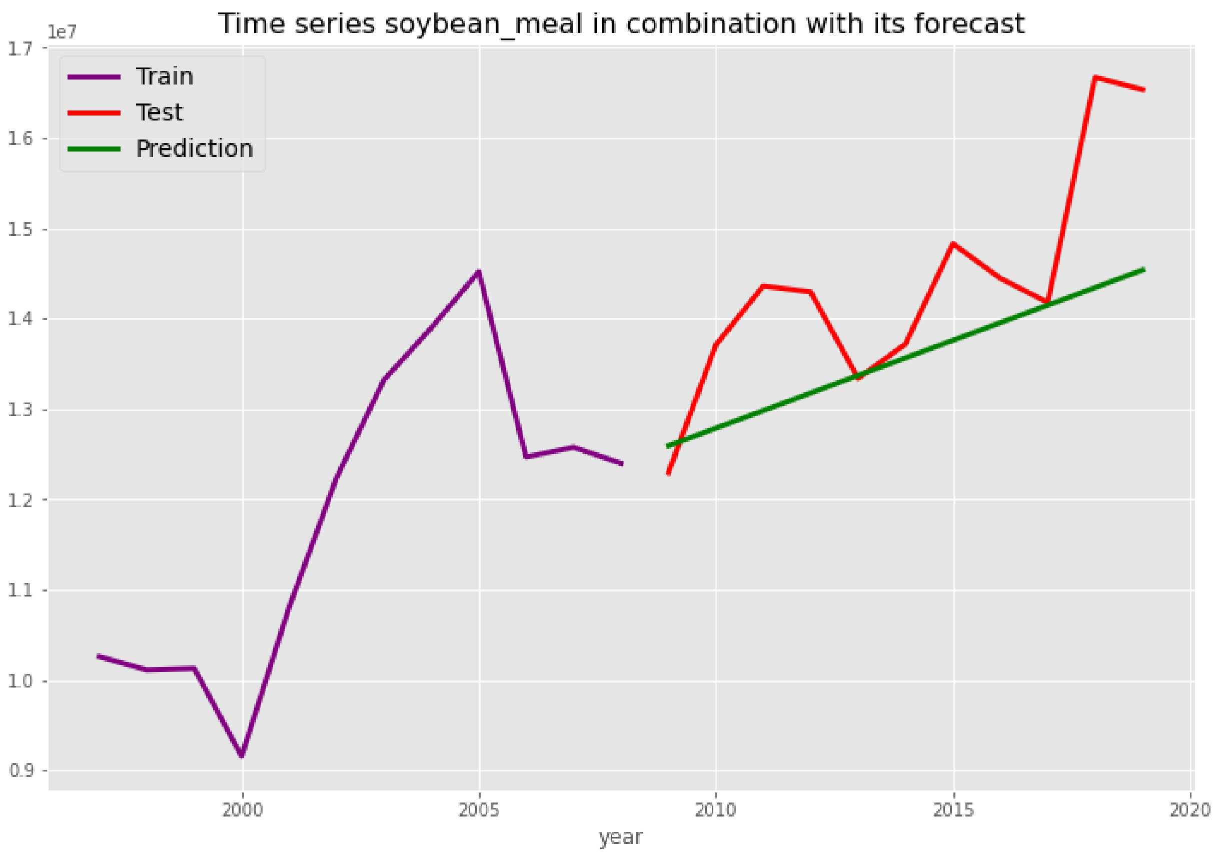
In [425]:
```
stepwise_model_soybean_meal.fit(train_soybean_meal_year)
```

Out[425]:
```
ARIMA(order=(0, 1, 0), scoring_args={}, seasonal_order=(0, 0, 0, 1),
      suppress_warnings=True)
```

In [426]:
```
future_forecast_soybean_meal = stepwise_model_soybean_meal.predict(n_periods=11)
```

In [427]:
```
new_future_forecast_soybean_meal = pd.DataFrame(future_forecast_soybean_meal, inc
```

In [428]:
```
plt.figure(figsize=(12,8))
train_soybean_meal_year['tons'].plot(linewidth=3, color='purple')
test_soybean_meal_year['tons'].plot(linewidth=3, color='red')
new_future_forecast_soybean_meal['tons'].plot(linewidth=3, color='green')

plt.title('Time series soybean_meal in combination with its forecast', fontsize=1
plt.legend(['Train', 'Test', 'Prediction'], fontsize=14)

plt.show()
```



In [429]:
```
mean_absolute_error(test_soybean_meal_year['tons'], new_future_forecast_soybean_m
```

Out[429]: 892713.3051157042

In [430]:
```
np.sqrt(mean_squared_error(test_soybean_meal_year['tons'], new_future_forecast_sc
```

Out[430]: 1164312.1626250916

In [431]:
```
stepwise_model.fit(soybean_meal_year)
```

Out[431]:
```
ARIMA(order=(1, 1, 0), scoring_args={}, seasonal_order=(0, 0, 0, 1),
      suppress_warnings=True)
```

In [432]:
```
future_forecast_soybean_meal = stepwise_model.predict(n_periods=11)
```

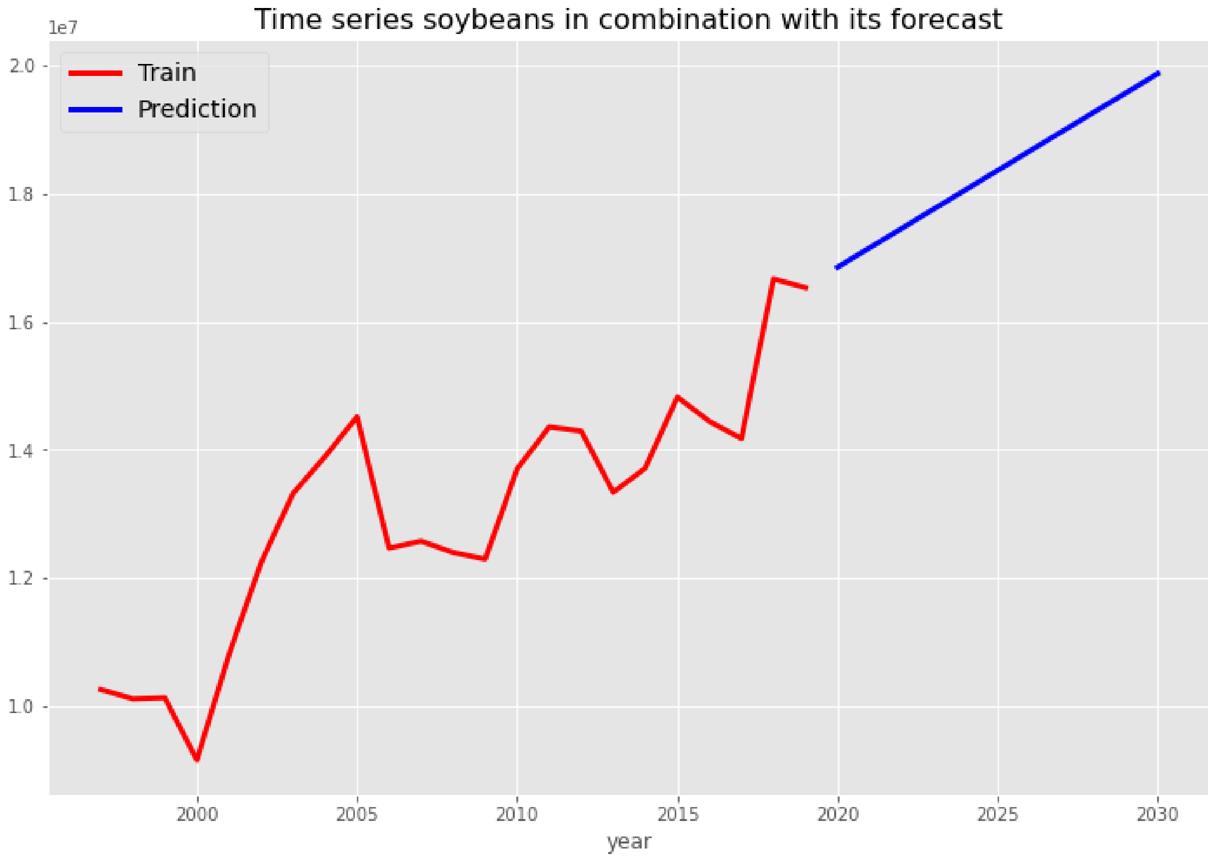
Soybean_meal forecast for next 11 years

In [433]:
```
new_future_forecast_soybean_meal = pd.DataFrame(future_forecast_soybean_meal, inc
new_future_forecast_soybean_meal
```

Out[433]:

	tons_soybean_meal
2020	1.685477e+07
2021	1.715644e+07
2022	1.745894e+07
2023	1.776141e+07
2024	1.806387e+07
2025	1.836634e+07
2026	1.866881e+07
2027	1.897128e+07
2028	1.927375e+07
2029	1.957622e+07
2030	1.987868e+07

In [434]:
```
plt.figure(figsize=(12,8))
soybean_meal_year['tons'].plot(linewidth=3, color='red')
new_future_forecast_soybean_meal['tons_soybean_meal'].plot(linewidth=3, color='bl
plt.title('Time series soybeans in combination with its forecast', fontsize=16)
plt.legend(['Train', 'Prediction'], fontsize=14)

plt.show()
```



10 Conclusion

In [435]:
```
summary = pd.concat([new_future_forecast_corn, new_future_forecast_soybeans, new_
```

In [437]:
```
print('PREDICTIONS IN TONS')

summary
```

```
PREDICTIONS IN TONS
```

Out[437]:

	Corn	tons_soybeans	Soybean_meal
2020	3.118020e+07	7.793665e+07	1.685477e+07
2021	4.322437e+07	7.959537e+07	1.715644e+07
2022	3.688005e+07	8.300983e+07	1.745894e+07
2023	4.453387e+07	8.589586e+07	1.776141e+07
2024	4.153168e+07	8.894093e+07	1.806387e+07
2025	4.664132e+07	9.193813e+07	1.836634e+07
2026	4.557588e+07	9.494974e+07	1.866881e+07
2027	4.921118e+07	9.795702e+07	1.897128e+07
2028	4.926807e+07	1.009656e+08	1.927375e+07
2029	5.204901e+07	1.039738e+08	1.957622e+07
2030	5.275628e+07	1.069821e+08	1.987868e+07

The predictions of the presented problem were made using the ARIMA model, considering the time series of the products did not present seasonality and trend, then the Holt Winters model was not used.

More complex models like LSTM were not used due to the short leadtime for delivering the test.

The main results in terms of data analysis were presented graphically, the maritime transport being the most used and this is due to the lower cost and great reach for deliveries in other continents.

Sugar is the most exported product and São Paulo is the state with the most exports. These are some of the findings made in the data analysis that is described throughout the notebook.

References

[https://alkaline-ml.com/pmdarima/0.9.0/modules/generated/pyramid.arima.auto_arima.html (https://alkaline-ml.com/pmdarima/0.9.0/modules/generated/pyramid.arima.auto_arima.html)](https://alkaline-ml.com/pmdarima/0.9.0/modules/generated/pyramid.arima.auto_arima.html)

[https://thenewstack.io/when-holt-winters-is-better-than-machine-learning/ (https://thenewstack.io/when-holt-winters-is-better-than-machine-learning/)](https://thenewstack.io/when-holt-winters-is-better-than-machine-learning/)

In [ ]: