Customer Insight Analyst/Marketing Analyst Project

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As a Customer Insight Analyst for Kernal Limited, I have been requested to carry out a detailed customer analysis on behalf of client to help explore and identify targeting opportunities to drive growth penetration for key products and market segments, however, the focus is to target high value propositions at the right audience from the campaign. In this scenario, a High Value Proposition is defined as a total basket value exceeding £1,500 (Market Basket Analysis).

Insight from the analysis will be used to determine consumer groups to be targeted for this campaign including new prospects as well as existing customers who fit the profile of high value target, but are not currently engaging or classified as high value based on their current transaction levels.

Kernal Limited needs to better understand both size of opportunity, identify treatment groups as well as make actionable recommendations for the groups.

Library

In [1]:
```
# Import all packages
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
%matplotlib inline
plt.style.use('ggplot')

import seaborn as sns
sns.set(style='darkgrid')

from datetime import datetime, timedelta
from functools import partial
to_datetime_fmt = partial(pd.to_datetime, format='%Y/%m/%d')
```

Gather Data

1. Customer csv file

In [2]:
```
# Use only the neccessary variables from 'dbo_dimcustomer.csv' tabl
e
cust_usecols = [
    'CustomerKey','GeographyKey','BirthDate','MaritalStatus',
    'Gender','YearlyIncome', 'TotalChildren',
    'EnglishEducation', 'EnglishOccupation', 'HouseOwnerFlag',
    'NumberCarsOwned', 'DateFirstPurchase', 'CommuteDistance'
]
```

In [3]:
```
# Import and read csv file into a dataframe that contains Customers
' information
cust = pd.read_csv('dbo_dimcustomer.csv', encoding='iso-8859-1', us
ecols=cust_usecols)
```

2. Product csv file

In [4]:
```
# Use only the neccessary variables from 'dbo_dimproduct.csv' table
product_usecols = [
    'ProductKey', 'ProductSubcategoryKey','EnglishProductName'
                  ]
```

In [5]:
```
# Import and read csv file into a dataframe that contains Product i
nformation
product = pd.read_csv('dbo_dimproduct.csv', encoding='iso-8859-1',
usecols=product_usecols)
```

3. Product Category csv file

In [6]:
```
# Use only the neccessary variables from 'dbo_dimproductcategory.cs
v' table
product_cat_usecols = ['ProductCategoryKey','EnglishProductCategory
Name']
```

In [7]:
```
# Import and read csv file into a dataframe that contains Product C
ategory information
product_cat = pd.read_csv('dbo_dimproductcategory.csv', usecols=pro
duct_cat_usecols)
```

4. Product SubCategory csv file

In [8]:
```
# Use only the neccessary variables from 'dbo_dimproductsubcategory
.csv' table
product_subcat_usecols = [
    'ProductSubcategoryKey','EnglishProductSubcategoryName','Produc
tCategoryKey'
]
```

In [9]:
```
# Import and read csv file into a dataframe that contains Product S
ubCategory information
product_subcat = pd.read_csv('dbo_dimproductsubcategory.csv', encod
ing='iso-8859-1', usecols=product_subcat_usecols)
```

5. Fact Internet Sales csv file

In [10]:
```
# Use only the neccessary variables from 'dbo_factinternetsales.csv
' table
fis_usecols = [
    'ProductKey', 'OrderDateKey', 'CustomerKey', 'PromotionKey', 'S
alesTerritoryKey',
     'SalesOrderNumber', 'SalesOrderLineNumber', 'RevisionNumber','
OrderQuantity',
     'UnitPrice', 'TotalProductCost','OrderDate'
]
```

In [11]:
```
# Import and read csv file into a dataframe that contains Fact Inte
rnet Sales information
fis = pd.read_csv('dbo_factinternetsales.csv', usecols=fis_usecols)
```

6. Date csv file

In [12]:
```
# Use only the neccessary variables from 'dbo.DimDate.csv' table
dim_date_usecols = [
    'DateKey','EnglishDayNameOfWeek','DayNumberOfMonth',
    'MonthNumberOfYear','CalendarYear'
]
```

In [13]:
```
# Import and read csv file into a dataframe that contains Date info
rmation
dim_date = pd.read_csv('dbo.DimDate.csv', encoding='iso-8859-1', us
ecols=dim_date_usecols)
```

7. Promotion csv file

In [14]:
```
# Use only the neccessary variables from 'dbo.DimPromotion.csv' tab
le
dim_promotion_usecols = [
    'PromotionKey', 'EnglishPromotionName','EnglishPromotionType',
    'EnglishPromotionCategory'
]
```

In [15]:
```
# Import and read csv file into a dataframe that contains Promotion
information
dim_promotion = pd.read_csv('dbo.DimPromotion.csv', usecols=dim_pro
motion_usecols)
```

8. Sales Territory csv file

In [16]:
```
# Use only the neccessary variables from 'dbo_dimsalesterritory.csv
' table
sales_territory_usecols = [
    'SalesTerritoryKey','SalesTerritoryCountry'
]
```

In [17]:
```
# Import and read csv file into a dataframe that contains Sales Ter
ritory information
sales_territory = pd.read_csv('dbo_dimsalesterritory.csv', usecols=
sales_territory_usecols)
```

9. Geography csv file

In [18]:
```
# Use only the neccessary variables from 'dbo_dimgeography.csv' tab
le
geo_usecols = ['GeographyKey','EnglishCountryRegionName','SalesTerr
itoryKey']
```

In [19]:
```
# Import and read csv file into a dataframe that contains Geography
information
geo = pd.read_csv('dbo_dimgeography.csv', encoding='iso-8859-1', us
ecols=geo_usecols)
```

Join Tables

1. Join Product Category AND Product Subcategory Tables

In [20]:
```
# Using an Outer join to merge Product Category and Product SubCate
gory using the Key 'ProductCategoryKey'
product_cat_subcat = pd.merge(product_cat, product_subcat, on=['Pro
ductCategoryKey'], how='outer')
```

2. Join Product AND Product Category, Subcategory Tables

In [21]:
```
# Using a Left join to merge Product AND Product Category&SubCatego
ry using the Key 'ProductSubcategoryKey'
prod_sub_cat = pd.merge(product, product_cat_subcat, on='ProductSub
categoryKey', how='left')
```

3. Join Fact Internet Sales AND Product, Category, SubCategory Tables

In [22]:
```
# Using a Left join to merge Fact Internet Sales AND Product, Produ
ct Category&SubCategory using the Key 'ProductKey'
fis_prod_sub_cat = pd.merge(fis, prod_sub_cat, on='ProductKey', how
='left')
```

4. Join Fact Internet Sales, Product, Category, SubCategory AND Date Tables

In [23]:
```
# Using a Left join to merge Fact Internet Sales, Product, Category
, SubCategory AND Date using the Keys 'OrderDateKey' & 'DateKey'
fis_prod_subcat_dimdate = pd.merge(fis_prod_sub_cat, dim_date, left
_on='OrderDateKey', right_on='DateKey', how='left')
```

5. Join Fact Internet Sales, Product, Category, SubCategory, Date AND Promotion Tables

In [24]:
```
# Using a Left join to merge Fact Internet Sales, Product, Category
, SubCategory, Date,
# Currency AND Promotion using the Key 'PromotionKey'
fis_prod_subcat_dimdate_promo = pd.merge(fis_prod_subcat_dimdate, d
im_promotion, on='PromotionKey', how='left')
```

6. Join Sales Territory AND Geography Tables

In [25]:
```
# Using an Inner join to merge Sales Territory AND Geography using the Key 'SalesTerritoryKey'
sales_territory_geo = pd.merge(geo,sales_territory, on='SalesTerritoryKey', how='inner')
```

7. Join Customer AND Sales Territory, Geography Tables

In [26]:
```
# Using a Left join to merge Customer AND Sales Territory, Geography using the Key 'GeographyKey'
cust_sales_territory_geo = pd.merge(cust, sales_territory_geo, on='GeographyKey', how='left')
```

8. Join Customer, Sales Territory, Geography AND Fact Internet Sales, Product, Category, SubCategory, Date, Promotion Tables

In [27]:
```
# Using a Left join to merge Customer, Sales Territory, Geography AND Fact Internet Sales,
# Product, Category, SubCategory, Date, Promotion using the Keys 'CustomerKey' & 'SalesTerritoryKey
master_df = pd.merge(cust_sales_territory_geo, fis_prod_subcat_dimdate_promo,
                          on=['CustomerKey','SalesTerritoryKey'], how='left')
```

Assess Data

Issues

1. Variables of Birthdate, DateFirstPurchase and OrderDate should be converted to datetime
2. Rename and shorten lengthy variable names
3. Create and calculate the variable Profit
4. Round UnitPrice, TotalProductCost and Profit to two decimal points
5. Create and calculate Age
6. Define function and create 4 different age groups
7. Create and calculate Account_Length
8. Define function and create TypeOfEarner
9. Concatenate Gender and MaritalStatus together to create Status_Gender
10. Convert the following float type variables to integers

In [28]:
```
# Shape
print(master_df.shape)
```

```
(60398, 39)
```

In [29]:
```
# List all of the variables
master_df.columns
```

Out[29]:
```
Index(['CustomerKey', 'GeographyKey', 'BirthDate', 'MaritalStatus'
, 'Gender',
       'YearlyIncome', 'TotalChildren', 'EnglishEducation',
       'EnglishOccupation', 'HouseOwnerFlag', 'NumberCarsOwned',
       'DateFirstPurchase', 'CommuteDistance', 'EnglishCountryRegi
onName',
       'SalesTerritoryKey', 'SalesTerritoryCountry', 'ProductKey',
       'OrderDateKey', 'PromotionKey', 'SalesOrderNumber',
       'SalesOrderLineNumber', 'RevisionNumber', 'OrderQuantity',
'UnitPrice',
       'TotalProductCost', 'OrderDate', 'ProductSubcategoryKey',
       'EnglishProductName', 'ProductCategoryKey',
       'EnglishProductCategoryName', 'EnglishProductSubcategoryNam
e',
       'DateKey', 'EnglishDayNameOfWeek', 'DayNumberOfMonth',
       'MonthNumberOfYear', 'CalendarYear', 'EnglishPromotionName'
,
       'EnglishPromotionType', 'EnglishPromotionCategory'],
      dtype='object')
```

In [30]:
```
# Showing the first 5 rows of the dataset
master_df.head()
```

Out[30]:

	CustomerKey	GeographyKey	BirthDate	MaritalStatus	Gender	YearlyIncome	T
0	11000.0	26.0	1966-04-08	M	M	90000.0	2
1	11000.0	26.0	1966-04-08	M	M	90000.0	2
2	11000.0	26.0	1966-04-08	M	M	90000.0	2
3	11000.0	26.0	1966-04-08	M	M	90000.0	2
4	11000.0	26.0	1966-04-08	M	M	90000.0	2

5 rows × 39 columns

In [31]:
```
# Showing the last 5 rows of the dataset
master_df.tail()
```

Out[31]:

	CustomerKey	GeographyKey	BirthDate	MaritalStatus	Gender	YearlyIncor
60393	29480.0	248.0	1960-11-10	S	F	30000.0
60394	29480.0	248.0	1960-11-10	S	F	30000.0
60395	29481.0	120.0	1960-01-05	S	M	30000.0
60396	29482.0	179.0	1959-03-05	M	M	30000.0
60397	29483.0	217.0	1959-12-08	M	M	30000.0

5 rows × 39 columns

In [32]:
```
# Showing the 5 random samples
master_df.sample(5)
```

Out[32]:

	CustomerKey	GeographyKey	BirthDate	MaritalStatus	Gender	YearlyIncor
29094	17806.0	127.0	1964-04-14	M	M	20000.0
19106	14999.0	261.0	1973-05-06	S	F	10000.0
43706	22863.0	542.0	1956-05-11	M	M	70000.0
34867	19682.0	623.0	1972-08-07	M	M	50000.0
42235	22305.0	248.0	1972-11-21	S	F	20000.0

5 rows × 39 columns

In [33]:
```
# Check descriptive statistics of the dataset
master_df.describe()
```

Out[33]:

	CustomerKey	GeographyKey	YearlyIncome	TotalChildren	HouseOwnerFl
count	60398.000000	60398.000000	60398.000000	60398.00000	60398.000000
mean	18841.685420	230.516292	59715.056790	1.85074	0.690404
std	5432.430404	192.403184	33065.426837	1.62107	0.462331
min	11000.000000	2.000000	10000.000000	0.00000	0.000000
25%	14003.000000	51.000000	30000.000000	0.00000	0.000000
50%	18143.000000	211.000000	60000.000000	2.00000	1.000000
75%	23429.750000	329.000000	80000.000000	3.00000	1.000000
max	29483.000000	654.000000	170000.000000	5.00000	1.000000

In [34]:
```
# Show the number of duplicated entries in the dataset
sum(master_df.duplicated())
```

Out[34]: 0

In [35]:
```
# Show the number of entries for each uniquw element
master_df['TotalChildren'].value_counts()
```

Out[35]:
```
0.0    17048
2.0    12285
1.0    11561
4.0     7748
3.0     7061
5.0     4695
Name: TotalChildren, dtype: int64
```

In [36]:
```
master_df['EnglishOccupation'].value_counts()
```

Out[36]:
```
Professional      18995
Skilled Manual    14261
Management        10594
Clerical           9624
Manual             6924
Name: EnglishOccupation, dtype: int64
```

In [37]:
```
master_df['CommuteDistance'].value_counts()
```

Out[37]:
```
0-1 Miles     21307
5-10 Miles    10615
1-2 Miles     10170
2-5 Miles     10084
10+ Miles      8222
Name: CommuteDistance, dtype: int64
```

In [38]:
```
master_df['EnglishCountryRegionName'].value_counts()
```

Out[38]:
```
United States     21344
Australia         13345
Canada             7620
United Kingdom     6906
Germany            5625
France             5558
Name: EnglishCountryRegionName, dtype: int64
```

In [39]:
```
master_df['SalesTerritoryCountry'].value_counts()
```

Out[39]:
```
United States     21344
Australia         13345
Canada             7620
United Kingdom     6906
Germany            5625
France             5558
Name: SalesTerritoryCountry, dtype: int64
```

In [40]:
```
master_df['EnglishProductCategoryName'].value_counts()
```

Out[40]:
```
Accessories    36092
Bikes          15205
Clothing        9101
Name: EnglishProductCategoryName, dtype: int64
```

In [41]:
```
master_df['EnglishProductSubcategoryName'].value_counts()
```

Out[41]:
```
Tires and Tubes      17332
Road Bikes            8068
Bottles and Cages     7981
Helmets               6440
Mountain Bikes        4970
Jerseys               3332
Caps                  2190
Touring Bikes         2167
Fenders               2121
Gloves                1430
Shorts                1019
Cleaners               908
Hydration Packs        733
Socks                  568
Vests                  562
Bike Racks             328
Bike Stands            249
Name: EnglishProductSubcategoryName, dtype: int64
```

Clean Data

In [42]:
```
# Copy the master_df for the cleaning process
master_df_clean = master_df.copy()
```

Issue #1

Define

Variables of Birthdate, DateFirstPurchase and OrderDate should be converted to datetime

Code

In [43]:
```
# Use a for loop to convert the variables to date format
for col in ['BirthDate', 'DateFirstPurchase']:
    master_df_clean[col] = master_df_clean[col].apply(to_datetime_f
mt)
```

In [44]:
```
# Convert the following variable to Date format
master_df_clean['OrderDate'] = pd.to_timedelta(master_df_clean['Ord
erDate'], unit='s') + pd.datetime(1960, 1, 1)
```

Test

In [45]:
```
print(master_df_clean['BirthDate'].dtypes)
print(master_df_clean['DateFirstPurchase'].dtypes)
print(master_df_clean['OrderDate'].dtypes)
```

```
datetime64[ns]
datetime64[ns]
datetime64[ns]
```

Issue #2

Define

Rename and shorten lengthy variable names

In [46]:
```
# Rename the following variables to shorter titles
master_df_clean.rename(columns={'CalendarYear': 'Year', 'MonthNumbe
rOfYear': 'Month',
                               'DayNumberOfMonth':'Day','EnglishDay
NameOfWeek':'Weekday',
                              'EnglishEducation': 'Education',
                              'EnglishOccupation':'Occupation',
                              'EnglishCountryRegionName': 'CountryR
egion',
                              'EnglishProductName': 'ProductName',
                               'EnglishProductCategoryName': 'Produ
ctCategory',
                              'EnglishProductSubcategoryName': 'Pro
ductSubcategory',
                               'EnglishPromotionName': 'Promotion',
                               'EnglishPromotionType':'PromotionTyp
e',
                               'EnglishPromotionCategory': 'Promoti
onCategory'}, inplace=True)
```

In [47]:
```
master_df_clean.columns
```

Out[47]:
```
Index(['CustomerKey', 'GeographyKey', 'BirthDate', 'MaritalStatus'
, 'Gender',
       'YearlyIncome', 'TotalChildren', 'Education', 'Occupation',
       'HouseOwnerFlag', 'NumberCarsOwned', 'DateFirstPurchase',
       'CommuteDistance', 'CountryRegion', 'SalesTerritoryKey',
       'SalesTerritoryCountry', 'ProductKey', 'OrderDateKey', 'Pro
motionKey',
       'SalesOrderNumber', 'SalesOrderLineNumber', 'RevisionNumber
',
       'OrderQuantity', 'UnitPrice', 'TotalProductCost', 'OrderDat
e',
       'ProductSubcategoryKey', 'ProductName', 'ProductCategoryKey
',
       'ProductCategory', 'ProductSubcategory', 'DateKey', 'Weekda
y', 'Day',
       'Month', 'Year', 'Promotion', 'PromotionType', 'PromotionCa
tegory'],
      dtype='object')
```

Test

In [48]:
```
master_df_clean.loc[:, ['Year', 'Month', 'Day', 'Weekday']].sample(
)
```

Out[48]:

	Year	Month	Day	Weekday
35163	2007	11	1	Thursday

Issue #3

Define

Create and calculate the variable 'Profit'

In [49]:
```
# Create a new variable that calculates the Profit between 'UnitPri
ce' and 'TotalProductCost'
master_df_clean['Profit'] = master_df_clean['UnitPrice'] - master_d
f_clean['TotalProductCost']
```

Test

In [50]:
```
master_df_clean['Profit'].sample(3)
```

Out[50]:
```
30681      21.9037
27986      13.7595
33973    1054.3705
Name: Profit, dtype: float64
```

Issue #4

Define

Round UnitPrice, TotalProductCost and Profit to two decimal points

In [51]:
```
# Round the following variables to two decimal points
for col in ['UnitPrice','TotalProductCost', 'Profit'
           ]:

    master_df_clean[col] = round(master_df_clean[col],2)
```

Test

In [52]:
```
master_df_clean.loc[:, ['UnitPrice','TotalProductCost', 'Profit']].
sample(3)
```

Out[52]:

	UnitPrice	TotalProductCost	Profit
2931	3399.99	1912.15	1487.84
15815	2294.99	1251.98	1043.01
14558	28.99	10.84	18.15

Issue #5

Define

Create and calculate the variable 'Age'

In [53]:
```
# Create a variable that calculates the number of days between 'Ord
erDate' and 'BirthDate'
master_df_clean['Diff_In_Days'] = master_df_clean['OrderDate'] - ma
ster_df_clean['BirthDate']

# Turn the above variable into Years instead of days thereby creati
ng a new variable 'Age' of each Customer
master_df_clean['Age'] = master_df_clean['Diff_In_Days'] / timedelt
a(days=365)

# Round the Age variable to one decimal place
master_df_clean['Age'] = round(master_df_clean['Age'],1)
```

Test

In [54]:
```
master_df_clean['Age'].sample(3)
```

Out[54]:
```
12198    50.9
3873     53.3
40458    44.9
Name: Age, dtype: float64
```

Issue #6

Define

Define function and create 4 different age groups

In [55]:
```
# Defining a function that creates a variable of 4 different age gr
oups '18-29', '30-44', '45-59' & '60+'
def age_group(age):
    if age['Age'] >=18 and age['Age'] <=29:
        return '18-29'
    elif age['Age'] >=30 and age['Age'] <=44:
        return '30-44'
    elif age['Age'] >=45 and age['Age'] <=59:
        return '45-59'
    else:
        return '60+'

master_df_clean['Age_Group'] = master_df_clean.apply(age_group, axi
s=1)
```

Test

In [56]:
```
master_df_clean['Age_Group'].value_counts()
```

Out[56]:
```
30-44    26723
45-59    20377
60+      11382
18-29     1916
Name: Age_Group, dtype: int64
```

Issue #7

Define

Create and calculate Account_Length

In [57]:
```
# Creating a variable that calculates the customers' tenure in days
between 'OrderDate' and 'DateFirstPurchase'
master_df_clean['Tenure(Days)'] = master_df_clean['OrderDate'] - ma
ster_df_clean['DateFirstPurchase']
```

Test

In [58]:
```
master_df_clean.loc[:,'Tenure(Days)'].sample(10)
```

Out[58]:
```
36424      0 days
2001     283 days
757      128 days
55128      0 days
16003    240 days
21531    396 days
24531    292 days
36765    575 days
26769      0 days
59952      0 days
Name: Tenure(Days), dtype: timedelta64[ns]
```

Issue #8

Define

Define function and create TypeOfEarner

In [59]:
```
# Defining a function that creates a variable of 4 different types of Earners 'LowEarners', 'MediumEarners',
# 'HighEarners' & 'PremiumEarners'
def income(amount):
    if amount['YearlyIncome'] <25000:
        return 'LowEarners'
    elif amount['YearlyIncome'] >=25000 and amount['YearlyIncome'] <40000:
        return 'MediumEarners'
    elif amount['YearlyIncome'] >=40000 and amount['YearlyIncome'] <80000:
        return 'HighEarners'
    else:
        return 'PremiumEarners'

master_df_clean['TypeOfEarner'] = master_df_clean.apply(income, axis=1)
```

Test

In [60]:
```
master_df_clean['TypeOfEarner'].value_counts()
```

Out[60]:
```
HighEarners       28895
PremiumEarners    16029
LowEarners         8480
MediumEarners      6994
Name: TypeOfEarner, dtype: int64
```

Issue #9

Define

Concatenate Gender and MaritalStatus together to create Status_Gender

In [61]:
```
# Create a new variable 'Full_Gender' that turns 'M' to 'Male' and
'F' to Female
master_df_clean.loc[master_df_clean['Gender'].str.contains('M'), 'F
ull_Gender'] = 'Male'
master_df_clean.loc[master_df_clean['Gender'].str.contains('F'), 'F
ull_Gender'] = 'Female'

# Create another new variable 'Full_Status' that turns 'M' to 'Marr
ied' and 'S' to 'Single'
master_df_clean.loc[master_df_clean['MaritalStatus'].str.contains('
M'), 'Full_Status'] = 'Married'
master_df_clean.loc[master_df_clean['MaritalStatus'].str.contains('
S'), 'Full_Status'] = 'Single'

# Combine the two variables together and create one variable 'Statu
s_Gender'
master_df_clean['Status_Gender'] = master_df_clean['Full_Status'] +
master_df_clean['Full_Gender']
```

Test

In [62]:
```
master_df_clean['Status_Gender'].value_counts()
```

Out[62]:
```
MarriedMale      17503
MarriedFemale    15770
SingleFemale     14247
SingleMale       12878
Name: Status_Gender, dtype: int64
```

Issue #10

Define

Convert the following float type variables to integers

In [63]:
```
# Use a for loop to convert the following variables to integers
for col in [
    'CustomerKey', 'YearlyIncome','TotalChildren', 'NumberCarsOwned
', 'SalesOrderLineNumber',
    'RevisionNumber', 'OrderQuantity'
]:
    master_df_clean[col] = master_df_clean[col].astype(int)
```

Test

In [64]:
```
master_df_clean.loc[:, ['CustomerKey', 'YearlyIncome','TotalChildre
n', 'NumberCarsOwned', 'SalesOrderLineNumber',
    'RevisionNumber', 'OrderQuantity']].sample(5)
```

Out[64]:

	CustomerKey	YearlyIncome	TotalChildren	NumberCarsOwned	SalesOrder
43572	22810	90000	5	2	1
5603	11844	50000	4	3	3
36395	20223	70000	5	4	1
43224	22683	30000	3	0	3
28513	17632	40000	1	1	3

In [65]:
```
master_df_clean.loc[:, ['TotalChildren', 'Education','TotalChildren
', 'Occupation', 'CommuteDistance',
    'CountryRegion', 'SalesTerritoryCountry', 'ProductCategory', 'P
roductSubcategory',
    'Weekday', 'PromotionType', 'PromotionCategory', 'Age_Group', '
TypeOfEarner',
    'Status_Gender']].sample(5)
```

Out[65]:

	TotalChildren	Education	TotalChildren	Occupation	CommuteDistance	Co
8559	1	Partial College	1	Clerical	1-2 Miles	Ur
21703	3	Bachelors	3	Clerical	0-1 Miles	Ur Ki
2313	1	Bachelors	1	Management	2-5 Miles	Ur
20469	4	Partial College	4	Professional	10+ Miles	Ur
37013	2	High School	2	Professional	5-10 Miles	Ur

Finalised Dataset

In [66]:
```
# Finalise the dataset by removing unneccessary variables
columns = [
    'GeographyKey', 'BirthDate', 'MaritalStatus', 'Gender', 'DateFi
rstPurchase', 'SalesTerritoryKey', 'ProductKey',
    'OrderDateKey', 'PromotionKey','ProductSubcategoryKey', 'Produc
tCategoryKey', 'DateKey', 'Diff_In_Days',
    'Full_Gender', 'Full_Status'
      ]

master_df_clean_drop = master_df_clean.drop(columns, inplace=True,
axis=1)
```

In [67]:
```
master_df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 60398 entries, 0 to 60397
Data columns (total 33 columns):
CustomerKey             60398 non-null int32
YearlyIncome            60398 non-null int32
TotalChildren           60398 non-null int32
Education               60398 non-null object
Occupation              60398 non-null object
HouseOwnerFlag          60398 non-null int64
NumberCarsOwned         60398 non-null int32
CommuteDistance         60398 non-null object
CountryRegion           60398 non-null object
SalesTerritoryCountry   60398 non-null object
SalesOrderNumber        60398 non-null object
SalesOrderLineNumber    60398 non-null int32
RevisionNumber          60398 non-null int32
OrderQuantity           60398 non-null int32
UnitPrice               60398 non-null float64
TotalProductCost        60398 non-null float64
OrderDate               60398 non-null datetime64[ns]
ProductName             60398 non-null object
ProductCategory         60398 non-null object
ProductSubcategory      60398 non-null object
Weekday                 60398 non-null object
Day                     60398 non-null int64
Month                   60398 non-null int64
Year                    60398 non-null int64
Promotion               60398 non-null object
PromotionType           60398 non-null object
PromotionCategory       60398 non-null object
Profit                  60398 non-null float64
Age                     60398 non-null float64
Age_Group               60398 non-null object
Tenure(Days)            60398 non-null timedelta64[ns]
TypeOfEarner            60398 non-null object
Status_Gender           60398 non-null object
dtypes: datetime64[ns](1), float64(4), int32(7), int64(4), object(
16), timedelta64[ns](1)
memory usage: 16.6+ MB
```

DATA ANALYSIS AND VISUALISATION

After learning about the dataset, I want to investigate more with the list of questions that I have in mind:

- Who are our high value customers?
- What do the high value customers buy?
- Why do the high value customers buy from Kernal Limited?
- What is the impact of customer churn?
- How should we communicate the products to customers?

Based on the questions from above I will carry out exploratory analysis to understand buying patterns of high value customers.

High Value Customers

As part of my campaign, I am only going to target high value customers with a total basket value of £1,500 or over.

In [68]:
```
# Create a variable that shows the total sum of basket value for ea
ch customer
master_df_clean['TotalBasketValue'] = master_df_clean.groupby('Sale
sOrderNumber')['UnitPrice'].transform('sum')
```

In [69]:
```
# After creating the above variable, I will apply a lambda function
to categorise each customer whether he/she is a
# high value customer or not so 0 and 1 (1 means high value custome
r)
master_df_clean['High_Value_Flag'] = master_df_clean['TotalBasketVa
lue'].map(lambda x: (1 if x>=1500 else(0)))
```

In [70]:
```
# Show the first few rows of the dataset
master_df_clean.loc[:,['CustomerKey','SalesOrderNumber', 'TotalBask
etValue','High_Value_Flag']].head()
```

Out[70]:

	CustomerKey	SalesOrderNumber	TotalBasketValue	High_Value_Flag
0	11000	SO43793	3399.99	1
1	11000	SO51522	2341.97	1
2	11000	SO51522	2341.97	1
3	11000	SO57418	2507.03	1
4	11000	SO57418	2507.03	1

In [71]:
```
# Create a variable that only contains high value customers
high_cust = master_df_clean[master_df_clean['High_Value_Flag']==1]
```

In [72]:
```
# Create a groupby table that only shows customers with a total bas
ket value of £1,500

hv_1k5 = high_cust.groupby('CustomerKey').agg({'SalesOrderNumber':'
count','UnitPrice':['sum','min','max','mean'],
                             'OrderQuantity':'sum', 'High_Value_Flag
':'max'}).rename(columns={'SalesOrderNumber':'Frequency'})
hv_1k5.head()
```

Out[72]:

	Frequency	UnitPrice				OrderQuantity	Hig
	count	sum	min	max	mean	sum	ma
CustomerKey							
11000	8	8248.99	4.99	3399.99	1031.123750	8	1
11001	7	5794.92	4.99	3374.99	827.845714	7	1
11002	4	8114.04	34.99	3399.99	2028.510000	4	1
11003	9	8139.29	2.29	3399.99	904.365556	9	1
11004	6	8196.01	21.98	3399.99	1366.001667	6	1

In [73]:
```
# Set the index to OrderDate
high_cust = high_cust.set_index('OrderDate')
```

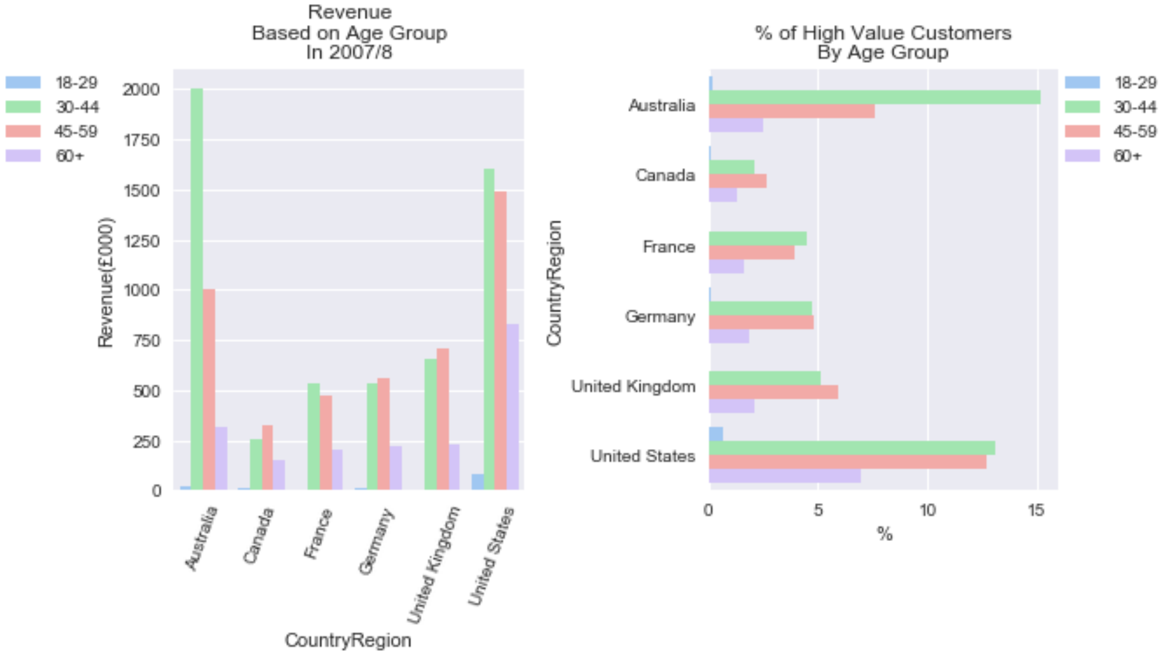
In [74]:
```
# Filter the OrderDate and analyse only from July 2007 to June 2008
as that is the lastest period in this dataset
high_cust = high_cust.loc['2007-07':'2008-06']
```

Analysis #1

High Value Customers By Age

In [75]:
```
# First plot
plt.subplot(1,2,1)
# Create a groupby that list the total sum of unit price for each a
ge group for every country region
hv_age_groupby = (high_cust.groupby(['CountryRegion','Age_Group'])[
'UnitPrice'].sum())
# Divide by 1,000 to make visualisation easier to read
```

```
hv_age_groupby = hv_age_groupby/1000
# Convert variable to an integer
hv_age_groupby = hv_age_groupby.astype(int)

# Add pipeline to use the above groupby function and create a bar c
hart with an x axis of 'CountryRegion'
# and a y axis of 'UnitPrice' in the order of the 4 age groups
ax = hv_age_groupby.reset_index().pipe((sns.barplot, 'data'),
x='CountryRegion', y='UnitPrice', palette='pastel', hue='Age_Group'
)
plt.xticks(rotation=70)
plt.xlabel('CountryRegion')
plt.ylabel('Revenue(£000)')
plt.title('Revenue' + '\n' + 'Based on Age Group' + '\n' + 'In 2007
/8')
# To locate and position the legend box
handles, labels = ax.get_legend_handles_labels()
l = plt.legend(handles[0:4], labels[0:4], bbox_to_anchor=(-0.5,1),
loc=2, borderaxespad=0.)

# Second plot
plt.subplot(1,2,2)
# Create a groupby that counts the number of customers for each age
group for every country region
groupby_age = (high_cust.groupby(['CountryRegion','Age_Group'])['Cu
stomerKey'].count())
# Sum the total number of customers as a denominator
total_age = groupby_age.sum()
# Divide each age group by the denominator and times by 100 to crea
te a percentage and round it by one decimal place
age = round(groupby_age/total_age*100,1)

# Add pipeline to use the above groupby function and create a bar c
hart with an x axis of 'CustomerKey'
# and a y axis of 'UnitPrice' in the order of the 4 age groups
ax = age.reset_index().pipe((sns.barplot, 'data'),
y='CountryRegion', x='CustomerKey', palette='pastel', hue='Age_Grou
p')
plt.xlabel('%')
plt.ylabel('CountryRegion')
plt.title('% of High Value Customers' + '\n' + 'By Age Group')
# To locate and position the legend box
handles, labels = ax.get_legend_handles_labels()
l = plt.legend(handles[0:4], labels[0:4], bbox_to_anchor=(1,1), loc
=2, borderaxespad=0.)

plt.tight_layout()
plt.show()
```



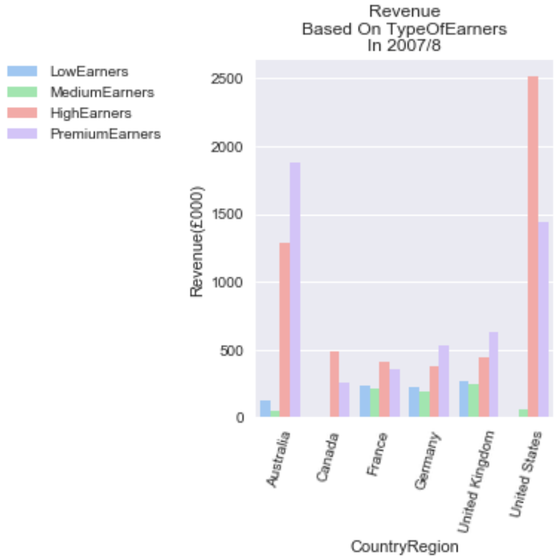
According to the plots, customers aged 30-44 from Australia are the first largest in terms of revenue accounting to £2m followed by United States being the second largest (£1.6m). However, customers aged 18-29 are the lowest (less than 1%) in all country regions. This means Kernal Ltd should aim to promote their products towards young people.

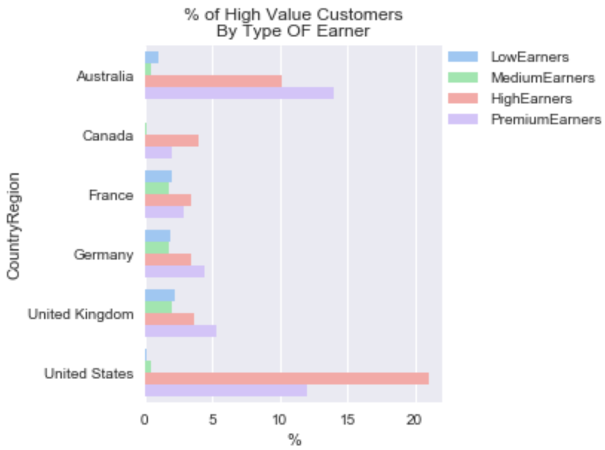
Analysis #2

High Value Customers By Income

In [76]:
```
# First plot
plt.subplot(1,2,1)
# Create a groupby that list the total sum of unit price for each T
ypeOfEarner for every country region
hv_earner_groupby = (high_cust.groupby(['CountryRegion','TypeOfEarn
er'])['UnitPrice'].sum())
# Divide by 1,000 to make visualisation easier to read
hv_earner_groupby = hv_earner_groupby/1000
# Convert variable to an integer
hv_earner_groupby = hv_earner_groupby.astype(int)

# Create a hue order of 4 different types of earners
hue_order  = ['LowEarners','MediumEarners','HighEarners','PremiumEa
rners']

# Add pipeline to use the above groupby function and create a bar c
hart with an x axis of 'CountryRegion'
# and a y axis of 'UnitPrice' in the order of the 4 TypeOfEarner gr
```

```
oups
ax = hv_earner_groupby.reset_index().pipe((sns.barplot, 'data'),
x='CountryRegion', y='UnitPrice', palette='pastel', hue='TypeOfEarn
er', hue_order=hue_order)
plt.xticks(rotation=75)
plt.xlabel('CountryRegion')
plt.ylabel('Revenue(£000)')
plt.title('Revenue'+ '\n' + 'Based On TypeOfEarners' + '\n' +'In 20
07/8')
# To locate and position the legend box
handles, labels = ax.get_legend_handles_labels()
l = plt.legend(handles[0:4], labels[0:4], bbox_to_anchor=(-0.85,1),
loc=2, borderaxespad=0.)

# Second plot
plt.subplot(1,2,2)
# Create a groupby that counts the number of customers for each Typ
eOfEarner group for every country region
groupby_earner = (high_cust.groupby(['CountryRegion','TypeOfEarner'
])['CustomerKey'].count())
# Sum the total number of customers as a denominator
total_earner = groupby_earner.sum()
# Divide each TypeOfEarner group by the denominator and times by 10
0 to create a percentage
# and round it by one decimal place
hv_earner = round(groupby_earner/total_earner*100,1)

# Add pipeline to use the above groupby function and create a bar c
hart with an x axis of 'CustomerKey'
# and a y axis of 'CountryRegion' in the order of the 4 TypeOfEarne
r groups
ax = hv_earner.reset_index().pipe((sns.barplot, 'data'),
y='CountryRegion', x='CustomerKey', palette='pastel', hue='TypeOfEa
rner', hue_order=hue_order)
plt.xlabel('%')
plt.ylabel('CountryRegion')
plt.title('% of High Value Customers' + '\n' + 'By Type OF Earner')
# To locate and position the legend box
handles, labels = ax.get_legend_handles_labels()
l = plt.legend(handles[0:4], labels[0:4], bbox_to_anchor=(1,1), loc
=2, borderaxespad=0.)

plt.tight_layout()
plt.show()
```





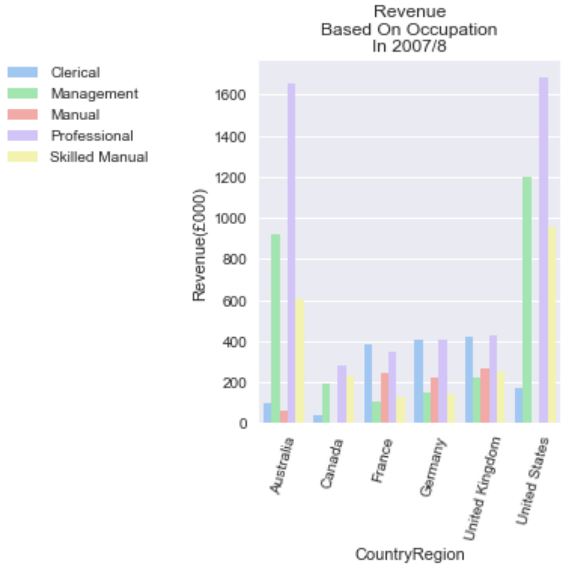
It can be seen that Low and Medium Earners are the least in terms of revenue and account for less than 3% in every country region. Whereas in Australia, High Earners account for 10% (£1.28m) in revenue and 14% for Premium Earners (£1.88m). Moreover, in United States, High Earners account for 12% (£2.5m) and interestingly Premium earners account for over 20% (£1.438m) which makes it the first largest in terms of revenue. This signifies that customers who shops at Kernal Ltd are mainly High and Premium Earners.

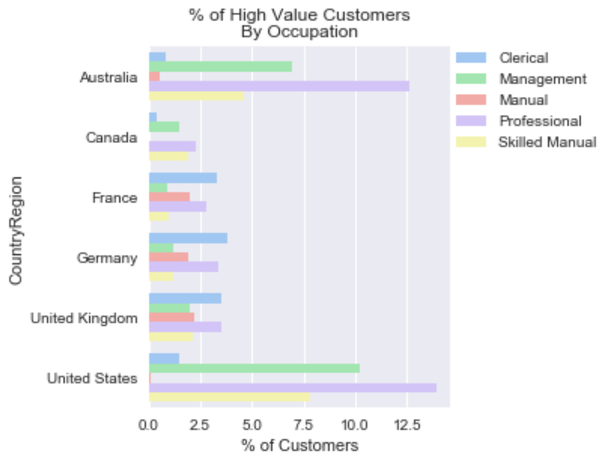
Analysis #3

High Value Customers By Occupation

In [77]:
```
# First plot
plt.subplot(1,2,1)
# Create a groupby that list the total sum of unit price for each T
ypeOfEarner for every country region
hv_occ_groupby = (high_cust.groupby(['CountryRegion','Occupation'])
['UnitPrice'].sum())
# Divide by 1,000 to make visualisation easier to read
hv_occ_groupby = hv_occ_groupby/1000
# Convert variable to an integer
hv_occ_groupby = hv_occ_groupby.astype(int)

# Add pipeline to use the above groupby function and create a bar c
hart with an x axis of 'CountryRegion'
# and a y axis of 'UnitPrice' in the order of the 4 Occupational gr
oups
ax = hv_occ_groupby.reset_index().pipe((sns.barplot, 'data'),
x='CountryRegion', y='UnitPrice', palette='pastel', hue='Occupation
')
```

```
plt.xticks(rotation=75)
plt.xlabel('CountryRegion')
plt.ylabel('Revenue(£000)')
plt.title('Revenue'+ '\n' + 'Based On Occupation' + '\n' +'In 2007/
8')
# To locate and position the legend box
handles, labels = ax.get_legend_handles_labels()
l = plt.legend(handles[0:], labels[0:], bbox_to_anchor=(-0.85,1), l
oc=2, borderaxespad=0.)

# Second plot
plt.subplot(1,2,2)
# Create a groupby that counts the number of customers for each occ
upation group for every country region
groupby_occ = high_cust.groupby(['CountryRegion','Occupation'])['Cu
stomerKey'].count()
# Sum the total number of customers as a denominator
total_occ = groupby_occ.sum()
# Divide each TypeOfEarner group by the denominator and times by 10
0 to create a percentage
# and round it by one decimal place
occ = round(groupby_occ/total_occ*100,1)

# Add pipeline to use the above groupby function and create a bar c
hart with an x axis of 'CustomerKey'
# and a y axis of 'CountryRegion' in the order of the 4 Occupationa
l groups
ax = occ.reset_index().pipe((sns.barplot, 'data'),
y='CountryRegion', x='CustomerKey', palette='pastel', hue='Occupati
on')
plt.xlabel('% of Customers')
plt.ylabel('CountryRegion')
plt.title('% of High Value Customers' + '\n' + 'By Occupation')
# To locate and position the legend box
handles, labels = ax.get_legend_handles_labels()
l = plt.legend(handles[0:], labels[0:], bbox_to_anchor=(1,1), loc=2
, borderaxespad=0.)
plt.tight_layout()

plt.show()
```





It can be seen that customers who work as Professionals are the first largest in revenue in all countries with Management customers being the second largest. Professional customers account for £1.6m each in Australia and United States and account for over 12.5% in both countries.

Manual customers are the least in revenue with less than 3% in every country. Additionally Manual customers in Canada are the first lowest with £4k in revenue.

Analysis #4

What They Buy By Product Category

In [78]:

```
# What They Buy by Product Category
# First plot
plt.subplot(1,2,1)
# Create a groupby that list the total number of Order Quantity for
each Product Category for every country region
groupby_product = high_cust.groupby(['CountryRegion','ProductCatego
ry'])['OrderQuantity'].sum()
# Sum the total number of Order Quantity as a denominator
total_product = groupby_product.sum()
# Divide each Product Category group by the denominator and times b
y 100 to create a percentage
# and round it by one decimal place
product = round(groupby_product/total_product*100,1)

# Add pipeline to use the above groupby function and create a bar c
hart with an x axis of 'OrderQuantity'
# and a y axis of 'CountryRegion' in the order of the Product Categ
ory groups
```

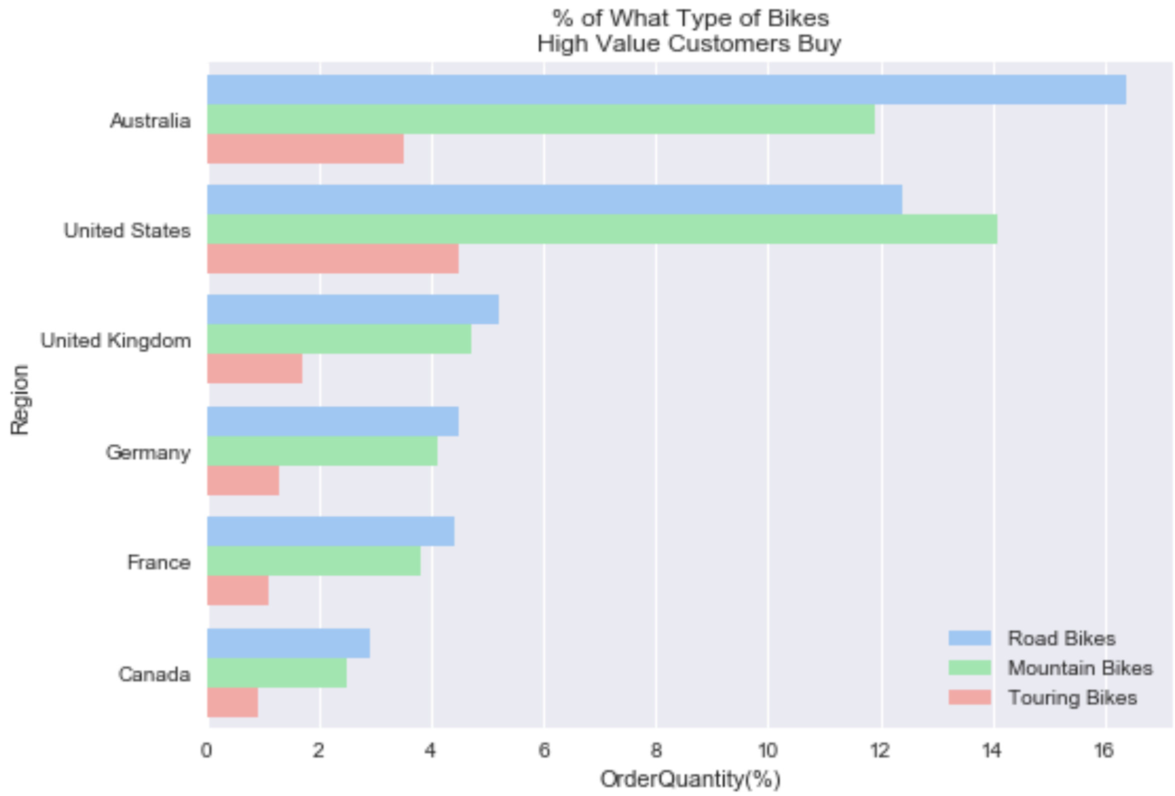
```
ax = product.reset_index().pipe((sns.barplot, 'data'),
y='CountryRegion', x='OrderQuantity', palette='pastel', hue='Produc
tCategory')
plt.xlabel('OrderQuantity(%)')
plt.ylabel('CountryRegion')
plt.title('Order Quantity (%)' + '\n' + 'By Product Category')
# To locate and position the legend box
handles, labels = ax.get_legend_handles_labels()
l = plt.legend(handles[0:4], labels[0:4], bbox_to_anchor=(-0.7,1),
loc=2, borderaxespad=0.)

# Second plot
plt.subplot(1,2,2)
# Create a groupby that list the total sum of unit price for each P
roduct Category for every country region
hv_product_groupby = high_cust.groupby(['CountryRegion','ProductCat
egory'])['UnitPrice'].sum()
# Divide by 1,000 to make visualisation easier to read
hv_product_groupby = hv_product_groupby/1000
# Convert variable to an integer
hv_product_groupby = hv_product_groupby.astype(int)
# Add pipeline to use the above groupby function and create a bar c
hart with an x axis of 'CountryRegion'
# and a y axis of 'UnitPrice' in the order of the three Product Cat
egories
ax = hv_product_groupby.reset_index().pipe((sns.barplot, 'data'),
x='CountryRegion', y='UnitPrice', palette='pastel', hue='ProductCat
egory')
plt.xticks(rotation=75)
plt.ylabel('Revenue(£000)')
plt.title('Revenue'+'\n' + 'By Product Category' + '\n' +'In 2007/8
')
# To locate and position the legend box
handles, labels = ax.get_legend_handles_labels()
l = plt.legend(handles[0:4], labels[0:4], bbox_to_anchor=(1,1), loc
=2, borderaxespad=0.)

plt.tight_layout()
plt.show()
```

Here we can see that Accessories are the largest in terms of order quantity. A vast majority of the products are sold in Australia and United States. Clothing are the lowest in order quantity out of the 3 product categories. Another surprising fact is that Bikes are the largest in revenue surpassing Accessories and Clothing greatly.

Analysis #5

What Type of Bikes They Buy

In [79]:
```
# Filtering the data analysis to only high value customers with a total basket value of £1,500 or over and showing only the
# Product Category of Bikes
high_cust_bike = master_df_clean[(master_df_clean['High_Value_Flag']==1) & (master_df_clean['ProductCategory']=='Bikes')]
# Create a groupby that list the total number of Order Quantity for the Product SubCategory of Bikes for every country region
groupby_product = high_cust_bike.groupby(['CountryRegion','ProductSubcategory'])['OrderQuantity'].sum()
# Sum the total number of Order Quantity as a denominator
total_product = groupby_product.sum()
# Divide the Product SubCategory of Bikes by the denominator and times by 100 to create a percentage.
# Then round it by one decimal place and sort it in ascending order
product = round(groupby_product/total_product*100,1).sort_values(ascending=False)

# Add pipeline to use the above groupby function and create a bar chart with an x axis of 'OrderQuantity'
# and a y axis of 'CountryRegion' and displaying the order of the Product SubCategories by Bikes
ax = product.reset_index().pipe((sns.barplot, 'data'),
y='CountryRegion', x='OrderQuantity', palette='pastel', hue='ProductSubcategory')
plt.ylabel('Region')
plt.xlabel('OrderQuantity(%)')
plt.title('% of What Type of Bikes' + '\n' + 'High Value Customers Buy')
# To locate and position the legend box
plt.legend(loc='lower right')

plt.tight_layout()
plt.show()
```

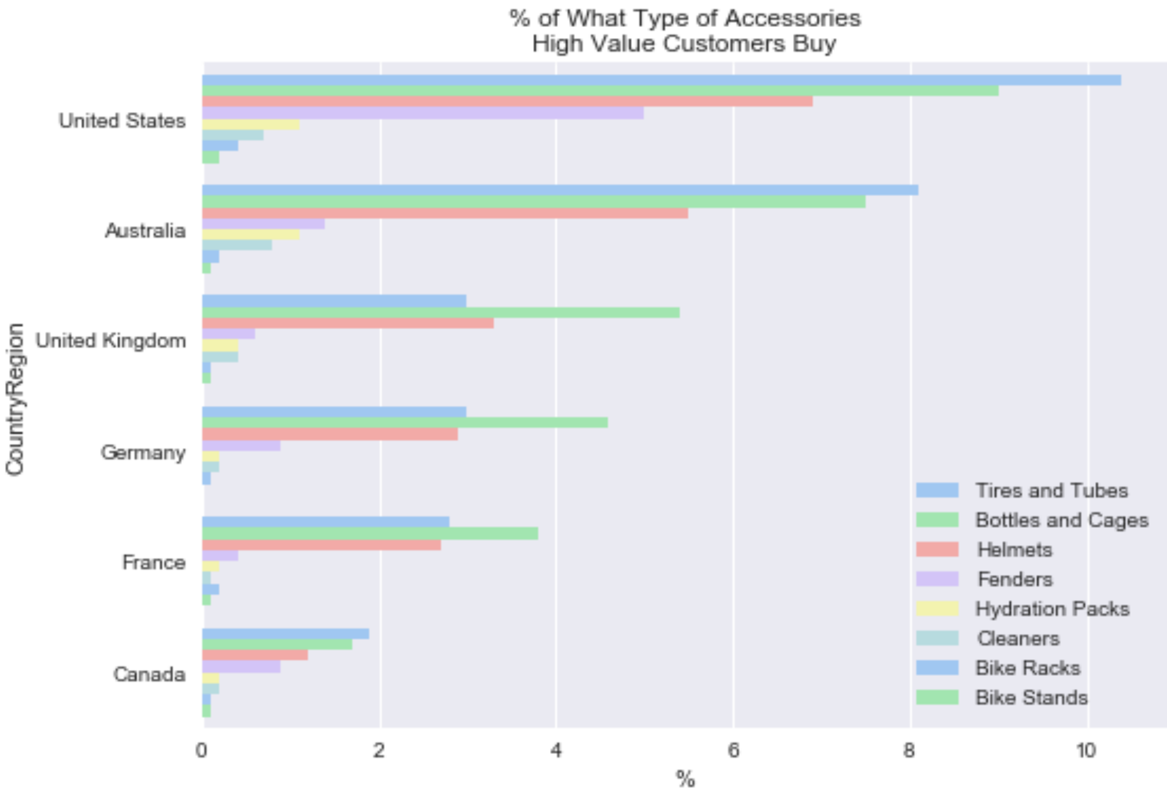


We can see that Road Bikes are the most commonly purchased in most countries. Yet Mountain Bikes are slightly more popular in United States while Touring Bikes are the least common in all countries.

Analysis #6

What Type of Accessories They Buy

In [80]:
```
# Filtering the data analysis to only high value customers with a t
otal basket value of £1,500 or over and showing only the
# Product Category of Accessories
high_cust_access = master_df_clean[(master_df_clean['High_Value_Fla
g']==1) & (master_df_clean['ProductCategory']=='Accessories')]
# Create a groupby that list the total number of Order Quantity for
the Product SubCategory of Accessories for every country region
groupby_product = high_cust_access.groupby(['CountryRegion','Produc
tSubcategory'])['OrderQuantity'].sum()
# Sum the total number of Order Quantity as a denominator
total_product = groupby_product.sum()
# Divide the Product SubCategory of Accessories by the denominator
and times by 100 to create a percentage.
# Then round it by one decimal place and sort it in ascending order
product = round(groupby_product/total_product*100,1).sort_values(as
cending=False)

# Add pipeline to use the above groupby function and create a bar c
hart with an x axis of 'OrderQuantity'
# and a y axis of 'CountryRegion' and displaying the order of the P
roduct SubCategories by Accessories
ax = product.reset_index().pipe((sns.barplot, 'data'),
y='CountryRegion', x='OrderQuantity', palette='pastel', hue='Produc
tSubcategory')
plt.ylabel('CountryRegion')
plt.xlabel('%')
plt.title('% of What Type of Accessories' + '\n' + 'High Value Cust
omers Buy')
# To locate and position the legend box
plt.legend(loc='lower right')

plt.tight_layout()
plt.show()
```

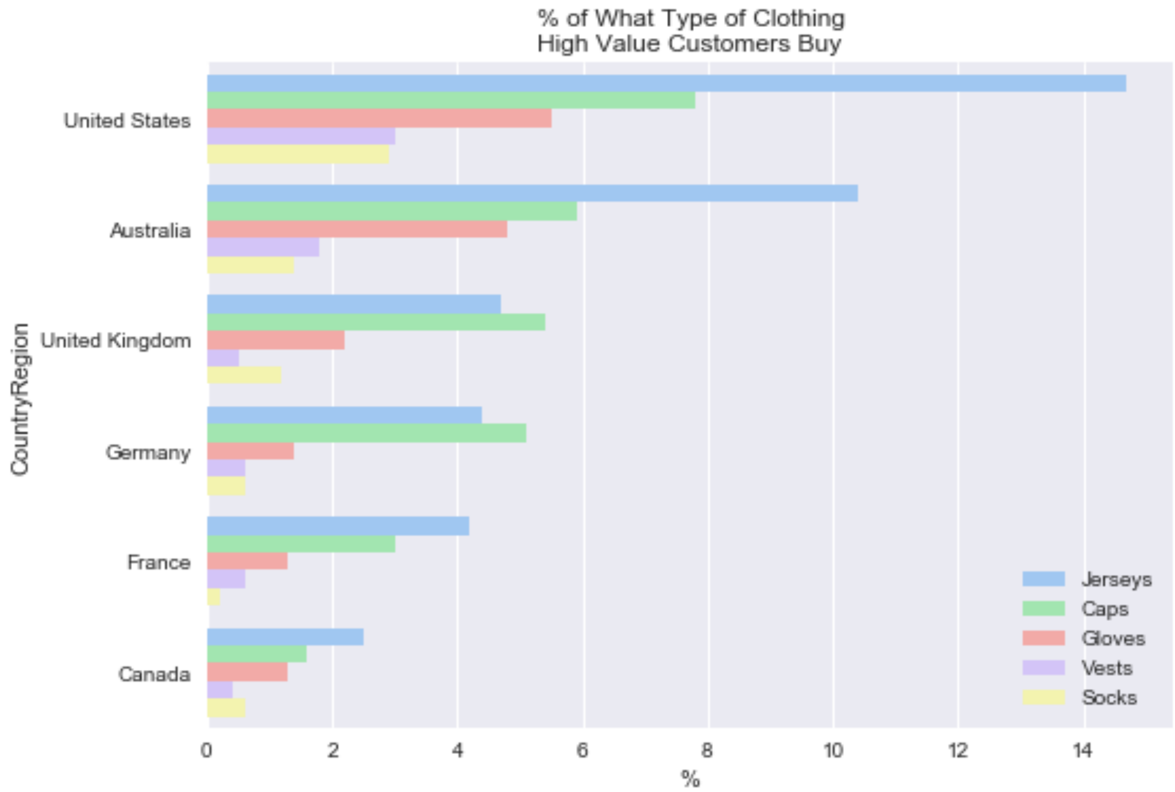


According to this plot, we can determine that Tires and Tubes are the most popular in United States, Australia and Canada. However, in United Kingdom, Germany and France customers tend to shop for Bottles and Cages. Bike Racks and Stands are the least in demand (less than 1% in every country).

Analysis #7

What Type of Clothings They Buy

In [81]:
```
# Filtering the data analysis to only high value customers with a t
otal basket value of £1,500 or over and showing only the
# Product Category of Clothings
high_cust_cloth = master_df_clean[(master_df_clean['High_Value_Flag
']==1) & (master_df_clean['ProductCategory']=='Clothing')]
# Create a groupby that list the total number of Order Quantity for
the Product SubCategory of Clothings for every country region
groupby_product = high_cust_cloth.groupby(['CountryRegion','Product
Subcategory'])['OrderQuantity'].sum()
# Sum the total number of Order Quantity as a denominator
total_product = groupby_product.sum()
# Divide the Product SubCategory of Clothings by the denominator an
d times by 100 to create a percentage.
# Then round it by one decimal place and sort it in ascending order
product = round(groupby_product/total_product*100,1).sort_values(as
cending=False)

# Add pipeline to use the above groupby function and create a bar c
hart with an x axis of 'OrderQuantity'
# and a y axis of 'CountryRegion' and displaying the order of the P
roduct SubCategories by Clothings
ax = product.reset_index().pipe((sns.barplot, 'data'),
y='CountryRegion', x='OrderQuantity', palette='pastel', hue='Produc
tSubcategory')
plt.ylabel('CountryRegion')
plt.xlabel('%')
plt.title('% of What Type of Clothing' + '\n' + 'High Value Custome
rs Buy')
# To locate and position the legend box
plt.legend(loc='lower right')

plt.tight_layout()
plt.show()
```



From this plot, a majority of customers purchase Jerseys in United States, Australia, France and Canada. Whereby a majority of customers in United Kingdom and Germany purchase Caps.

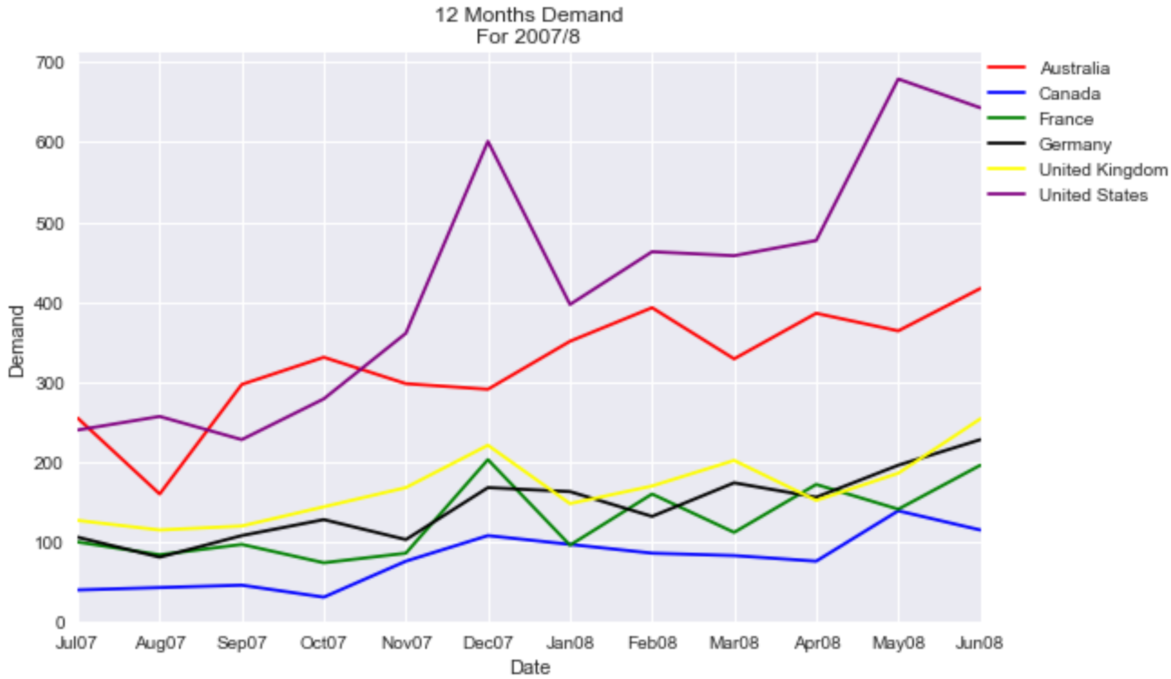
Analysis #8

When They Buy During The Year By Order Quantity

In [82]:
```
ticks = [0,1,2,3,4,5,6,7,8,9,10,11]
ticks2 = ['Jul07','Aug07','Sep07','Oct07','Nov07','Dec07','Jan08','
Feb08','Mar08','Apr08','May08','Jun08']

# Filtering the data analysis to only high value customers with a t
otal basket value of £1,500 or over
# and showing only Australia
high_cust_aus = master_df_clean[(master_df_clean['High_Value_Flag']
==1) & (master_df_clean['CountryRegion']=='Australia')]
# Set the index to 'OrderDate'
high_cust_aus = high_cust_aus.set_index('OrderDate')
# Filter and set the period from July 2007 until June 2008 (the lat
est data)
high_cust_aus = high_cust_aus.loc['2007-07':'2008-06']
# Create a groupby to show the sum of order quantity based on the y
ear and month for Australia
```

```
aus = high_cust_aus.groupby(['Year','Month'])['OrderQuantity'].sum(
).sort_index()
# Plot the groupby and colour the ax in red and label as 'Australia
'
ax = aus.plot(color='red',label='Australia')

# Filtering the data analysis to only high value customers with a t
otal basket value of £1,500 or over
# and showing only Canada
high_cust_ca = master_df_clean[(master_df_clean['High_Value_Flag']=
=1) & (master_df_clean['CountryRegion']=='Canada')]
# Set the index to 'OrderDate'
high_cust_ca = high_cust_ca.set_index('OrderDate')
# Filter and set the period from July 2007 until June 2008 (the lat
est data)
high_cust_ca = high_cust_ca.loc['2007-07':'2008-06']
# Create a groupby to show the sum of order quantity based on the y
ear and month for Canada
ca = high_cust_ca.groupby(['Year','Month'])['OrderQuantity'].sum().
sort_index()
# Plot the groupby and colour the ax in blue and label as 'Canada'
ax = ca.plot(color='blue',label='Canada')

# Filtering the data analysis to only high value customers with a t
otal basket value of £1,500 or over
# and showing only France
high_cust_fr = master_df_clean[(master_df_clean['High_Value_Flag']=
=1) & (master_df_clean['CountryRegion']=='France')]
# Set the index to 'OrderDate'
high_cust_fr = high_cust_fr.set_index('OrderDate')
# Filter and set the period from July 2007 until June 2008 (the lat
est data)
high_cust_fr = high_cust_fr.loc['2007-07':'2008-06']
# Create a groupby to show the sum of order quantity based on the y
ear and month for France
fr = high_cust_fr.groupby(['Year','Month'])['OrderQuantity'].sum().
sort_index()
# Plot the groupby and colour the ax in green and label as 'France'
ax = fr.plot(color='green',label='France')

# Filtering the data analysis to only high value customers with a t
otal basket value of £1,500 or over
# and showing only Germany
high_cust_ger = master_df_clean[(master_df_clean['High_Value_Flag']
==1) & (master_df_clean['CountryRegion']=='Germany')]
# Set the index to 'OrderDate'
high_cust_ger = high_cust_ger.set_index('OrderDate')
# Filter and set the period from July 2007 until June 2008 (the lat
est data)
high_cust_ger = high_cust_ger.loc['2007-07':'2008-06']
# Create a groupby to show the sum of order quantity based on the y
ear and month for Germany
ger = high_cust_ger.groupby(['Year','Month'])['OrderQuantity'].sum(
```

```
).sort_index()
# Plot the groupby and colour the ax in black and label as 'Germany
'
ax = ger.plot(color='k',label='Germany')

# Filtering the data analysis to only high value customers with a t
otal basket value of £1,500 or over
# and showing only United Kingdom
high_cust_uk = master_df_clean[(master_df_clean['High_Value_Flag']=
=1) & (master_df_clean['CountryRegion']=='United Kingdom')]
# Set the index to 'OrderDate'
high_cust_uk = high_cust_uk.set_index('OrderDate')
# Filter and set the period from July 2007 until June 2008 (the lat
est data)
high_cust_uk = high_cust_uk.loc['2007-07':'2008-06']
# Create a groupby to show the sum of order quantity based on the y
ear and month for United Kingdom
uk = high_cust_uk.groupby(['Year','Month'])['OrderQuantity'].sum().
sort_index()
# Plot the groupby and colour the ax in yellow and label as 'United
Kingdom'
ax = uk.plot(color='yellow',label='United Kingdom')

# Filtering the data analysis to only high value customers with a t
otal basket value of £1,500 or over
# and showing only United States
high_cust_us = master_df_clean[(master_df_clean['High_Value_Flag']=
=1) & (master_df_clean['CountryRegion']=='United States')]
# Set the index to 'OrderDate'
high_cust_us = high_cust_us.set_index('OrderDate')
# Filter and set the period from July 2007 until June 2008 (the lat
est data)
high_cust_us = high_cust_us.loc['2007-07':'2008-06']
# Create a groupby to show the sum of order quantity based on the y
ear and month for United States
us = high_cust_us.groupby(['Year','Month'])['OrderQuantity'].sum().
sort_index()
# Plot the groupby and colour the ax in purple and label as 'United
States'
ax = us.plot(color='purple',label='United States')

plt.ylabel('Demand')
plt.xlabel('Date')
plt.xticks(ticks, ticks2)
plt.title('12 Months Demand' + '\n' + 'For 2007/8')
# To locate and position the legend box
handles, labels = ax.get_legend_handles_labels()
l = plt.legend(handles[0:6], labels[0:6], bbox_to_anchor=(1,1), loc
=2, borderaxespad=0.)

plt.tight_layout()
plt.show()
```



December continues to be the busiest period in most countries while sales drop in Australia even though it is the most festive season. Sales are low in Summer especially in August in all countries.

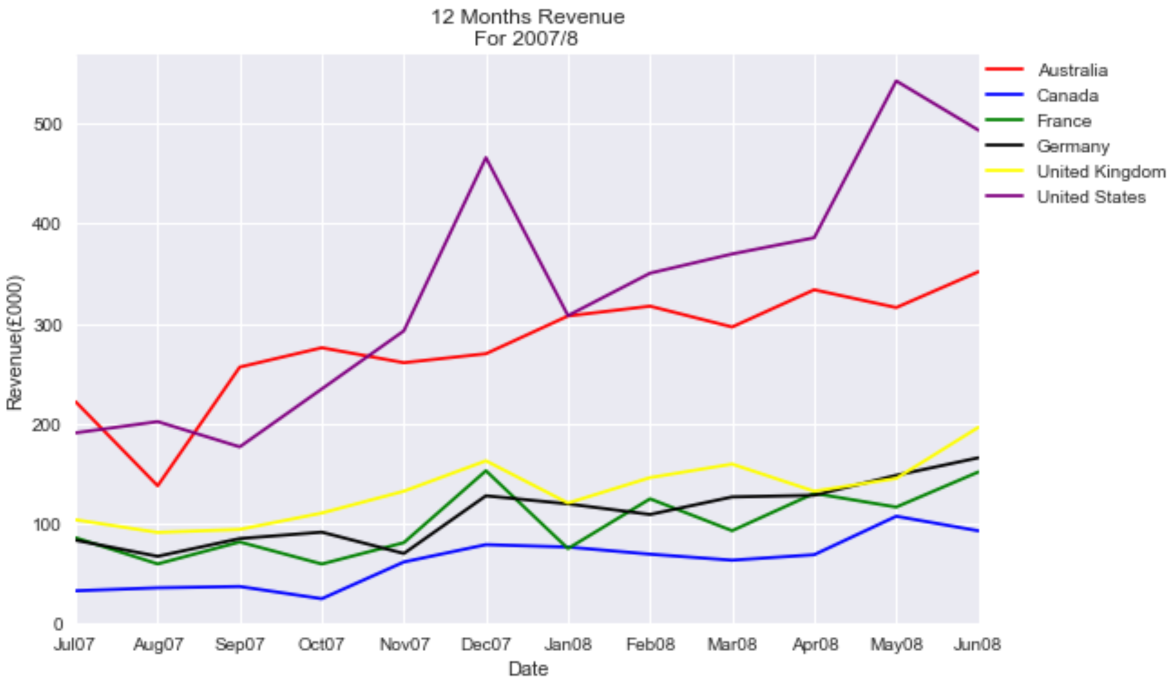
Analysis #9

When They Buy During The Year By Revenue

In [83]:
```
ticks = [0,1,2,3,4,5,6,7,8,9,10,11]
ticks2 = ['Jul07','Aug07','Sep07','Oct07','Nov07','Dec07','Jan08','Feb08','Mar08','Apr08','May08','Jun08']

# Create a groupby to show the total sum of Unit Price by Year and Month for Australia and then divide by 1,000
# to make visualisation easier to read
aus = high_cust_aus.groupby(['Year','Month'])['UnitPrice'].sum()/1000
# Sort the index by OrderDate
aus= aus.sort_index()
# Plot the groupby and colour the ax in red and label as 'Australia'
ax = aus.plot(color='red',label='Australia')

# Create a groupby to show the total sum of Unit Price by Year and Month for Canada and then divide by 1,000
# to make visualisation easier to read
ca = high_cust_ca.groupby(['Year','Month'])['UnitPrice'].sum()/1000
```

```
# Sort the index by OrderDate
ca = ca.sort_index()
# Plot the groupby and colour the ax in blue and label as 'Canada'
ax = ca.plot(color='blue',label='Canada')

# Create a groupby to show the total sum of Unit Price by Year and
Month for France and then divide by 1,000
# to make visualisation easier to read
fr = high_cust_fr.groupby(['Year','Month'])['UnitPrice'].sum()/1000
# Sort the index by OrderDate
fr = fr.sort_index()
# Plot the groupby and colour the ax in green and label as 'France'
ax = fr.plot(color='green',label='France')

# Create a groupby to show the total sum of Unit Price by Year and
Month for Germany and then divide by 1,000
# to make visualisation easier to read
ger = high_cust_ger.groupby(['Year','Month'])['UnitPrice'].sum()/10
00
# Sort the index by OrderDate
ger = ger.sort_index()
# Plot the groupby and colour the ax in black and label as 'Germany
'
ax = ger.plot(color='k',label='Germany')

# Create a groupby to show the total sum of Unit Price by Year and
Month for United Kingdom and then divide by 1,000
# to make visualisation easier to read
uk = high_cust_uk.groupby(['Year','Month'])['UnitPrice'].sum()/1000
# Sort the index by OrderDate
uk = uk.sort_index()
# Plot the groupby and colour the ax in yellow and label as 'United
Kingdom'
ax = uk.plot(color='yellow',label='United Kingdom')

# Create a groupby to show the total sum of Unit Price by Year and
Month for United Kingdom and then divide by 1,000
# to make visualisation easier to read
us = high_cust_us.groupby(['Year','Month'])['UnitPrice'].sum()/1000
# Sort the index by OrderDate
us = us.sort_index()
# Plot the groupby and colour the ax in purple and label as 'United
States'
ax = us.plot(color='purple',label='United States')


plt.ylabel('Revenue(£000)')
plt.xlabel('Date')
plt.xticks(ticks, ticks2)
plt.title('12 Months Revenue' + '\n' + 'For 2007/8')
# To locate and position the legend box
handles, labels = ax.get_legend_handles_labels()
l = plt.legend(handles[0:6], labels[0:6], bbox_to_anchor=(1,1), loc
```

```
=2, borderaxespad=0.)
plt.tight_layout()
plt.show()
```



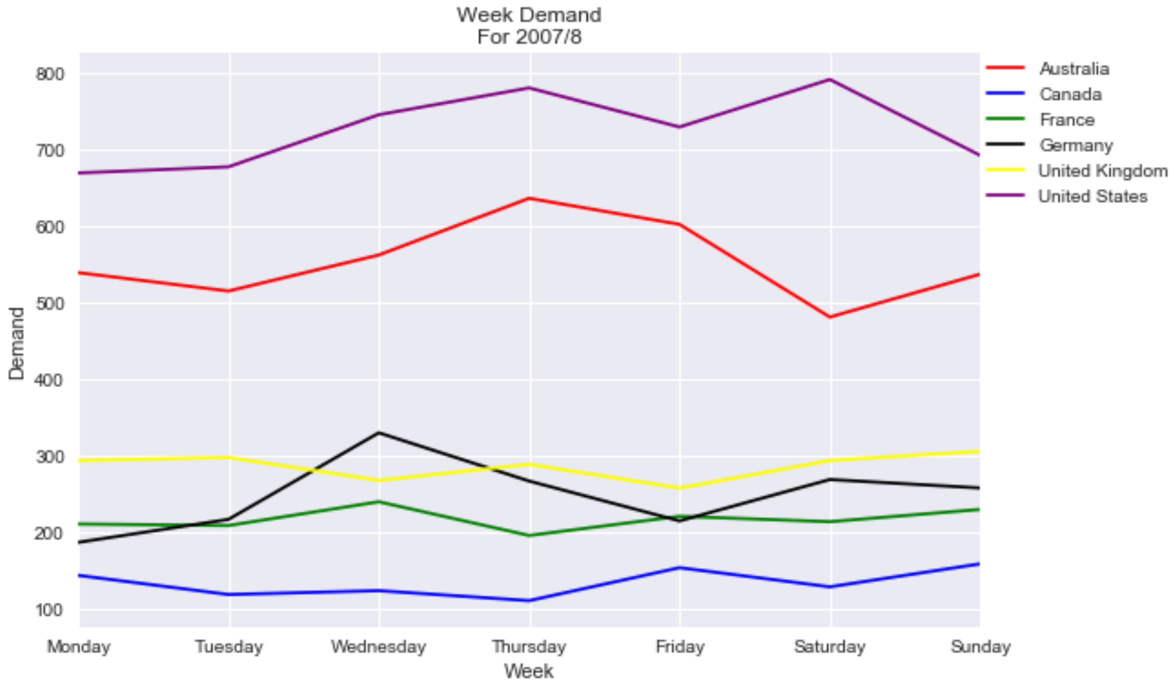
Simiiar to the previous chart, December remains to be the most profitable but plummets in Australia. Again sales are the lowest in Summer.

Analysis #10

When They Buy During The Week

In [84]:
```
day_order = ['Monday','Tuesday','Wednesday','Thursday','Friday','Sa
turday','Sunday']

# Create a groupby to show the sum of order quantity based on weekd
ay for Australia
aus = high_cust_aus.groupby('Weekday')['OrderQuantity'].sum().sort_
index()
# Plot the groupby and colour the ax in red and label as 'Australia
'
ax = aus.loc[day_order].plot(color='red',label='Australia')

# Create a groupby to show the sum of order quantity based on weekd
ay for Canada
ca = high_cust_ca.groupby('Weekday')['OrderQuantity'].sum().sort_in
dex()
```

```
# Plot the groupby and colour the ax in blue and label as 'Canada'
ax = ca.loc[day_order].plot(color='blue',label='Canada')

# Create a groupby to show the sum of order quantity based on weekd
ay for France
fr = high_cust_fr.groupby('Weekday')['OrderQuantity'].sum().sort_in
dex()
# Plot the groupby and colour the ax in green and label as 'France'
ax = fr.loc[day_order].plot(color='green',label='France')

# Create a groupby to show the sum of order quantity based on weekd
ay for Germany
ger = high_cust_ger.groupby('Weekday')['OrderQuantity'].sum().sort_
index()
# Plot the groupby and colour the ax in black and label as 'Germany
'
ax = ger.loc[day_order].plot(color='k',label='Germany')

# Create a groupby to show the sum of order quantity based on weekd
ay for United Kingdom
uk = high_cust_uk.groupby('Weekday')['OrderQuantity'].sum().sort_in
dex()
# Plot the groupby and colour the ax in yellow and label as 'United
Kingdom'
ax = uk.loc[day_order].plot(color='yellow',label='United Kingdom')

# Create a groupby to show the sum of order quantity based on weekd
ay for United States
us = high_cust_us.groupby('Weekday')['OrderQuantity'].sum().sort_in
dex()
# Plot the groupby and colour the ax in purple and label as 'United
States'
ax = us.loc[day_order].plot(color='purple',label='United States')

plt.ylabel('Demand')
plt.xlabel('Week')
plt.title('Week Demand' + '\n' 'For 2007/8')
# To locate and position the legend box
plt.legend(bbox_to_anchor=(1.05,1), loc=2, borderaxespad=0.)
handles, labels = ax.get_legend_handles_labels()
l = plt.legend(handles[0:6], labels[0:6], bbox_to_anchor=(1,1), loc
=2, borderaxespad=0.)

plt.tight_layout()
plt.show()
```

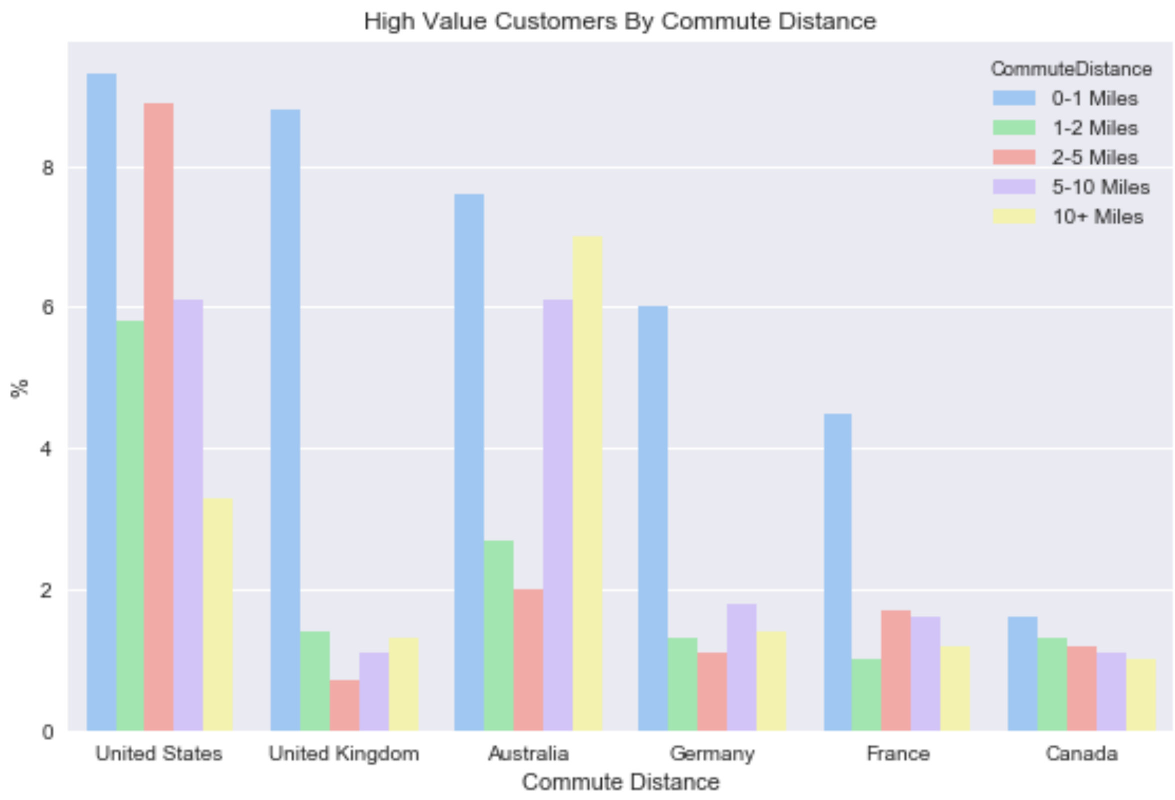


Overall, the weekends are recorded to be the busiest time during the week in most countries, while not so busy in Australia. Tuesdays and Fridays have been the least busiest, but not the case in Canada.

Analysis #11

Why They Buy - Commute Distance

In [85]:
```
# Create a hue order of 4 different types of commute distance
hue_order = ['0-1 Miles','1-2 Miles','2-5 Miles','5-10 Miles','10+
Miles']

# Create a groupby that counts the number of customers for each typ
e of commute distance group for every country region
groupby_commute = high_cust.groupby(['CountryRegion','CommuteDistan
ce'])['CustomerKey'].count()
# Sum the total number of customers as a denominator
total_commute = groupby_commute.sum()
# Divide each commute distance group by the denominator and times b
y 100 to create a percentage
# and round it by one decimal place sorted in ascending order
product = round(groupby_commute/total_commute*100,1).sort_values(as
cending=False)

# Add pipeline to use the above groupby function and create a bar c
hart with an x axis of 'CountryRegion'
# and a y axis of 'CustomerKey' in the order of the commute distanc
e groups
product.reset_index().pipe((sns.barplot, 'data'),
x='CountryRegion', y='CustomerKey', palette='pastel', hue='CommuteD
istance', hue_order=hue_order)
plt.title('High Value Customers By Commute Distance')
plt.ylabel('%')
plt.xlabel('Commute Distance')
plt.tight_layout()

plt.show()
```



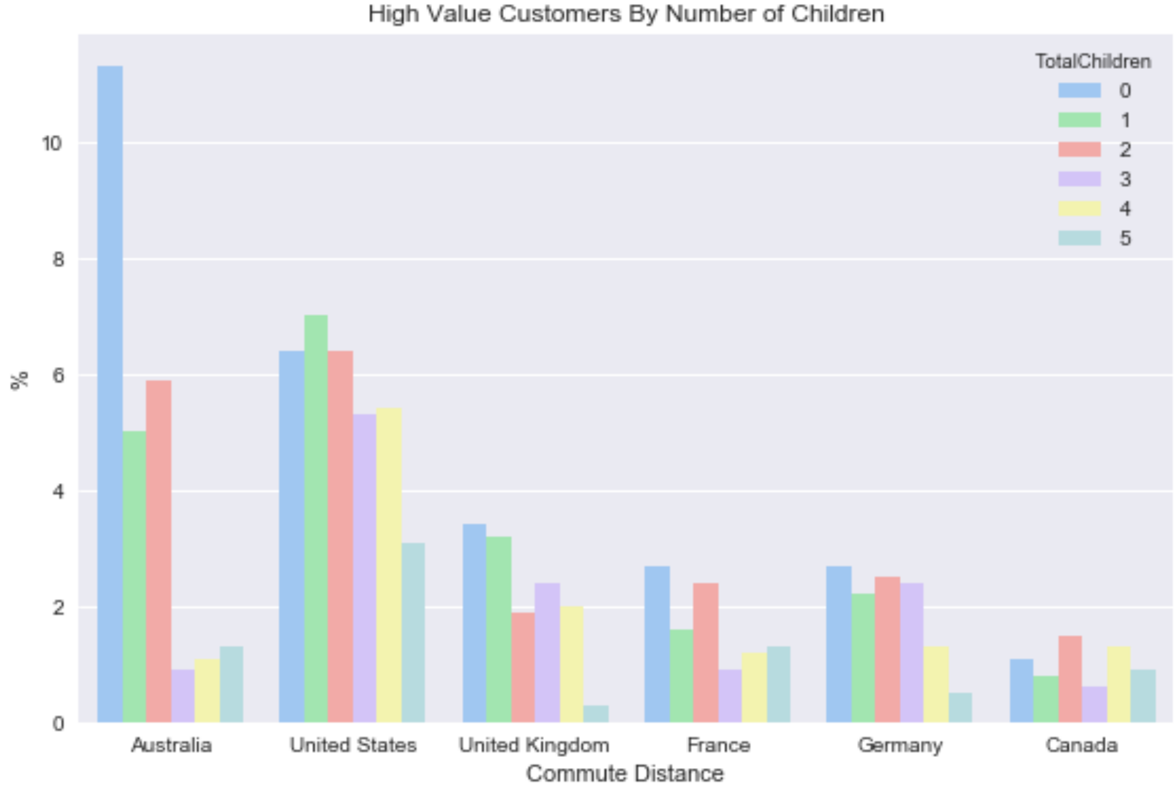
A majority of customers travel short distances making the commute distance of 0-1 miles the first largest. Interestingly, in Australia many customers travel 5-10 miles and 10+ miles.

Analysis #12

Why They Buy - Number Of Children

In [86]:

```
# Create a groupby that counts the number of customers for each category of the number of children group for every country region
groupby_kids = high_cust.groupby(['CountryRegion','TotalChildren'])['CustomerKey'].count()
# Sum the total number of customers as a denominator
total_kids = groupby_kids.sum()
# Divide each group by the denominator and times by 100 to create a percentage
# and round it by one decimal place sorted in ascending order
kids = round(groupby_kids/total_kids*100,1).sort_values(ascending=False)

# Add pipeline to use the above groupby function and create a bar chart with an x axis of 'CountryRegion'
# and a y axis of 'CustomerKey' in the order of the Total Children groups
kids.reset_index().pipe((sns.barplot, 'data'),
x='CountryRegion', y='CustomerKey', palette='pastel', hue='TotalChildren')
plt.title('High Value Customers By Number of Children')
plt.ylabel('%')
plt.xlabel('Commute Distance')
plt.tight_layout()

plt.show()
```



Customers generally have more than one child in every coutnry region. However, in Australia more than 10% of customers do not have children.

Customer Profiling

For this section, I will create a customer profile that provides a description and analysis of high value customers based on a set of attributes such as demographic, geographic, psychographic and behavioural characteristics

In [87]:
```
# Create a variable that shows the total sum of revenue for each cu
stomer
master_df_clean['Total_Revenue'] = master_df_clean.groupby('Custome
rKey')['UnitPrice'].transform('sum')
```

In [88]:
```
# Create a variable that shows the total sum of cost for each custo
mer
master_df_clean['Total_Cost'] = master_df_clean.groupby('CustomerKe
y')['TotalProductCost'].transform('sum')
```

In [89]:
```
# Create a variable that shows the total profit for each customer
master_df_clean['Total_Profit'] = master_df_clean.groupby('Customer
Key')['Profit'].transform('sum')
```

In [90]:
```
# Create a variable that shows the total sum of order quantity for
each customer
master_df_clean['Frequency'] = master_df_clean.groupby('CustomerKey
')['SalesOrderNumber'].transform('count')
```

In [91]:
```
# Create a variable that shows the total account length of time for
each customer
master_df_clean['Tenure'] = master_df_clean.groupby('CustomerKey')[
'Tenure(Days)'].transform('max')
```

In [92]:
```
# Create a variable that only contains high value customers
high_cust_pro = master_df_clean[master_df_clean['High_Value_Flag']=
=1]
```

In [93]:
```
# Create a variable to show customers' profile
cust_pro = high_cust_pro.loc[:,['CustomerKey','Age','Age_Group','Ma
ritalStatus','Gender','Status_Gender','YearlyIncome','TypeOfEarner'
,'TotalChildren',
                'Education','Occupation','HouseOwnerFlag','NumberCa
rsOwned','CommuteDistance',
                 'Tenure','Frequency','Total_Revenue','Total_Cost',
'Total_Profit']]
```

In [94]:
```
cust_pro = cust_pro.drop_duplicates(subset='CustomerKey',keep='last
')
```

In [95]:
```
# Showing the 5 random samples
cust_pro.sample(5)
```

Out[95]:

	CustomerKey	Age	Age_Group	MaritalStatus	Gender	Status_Gender	Yea
41846	22173	54.5	45-59	NaN	NaN	MarriedFemale	300(
8376	12381	33.7	30-44	NaN	NaN	MarriedMale	400(
9279	12630	53.1	45-59	NaN	NaN	MarriedMale	800(
24626	16452	28.8	18-29	NaN	NaN	SingleFemale	300(
51316	25737	48.0	45-59	NaN	NaN	MarriedMale	400(

New Treatment Group: Prospective Buyers

I will now compare the existing customers to a new treatment group of prospective buyers in order to find out if Kernal Ltd have been targeting at the right customers and look for ways to approach and communicate to this particular group as a benchmark.

In [96]:
```
# Import and read csv file into a dataframe that contains Prospecti
ve buyers' information
prospective = pd.read_csv('dbo_prospectivebuyer.csv',index_col=0)
```

In [97]:
```
# Convert the variable to date format
prospective['BirthDate'] = pd.to_timedelta(prospective['BirthDate']
, unit='s') + pd.datetime(1960, 1, 1)
```

In [98]:
```
# Clean the email address variable by removing the letter that begi
ns with 'a'
prospective['EmailAddress'] = prospective['EmailAddress'].str[1:]
```

In [99]:
```
# Create a variable that calculates the number of days between the
lastest date and birthdate
prospective['Diff_In_Days'] = datetime(2008,7,31) - prospective['Bi
rthDate']
# Turn the above variable into years instead of days thereby creati
ng a new variable 'Age' of each Customer
prospective['Age'] = prospective['Diff_In_Days'] / timedelta(days=3
65)
# Round the variable to one decimal point
prospective['Age'] = round(prospective['Age'],1)
```

In [100]:
```
# Apply the Age_Group function to age variable
prospective['Age_Group'] = prospective.apply(age_group, axis=1)
```

In [101]:
```
# Apply the TypeOfEarner function to the income variable
prospective['TypeOfEarner'] = prospective.apply(income, axis=1)
```

In [102]:
```
# Show the first 5 rows of the dataset
prospective.head()
```

Out[102]:

	ProspectiveBuyerKey	ProspectAlternateKey	FirstName	MiddleName	LastNam
0	1.0	21596444800	Adam	NaN	Alexander
1	2.0	3003	Adrienne	NaN	Alonso
2	3.0	1077	Alfredo	B	Alvarez
3	4.0	4779	Arthur	A	Arun
4	5.0	38032399400	Andrea	M	Bailey

5 rows × 28 columns

In [103]:
```
# Use a for loop to convert the following variables to integers
for col in [
    'ProspectiveBuyerKey','YearlyIncome','TotalChildren','NumberCar
sOwned'
]:
    prospective[col] = prospective[col].astype(int)
```

In [104]:
```
# Create a customer profile for prospective buyers
prospective.loc[:,['ProspectiveBuyerKey','Age','Age_Group','YearlyIncome','TypeOfEarner','MaritalStatus','Gender',
                              'TotalChildren','Education','Occupation','NumberCarsOwned']].sample(5)
```

Out[104]:

	ProspectiveBuyerKey	Age	Age_Group	YearlyIncome	TypeOfEarner	Marit
979	980	35.7	30-44	110000	PremiumEarners	M
345	346	35.3	30-44	90000	PremiumEarners	S
1706	1707	43.5	30-44	50000	HighEarners	M
106	107	31.3	30-44	80000	PremiumEarners	M
469	470	39.4	30-44	20000	LowEarners	M

In [105]:
```
# Our own Customer profile
cust_pro.sample(5)
```

Out[105]:

	CustomerKey	Age	Age_Group	MaritalStatus	Gender	Status_Gender	Yea
2308	11289	46.4	45-59	NaN	NaN	MarriedFemale	130
47421	24242	61.1	60+	NaN	NaN	MarriedFemale	300
20567	15374	73.4	60+	NaN	NaN	MarriedFemale	700
35982	20075	53.1	45-59	NaN	NaN	SingleMale	100
50468	25408	38.2	30-44	NaN	NaN	MarriedFemale	700

Data Analysis and Visualisation to Compare Two Groups

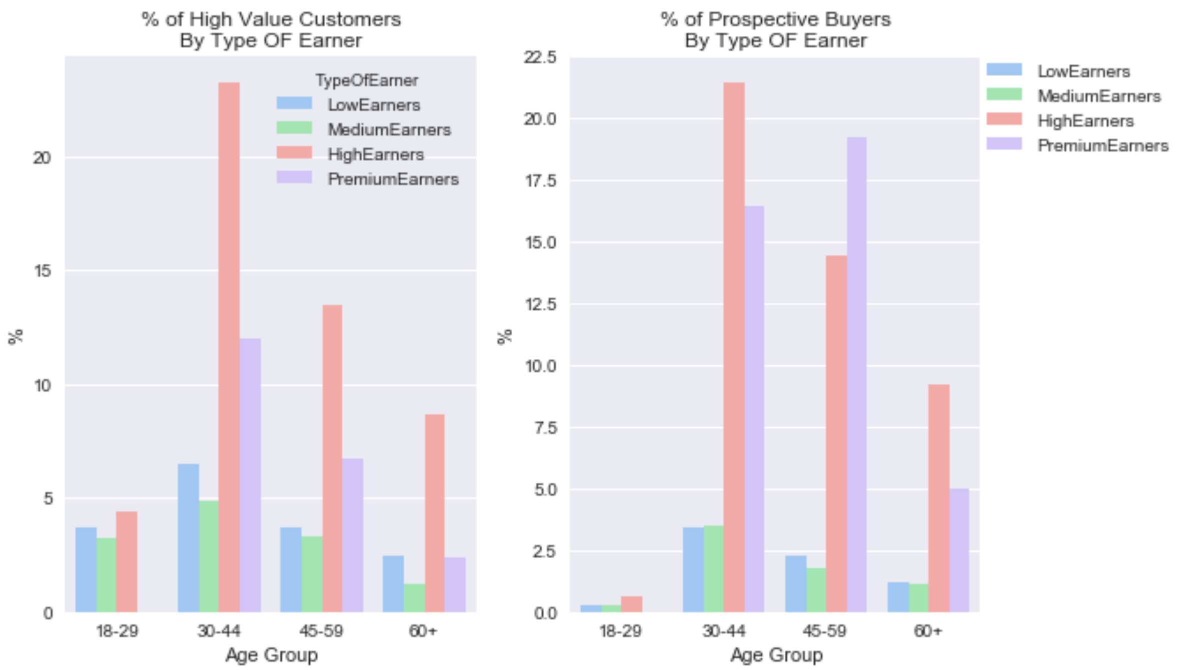
The next task is to use data visualisations to compare the two groups together

Analysis #13

High Value Customers VS Prospective Buyers By Age Group AND Type Of Earner

In [106]:
```
ticks = [0,1,2,3]
hue_order  = ['LowEarners','MediumEarners','HighEarners','PremiumEa
rners']
ticks2 = ['18-29','30-44','45-59','60+']

# First plot
plt.subplot(1,2,1)
# Create a groupby that counts the number of prospective buyers for
each TypeOfEarner group for every age group
pro_age_earner = prospective.groupby(['Age_Group','TypeOfEarner'])[
'ProspectiveBuyerKey'].count()
# Sum the total number of prospective buyers as a denominator
total_age_earner = pro_age_earner.sum()
# Divide each TypeOfEarner and age group by the denominator and tim
es by 100 to create a percentage
# and round it by one decimal place
age_earner = round(pro_age_earner/total_age_earner*100,1)

# Add pipeline to use the above groupby function and create a bar c
hart with an x axis of 'Age_Group'
# and a y axis of 'ProspectiveBuyerKey' in the order of the 4 TypeO
fEarner groups
ax = age_earner.reset_index().pipe((sns.barplot, 'data'),
x='Age_Group', y='ProspectiveBuyerKey', palette='pastel', hue='Type
OfEarner', hue_order=hue_order)
plt.xlabel('Age Group')
plt.xticks(ticks, ticks2)
plt.ylabel('%')
plt.title('% of High Value Customers' + '\n' + 'By Type OF Earner')

# Second plot
plt.subplot(1,2,2)
# Create a groupby that counts the number of customers for each Typ
eOfEarner for every age group
pro_age_earner = high_cust.groupby(['Age_Group','TypeOfEarner'])['C
ustomerKey'].count()
# Sum the total number of customers as a denominator
total_age_earner = pro_age_earner.sum()
# Divide each TypeOfEarner and age group by the denominator and tim
es by 100 to create a percentage
# and round it by one decimal place
age_earner = round(pro_age_earner/total_age_earner*100,1)
```

```
# Add pipeline to use the above groupby function and create a bar c
hart with an x axis of 'Age_Group'
# and a y axis of 'CustomerKey' in the order of the 4 TypeOfEarner
groups
ax = age_earner.reset_index().pipe((sns.barplot, 'data'),
x='Age_Group', y='CustomerKey', palette='pastel', hue='TypeOfEarner
', hue_order=hue_order)
plt.xlabel('Age Group')
plt.xticks(ticks,ticks2)
plt.ylabel('%')
plt.title('% of Prospective Buyers' + '\n' + 'By Type OF Earner')

# To locate and position the legend box
handles, labels = ax.get_legend_handles_labels()
l = plt.legend(handles[0:4], labels[0:4], bbox_to_anchor=(1,1), loc
=2, borderaxespad=0.)

plt.tight_layout()
plt.show()
```



We can see that there is a high number of Premium Earners particularly from the age of 30-44(16%) and 45-59(19%) under Prospectives Buyers. However, when comparing to our dataset there is only less than 12% for Premium Earners from the age of 30-44 and less than 7% for 45-59.

Analysis #14

High Value Customers VS Prospective Buyers By Type Of Earner AND Occupation

In [107]:

```
# First plot
plt.subplot(1,2,1)
# Create a groupby that counts the number of prospective buyers for
each Occupation group for every TypeOfEarner
pro_age_earner = prospective.groupby(['TypeOfEarner','Occupation'])
['ProspectiveBuyerKey'].count()
# Sum the total number of prospective buyers as a denominator
total_age_earner = pro_age_earner.sum()
# Divide each age group by the denominator and times by 100 to crea
te a percentage and round it by one decimal place
age_earner = round(pro_age_earner/total_age_earner*100,1)

# Add pipeline to use the above groupby function and create a bar c
hart with an x axis of 'Occupation'
# and a y axis of 'ProspectiveBuyerKe' in the order of the 4 TypeOf
Earner groups
ax = age_earner.reset_index().pipe((sns.barplot, 'data'),
x='Occupation', y='ProspectiveBuyerKey', palette='pastel', hue='Typ
eOfEarner', hue_order=hue_order)
plt.xlabel('Occupation')
plt.xticks(rotation=75)
plt.ylabel('%')
plt.title('% of High Value Customers' + '\n' + 'By Occupation')
# To locate and position the legend box
handles, labels = ax.get_legend_handles_labels()
l = plt.legend(handles[0:4], labels[0:4], bbox_to_anchor=(-0.6,1),
loc=2, borderaxespad=0.)

# Second plot
plt.subplot(1,2,2)
# Create a groupby that counts the number of customers for each Occ
upation for every TypeOfEarner group
pro_age_earner = high_cust.groupby(['TypeOfEarner','Occupation'])['
CustomerKey'].count()
# Sum the total number of customers as a denominator
total_age_earner = pro_age_earner.sum()
# Divide each age group by the denominator and times by 100 to crea
te a percentage and round it by one decimal place
age_earner = round(pro_age_earner/total_age_earner*100,1)

# Add pipeline to use the above groupby function and create a bar c
hart with an x axis of 'Occupation'
# and a y axis of 'CustomerKey' in the order of the 4 TypeOfEarner
groups
ax = age_earner.reset_index().pipe((sns.barplot, 'data'),
x='Occupation', y='CustomerKey', palette='pastel', hue='TypeOfEarne
r', hue_order=hue_order)
plt.xlabel('Occupation')
```

```
plt.xticks(rotation=75)
plt.ylabel('%')
plt.title('% of Prospective Buyers' + '\n' + 'By Occupation')
# To locate and position the legend box
handles, labels = ax.get_legend_handles_labels()
l = plt.legend(handles[0:4], labels[0:4], bbox_to_anchor=(1,1), loc
=2, borderaxespad=0.)

plt.tight_layout()
plt.show()
```

It is clear to say that Kernal Limited are not targeting enough to PremiumEarners who work in Management and Professional. According to the plot under Prospective Buyers, there is over 16% of Premium Earners who work in Management and over 17.5% under Professional. As you can see Kernal Ltd only reached to less than 12% of Premium Earners who work in Management and less than 10% under Professional. However, Kernal Ltd is paying more attention to Low Earners under Clerical and Manual as well as HighEarners under Skilled Manual.

Analysis #15

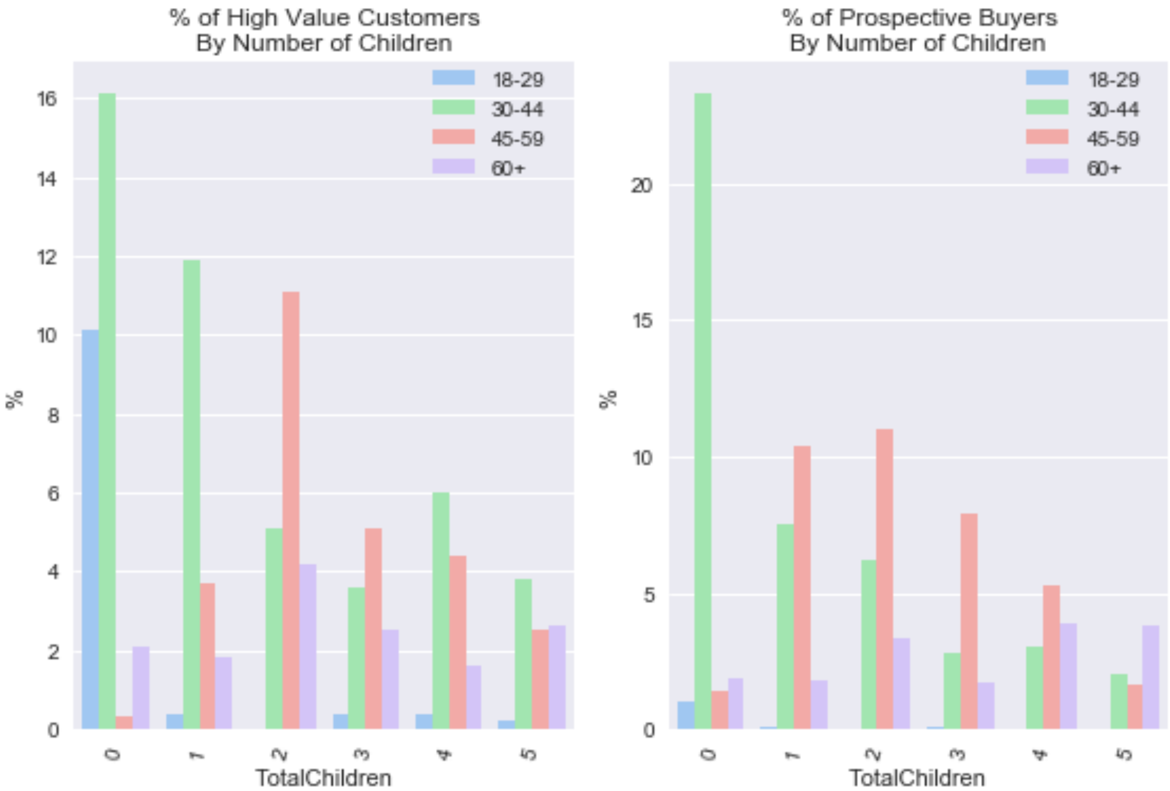
High Value Customers VS Prospective Buyers By Age Group AND Total Children

In [108]:

```
ticks = [0,1,2,3,4,5]
ticks2 = [0,1,2,3,4,5]

# First plot
plt.subplot(1,2,1)
# Create a groupby that counts the number of prospective buyers for
```

```
each TotalChildren group for every age group
pro_age_earner = prospective.groupby(['Age_Group','TotalChildren'])
['ProspectiveBuyerKey'].count()
# Sum the total number of prospective buyers as a denominator
total_age_earner = pro_age_earner.sum()
# Divide each age group by the denominator and times by 100 to crea
te a percentage and round it by one decimal place
age_earner = round(pro_age_earner/total_age_earner*100,1)

# Add pipeline to use the above groupby function and create a bar c
hart with an x axis of 'TotalChildren'
# and a y axis of 'ProspectiveBuyerKey' in the order of the 4 Age g
roups
ax = age_earner.reset_index().pipe((sns.barplot, 'data'),
x='TotalChildren', y='ProspectiveBuyerKey', palette='pastel', hue='
Age_Group')
plt.xlabel('TotalChildren')
plt.xticks(ticks,ticks2,rotation=75)
plt.ylabel('%')
plt.title('% of High Value Customers' + '\n' + 'By Number of Childr
en')
# To locate and position the legend box
handles, labels = ax.get_legend_handles_labels()
l = plt.legend(handles[0:4], labels[0:4], bbox_to_anchor=(0.7,1), l
oc=2, borderaxespad=0.)

# Second plot
plt.subplot(1,2,2)
# Create a groupby that counts the number of customers for each Tot
alChildren for every Age group
pro_age_earner = high_cust.groupby(['Age_Group','TotalChildren'])['
CustomerKey'].count()
# Sum the total number of customers as a denominator
total_age_earner = pro_age_earner.sum()
# Divide each age group by the denominator and times by 100 to crea
te a percentage and round it by one decimal place
age_earner = round(pro_age_earner/total_age_earner*100,1)

# Add pipeline to use the above groupby function and create a bar c
hart with an x axis of 'TotalChildren'
# and a y axis of 'CustomerKey' in the order of the 4 Age groups
ax = age_earner.reset_index().pipe((sns.barplot, 'data'),
x='TotalChildren', y='CustomerKey', palette='pastel', hue='Age_Grou
p')
plt.xlabel('TotalChildren')
plt.xticks(rotation=75)
plt.ylabel('%')
plt.title('% of Prospective Buyers' + '\n' + 'By Number of Children
')
# To locate and position the legend box
handles, labels = ax.get_legend_handles_labels()
l = plt.legend(handles[0:4], labels[0:4], bbox_to_anchor=(0.7,1), l
oc=2, borderaxespad=0.)
```

```
plt.tight_layout()

plt.show()
```



Kernal Ltd have over 10% of customers aged 18-29 who do not have children and nearly 12% only have one child aged 30-44, but when you look at Prospective Buyers there is only less than 3% who have no children and 8% who have only one child.

Customer Attrition

I will now analyse the impact of the overall analysis on customer attrition. Attrition on this case refers to customers who had in the six(6) months prior been active or in high value category, but now have not shopped twelve months later.

In [109]:
```
# Create and only use the last date for analysis as we would like t
o know if customers have been buying from
# Kernal Ltd within the last six months
max_trans_date = max(master_df_clean['OrderDate'])
max_trans_date
```

Out[109]:
```
Timestamp('2008-07-31 00:00:00')
```

In [110]:
```
# Name the variable to Max_trans_date
master_df_clean['Max_trans_date'] = datetime(2008,7,31)
master_df_clean['LastDayOfPurchase'] = master_df_clean['OrderDate']
master_df_clean['Twelve_Months'] = master_df_clean['Max_trans_date'
] - timedelta(days=365)
```

In [111]:
```
# Define a function to findout whether the customers churn or not
def churn(date):
    if date['LastDayOfPurchase'] > date['Twelve_Months']:
        return 1
    else:
        0

master_df_clean['Churn_Flag'] = master_df_clean.apply(churn, axis=1
)
```

In [112]:
```
# Replace NA entries to 0
master_df_clean['Churn_Flag'] = master_df_clean['Churn_Flag'].filln
a(0)
```

In [113]:
```
# Convert the variable to an integer
master_df_clean['Churn_Flag'] = master_df_clean['Churn_Flag'].astyp
e(int)
```

In [114]:
```
# Filter to only show customers who have a total basket value over
£1,500
high_cust_attr = master_df_clean[master_df_clean['High_Value_Flag']
==1]
```

In [115]:
```
# This is the finalised Customer Profile adding the last day of the
ir purchase and findout whether they came back or not
cust_at = high_cust_attr.loc[:,[
    'CustomerKey','Age','Age_Group','Status_Gender','YearlyIncome',
'TypeOfEarner','TotalChildren',
    'CountryRegion','Education','Occupation','HouseOwnerFlag','Numb
erCarsOwned',
    'CommuteDistance','Tenure','Frequency','Total_Revenue','LastDay
OfPurchase','Twelve_Months','Churn_Flag'
]]

cust_at = cust_at.drop_duplicates(subset='CustomerKey',keep='last')
cust_at.head()
```

Out[115]:

	CustomerKey	Age	Age_Group	Status_Gender	YearlyIncome	TypeOfEarner
7	11000	41.6	30-44	MarriedMale	90000	PremiumEarners
14	11001	42.2	30-44	SingleMale	60000	HighEarners
22	11002	42.1	30-44	MarriedMale	60000	HighEarners
31	11003	39.8	30-44	SingleFemale	70000	HighEarners
37	11004	39.3	30-44	SingleFemale	80000	PremiumEarners

In [116]:
```
# This shows the number of customers who have churn or not
churn = cust_at.groupby('Churn_Flag').size()
churn
```

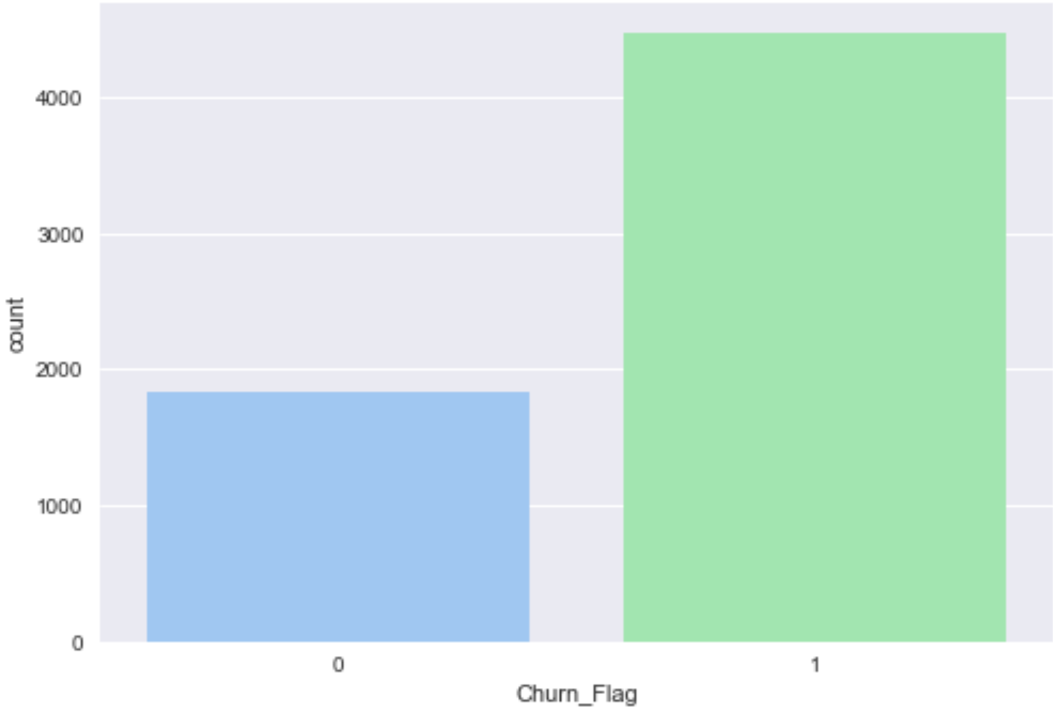
Out[116]:
```
Churn_Flag
0    1831
1    4472
dtype: int64
```

Data Visualisation on Customer Churn

Analysis #16

High Value Customers By Customer Churn

In [117]:
```
ax = sns.countplot(x='Churn_Flag', data=cust_at, palette='pastel')
```



Over 4,000 customers churns which may be due to:

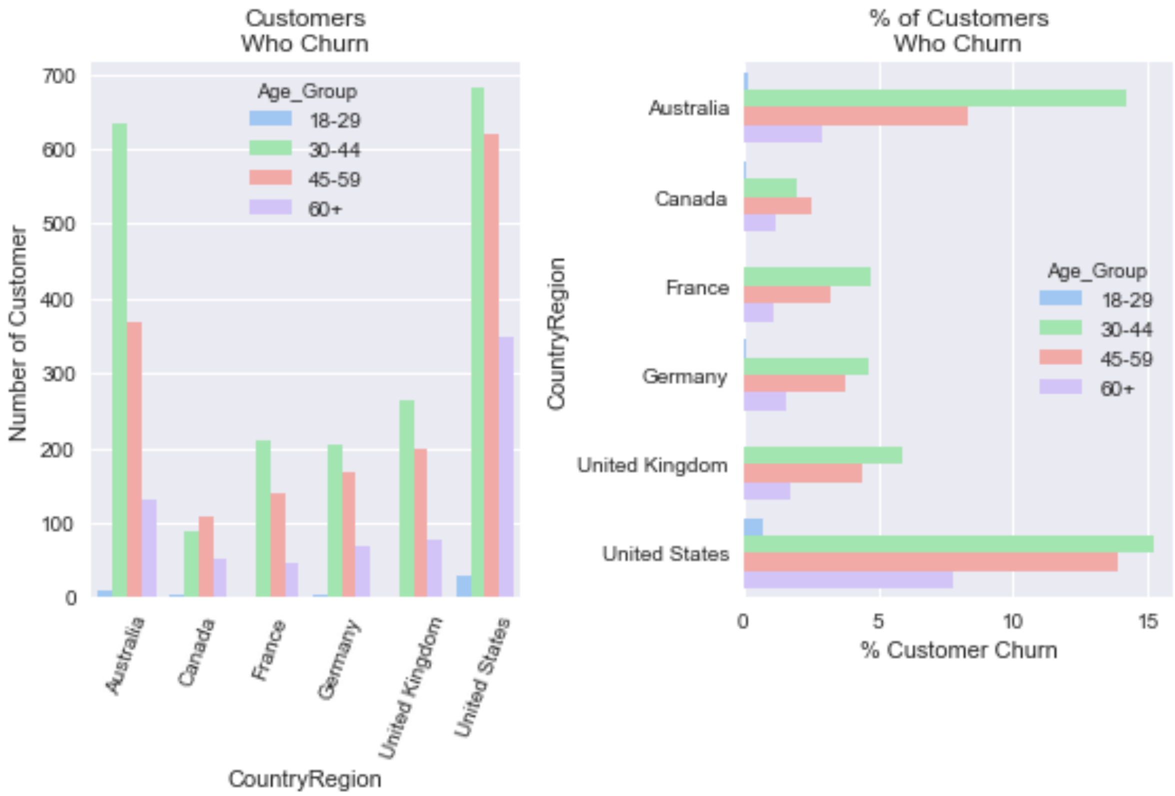
- Bad Customer Service
- Broken Promises
- No Loyalty
- Pushed too hard
- Unexpected Inconvenience

Analysis #17

Customer Churn By Country Region AND Age Group

In [118]:
```
# Filter to only show customers with a churn flag
churn_cust_1 = cust_at[cust_at['Churn_Flag']==1]
```

In [119]:
```
# # Create a groupby that list the total number of customer churns
for each age group for every country region
churn_groupby = (churn_cust_1.groupby(['CountryRegion','Age_Group']
)['Churn_Flag'].count())

plt.subplot(1,2,1)
# Add pipeline to use the above groupby function and create a bar c
hart with an x axis of 'Country'
# and a y axis of 'UnitPrice' in the order of the 4 age groups
ax = churn_groupby.reset_index().pipe((sns.barplot, 'data'),
x='CountryRegion', y='Churn_Flag', palette='pastel', hue='Age_Group
')
plt.xticks(rotation=70)
plt.xlabel('CountryRegion')
plt.ylabel('Number of Customer')
plt.title('Customers' + '\n' +  'Who Churn')

plt.subplot(1,2,2)
# Sum the total number of customers as a denominator
total_churn = churn_groupby.sum()
# Divide each age group by the denominator and times by 100 to crea
te a percentage and round it by one decimal place
age_earner = round(churn_groupby/total_churn*100,1)

# Add pipeline to use the above groupby function and create a bar c
hart with an x axis of 'Churn_Flag'
# and a y axis of 'CountryRegion' in the order of the 4 Age groups
ax = age_earner.reset_index().pipe((sns.barplot, 'data'),
x='Churn_Flag', y='CountryRegion', palette='pastel', hue='Age_Group
')
plt.xlabel('% Customer Churn')

plt.ylabel('CountryRegion')
plt.title('% of Customers' + '\n' + 'Who Churn')

plt.tight_layout()
plt.show()
```

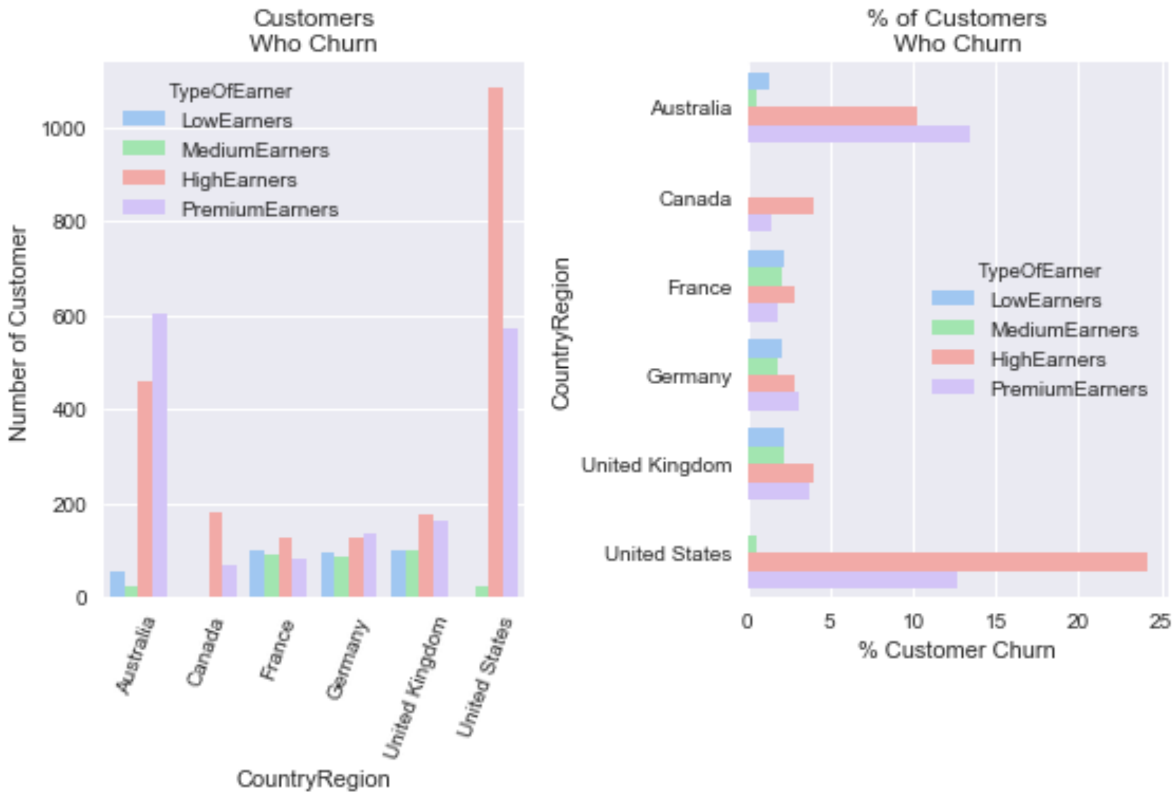


Customers who churn are mainly from the age of 30-44 and 45-59. Australia and United States have the most churns as they are both big countries so the number of customers are high.

Analysis #18

Customer Churn By Country Region AND Type Of Earner

In [120]:
```
# Create a groupby that list the total number of customer churns fo
r each age group for every country region
churn_groupby = (churn_cust_1.groupby(['CountryRegion','TypeOfEarne
r'])['Churn_Flag'].count())
hue_order = ['LowEarners','MediumEarners','HighEarners','PremiumEar
ners']

plt.subplot(1,2,1)

# Add pipeline to use the above groupby function and create a bar c
hart with an x axis of 'CountryRegion'
# and a y axis of 'Churn_Flag' in the order of the 4 TypeOfEarner g
roups
ax = churn_groupby.reset_index().pipe((sns.barplot, 'data'),
x='CountryRegion', y='Churn_Flag', palette='pastel', hue='TypeOfEar
ner',hue_order=hue_order)
plt.xticks(rotation=70)
plt.xlabel('CountryRegion')
plt.ylabel('Number of Customer')
plt.title('Customers' + '\n' +  'Who Churn')


plt.subplot(1,2,2)
# Sum the total number of customers as a denominator
total_churn = churn_groupby.sum()
# Divide each age group by the denominator and times by 100 to crea
te a percentage and round it by one decimal place
type_earner = round(churn_groupby/total_churn*100,1)

# Add pipeline to use the above groupby function and create a bar c
hart with an x axis of 'Churn_Flag'
# and a y axis of 'CountryRegion' in the order of the 4 Age groups
ax = type_earner.reset_index().pipe((sns.barplot, 'data'),
x='Churn_Flag', y='CountryRegion', palette='pastel', hue='TypeOfEar
ner',hue_order=hue_order)
plt.xlabel('% Customer Churn')

plt.ylabel('CountryRegion')
plt.title('% of Customers' + '\n' + 'Who Churn')

plt.tight_layout()
plt.show()
```



Most customers who are High Earners and Premium Earners decide to churn especially in the United states and Australia. This is a concern for Kernal Ltd as in my previous analysis HighEarners and PremiumEarners are the main source of income.

Market Basket Analysis

I will now analyse the data further and perform market basket analysis to identify relationships between the items that customers buy.

In [121]:
```
# Import packages to perform market basket analysis
from mlxtend.frequent_patterns import apriori
from mlxtend.frequent_patterns import association_rules
```

In [122]:
```
# Here is a sample of what a customer bought in the past
basket_df = high_cust.loc[:,[
    'SalesOrderNumber','SalesTerritoryCountry','ProductCategory',
    'ProductName','OrderQuantity','UnitPrice']]

basket_df.head(2)
```

Out[122]:

	SalesOrderNumber	SalesTerritoryCountry	ProductCategory	ProductN
OrderDate				
2007-07-22	SO51522	Australia	Bikes	Mountain-: Silver, 38
2007-07-22	SO51522	Australia	Accessories	Fender Se Mountain

In [123]:
```
# This is to simplify the results and ensure that any positive valu
es of order quantity
# are converted to a 1 and 0. This is because I am only interested
in what
# customers bought together as opposed to how many items bought

def encode_units(x):
    if x <=0:
        return 0
    if x >= 1:
        return 1
```

Australia

In [124]:
```
# Filtering the data analysis to only high value customers with a t
otal basket value of £1,500 or over
# and showing the basket only related to Australia
basket_aus = (master_df_clean[(master_df_clean['SalesTerritoryCount
ry'] == 'Australia') & (master_df_clean['High_Value_Flag']==1)]
          # Create groupby to find the total number of order quanti
ty based on SalesOrderNumber and Product Name
          .groupby(['SalesOrderNumber','ProductName'])['OrderQuanti
ty']
          # Unstack the table so that the data is structured proper
ly, reset the index and then fill the NA entries with 0
          .sum().unstack().reset_index().fillna(0)
          # Set the index to SalesOrderNumber
          .set_index('SalesOrderNumber'))
```

In [125]:
```
# Apply the function that was created to set the results to either
0 or 1
basket_sets = basket_aus.applymap(encode_units)
# Generate frequent item sets that have a support of at least 5% in
order to get enough useful examples
frequent_itemsets = apriori(basket_sets, min_support=0.05, use_coln
ames=True)
# Generate the rules with their corresponding support, confidence a
nd lift
rules = association_rules(frequent_itemsets, metric='lift', min_thr
eshold=1)
# Show results
rules
```

Out[125]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	
0	(Water Bottle - 30 oz.)	(Road Bottle Cage)	0.089954	0.068943	0.060079	0.667883	9.687
1	(Road Bottle Cage)	(Water Bottle - 30 oz.)	0.068943	0.089954	0.060079	0.871429	9.687

In [126]:
```
# Filter the results and set the lift to 6 or more and confidence t
o 0.8 or more
rules[ (rules['lift'] >=6) &
       (rules['confidence'] >= 0.8)
     ]
```

Out[126]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	
1	(Road Bottle Cage)	(Water Bottle - 30 oz.)	0.068943	0.089954	0.060079	0.871429	9.687

Looking at the rules, it can be seen that the Road Bottle Cage and Water Bottle - 30 oz are purchased together.

I now want to find out how much opportunity there is for selling Road Bottle Cage and improve sales for the Water Bottle.

In [127]:
```
# When we sell 210 Road Bottle Cages, 274 Water Bottles were sold w
hich drove even
# more sales and proved to be very effective
basket_aus['Road Bottle Cage'].sum()
```

Out[127]: 210.0

In [128]:
```
basket_aus['Water Bottle - 30 oz.'].sum()
```

Out[128]: 274.0

Canada

In [129]:
```
# Filtering the data analysis to only high value customers with a t
otal basket value of £1,500 or over
# and showing the basket only related to Canada
basket_ca = (master_df_clean[(master_df_clean['SalesTerritoryCountr
y'] == 'Canada') & (master_df_clean['High_Value_Flag']==1)]
          # Create groupby to find the total number of order quanti
ty based on SalesOrderNumber and Product Name
          .groupby(['SalesOrderNumber','ProductName'])['OrderQuanti
ty']
          # Unstack the table so that the data is structured proper
ly, reset the index and then fill the NA entries with 0
          .sum().unstack().reset_index().fillna(0)
          # Set the index to SalesOrderNumber
          .set_index('SalesOrderNumber'))
```

In [130]:
```
# Apply the function that was created to set the results to either 0 or 1
basket_sets = basket_ca.applymap(encode_units)
# Generate frequent item sets that have a support of at least 5% in order to get enough useful examples
frequent_itemsets = apriori(basket_sets, min_support=0.05, use_colnames=True)
# Generate the rules with their corresponding support, confidence and lift
rules = association_rules(frequent_itemsets, metric='lift', min_threshold=1)
# Show results
rules
```

Out[130]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	
0	(Mountain Bottle Cage)	(Water Bottle - 30 oz.)	0.067323	0.096880	0.050903	0.756098	7.80
1	(Water Bottle - 30 oz.)	(Mountain Bottle Cage)	0.096880	0.067323	0.050903	0.525424	7.80

In [131]:
```
# Filter the results and set the lift to 6 or more and confidence to 0.7 or more
rules[ (rules['lift'] >=6) &
       (rules['confidence'] >= 0.7)
     ]
```

Out[131]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	
0	(Mountain Bottle Cage)	(Water Bottle - 30 oz.)	0.067323	0.09688	0.050903	0.756098	7.80

In [132]:
```
# When we sell 41 Mountain Bottle Cage, 59 Water Bottles were sold
basket_ca['Mountain Bottle Cage'].sum()
```

Out[132]: 41.0

In [133]:
```
basket_ca['Water Bottle - 30 oz.'].sum()
```

Out[133]: 59.0

France

In [134]:
```
# Filtering the data analysis to only high value customers with a t
otal basket value of £1,500 or over
# and showing the basket only related to France
basket_fr = (master_df_clean[(master_df_clean['SalesTerritoryCountr
y'] == 'France') & (master_df_clean['High_Value_Flag']==1)]
          # Create groupby to find the total number of order quanti
ty based on SalesOrderNumber and Product Name
          .groupby(['SalesOrderNumber','ProductName'])['OrderQuanti
ty']
          # Unstack the table so that the data is structured proper
ly, reset the index and then fill the NA entries with 0
          .sum().unstack().reset_index().fillna(0)
          # Set the index to SalesOrderNumber
          .set_index('SalesOrderNumber'))
```

In [135]:
```
# Apply the function that was created to set the results to either
0 or 1
basket_sets = basket_fr.applymap(encode_units)
# Generate frequent item sets that have a support of at least 6% in
order to get enough useful examples
frequent_itemsets = apriori(basket_sets, min_support=0.06, use_coln
ames=True)
# Generate the rules with their corresponding support, confidence a
nd lift
rules = association_rules(frequent_itemsets, metric='lift', min_thr
eshold=1)
# Show results
rules
```

Out[135]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	
0	(Mountain Bottle Cage)	(Water Bottle - 30 oz.)	0.111111	0.150393	0.084175	0.757576	5.037
1	(Water Bottle - 30 oz.)	(Mountain Bottle Cage)	0.150393	0.111111	0.084175	0.559701	5.037
2	(Water Bottle - 30 oz.)	(Road Bottle Cage)	0.150393	0.071829	0.066218	0.440299	6.129
3	(Road Bottle Cage)	(Water Bottle - 30 oz.)	0.071829	0.150393	0.066218	0.921875	6.129

In [136]:
```
# Filter the results and set the lift to 6 or more and confidence t
o 0.7 or more
rules[ (rules['lift'] >=6) &
       (rules['confidence'] >= 0.7)
     ]
```

Out[136]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	
3	(Road Bottle Cage)	(Water Bottle - 30 oz.)	0.071829	0.150393	0.066218	0.921875	6.12

In [137]:
```
# When we sell 64 Road Bottle Cage, 134 Water Bottles were sold whi
ch sold twice as much
basket_fr['Road Bottle Cage'].sum()
```

Out[137]: 64.0

In [138]:
```
basket_fr['Water Bottle - 30 oz.'].sum()
```

Out[138]: 134.0

Germany

In [139]:
```
# Filtering the data analysis to only high value customers with a t
otal basket value of £1,500 or over
# and showing the basket only related to Germany
basket_ger = (master_df_clean[(master_df_clean['SalesTerritoryCount
ry'] == 'Germany') & (master_df_clean['High_Value_Flag']==1)]
          # Create groupby to find the total number of order quanti
ty based on SalesOrderNumber and Product Name
          .groupby(['SalesOrderNumber','ProductName'])['OrderQuanti
ty']
          # Unstack the table so that the data is structured proper
ly, reset the index and then fill the NA entries with 0
          .sum().unstack().reset_index().fillna(0)
           # Set the index to SalesOrderNumber
          .set_index('SalesOrderNumber'))
```

In [140]:
```
# Apply the function that was created to set the results to either 0 or 1
basket_sets = basket_ger.applymap(encode_units)
# Generate frequent item sets that have a support of at least 6% in order to get enough useful examples
frequent_itemsets = apriori(basket_sets, min_support=0.06, use_colnames=True)
# Generate the rules with their corresponding support, confidence and lift
rules = association_rules(frequent_itemsets, metric='lift', min_threshold=1)
# Show results
rules
```

Out[140]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	
0	(Mountain Bottle Cage)	(Water Bottle - 30 oz.)	0.128286	0.175605	0.106204	0.827869	4.714
1	(Water Bottle - 30 oz.)	(Mountain Bottle Cage)	0.175605	0.128286	0.106204	0.604790	4.714
2	(Water Bottle - 30 oz.)	(Road Bottle Cage)	0.175605	0.075710	0.069401	0.395210	5.220
3	(Road Bottle Cage)	(Water Bottle - 30 oz.)	0.075710	0.175605	0.069401	0.916667	5.220

In [141]:
```
# Filter the results and set the lift to 5 or more and confidence to 0.8 or more
rules[ (rules['lift'] >=5) &
       (rules['confidence'] >= 0.8)
     ]
```

Out[141]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	
3	(Road Bottle Cage)	(Water Bottle - 30 oz.)	0.07571	0.175605	0.069401	0.916667	5.220

In [142]:
```
# When we sell 72 Road Bottle Cage, 167 Water Bottles were sold
basket_ger['Road Bottle Cage'].sum()
```

Out[142]: 72.0

In [143]:
```
basket_ger['Water Bottle - 30 oz.'].sum()
```

Out[143]: 167.0

United Kingdom

In [144]:
```
# Filtering the data analysis to only high value customers with a t
otal basket value of £1,500 or over
# and showing the basket only related to United Kingdom
basket_uk = (master_df_clean[(master_df_clean['SalesTerritoryCountr
y'] == 'United Kingdom') & (master_df_clean['High_Value_Flag']==1)]
          # Create groupby to find the total number of order quanti
ty based on SalesOrderNumber and Product Name
          .groupby(['SalesOrderNumber','ProductName'])['OrderQuanti
ty']
          # Unstack the table so that the data is structured proper
ly, reset the index and then fill the NA entries with 0
          .sum().unstack().reset_index().fillna(0)
          # Set the index to SalesOrderNumber
          .set_index('SalesOrderNumber'))
```

In [145]:
```
# Apply the function that was created to set the results to either
0 or 1
basket_sets = basket_uk.applymap(encode_units)
# Generate frequent item sets that have a support of at least 6% in
order to get enough useful examples
frequent_itemsets = apriori(basket_sets, min_support=0.06, use_coln
ames=True)
# Generate the rules with their corresponding support, confidence a
nd lift
rules = association_rules(frequent_itemsets, metric='lift', min_thr
eshold=1)
# Show results
rules
```

Out[145]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	
0	(Mountain Bottle Cage)	(Water Bottle - 30 oz.)	0.116592	0.173991	0.087892	0.753846	4.332
1	(Water Bottle - 30 oz.)	(Mountain Bottle Cage)	0.173991	0.116592	0.087892	0.505155	4.332
2	(Water Bottle - 30 oz.)	(Road Bottle Cage)	0.173991	0.091480	0.086099	0.494845	5.409
3	(Road Bottle Cage)	(Water Bottle - 30 oz.)	0.091480	0.173991	0.086099	0.941176	5.409

In [146]:
```
# Filter the results and set the lift to 4 or more and confidence t
o 0.8 or more
rules[ (rules['lift'] >=4) &
       (rules['confidence'] >= 0.8)
     ]
```

Out[146]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	
3	(Road Bottle Cage)	(Water Bottle - 30 oz.)	0.09148	0.173991	0.086099	0.941176	5.409

In [147]:
```
# When we sell 102 Road Bottle Cage, 194 Water Bottles were sold
basket_uk['Road Bottle Cage'].sum()
```

Out[147]: 102.0

In [148]:
```
basket_uk['Water Bottle - 30 oz.'].sum()
```

Out[148]: 194.0

United States

In [149]:
```
# Filtering the data analysis to only high value customers with a total basket value of £1,500 or over
# and showing the basket only related to United States
basket_us = (master_df_clean[(master_df_clean['SalesTerritoryCountry'] == 'United States') & (master_df_clean['High_Value_Flag']==1)]
          # Create groupby to find the total number of order quantity based on SalesOrderNumber and Product Name
          .groupby(['SalesOrderNumber','ProductName'])['OrderQuantity']
          # Unstack the table so that the data is structured properly, reset the index and then fill the NA entries with 0
          .sum().unstack().reset_index().fillna(0)
          # Set the index to SalesOrderNumber
          .set_index('SalesOrderNumber'))
```

In [150]:
```
# Apply the function that was created to set the results to either 0 or 1
basket_sets = basket_us.applymap(encode_units)
# Generate frequent item sets that have a support of at least 6% in order to get enough useful examples
frequent_itemsets = apriori(basket_sets, min_support=0.06, use_colnames=True)
# Generate the rules with their corresponding support, confidence and lift
rules = association_rules(frequent_itemsets, metric='lift', min_threshold=1)
# Show results
rules
```

Out[150]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	
0	(Mountain Bottle Cage)	(Water Bottle - 30 oz.)	0.074983	0.112979	0.064896	0.865471	7.66(
1	(Water Bottle - 30 oz.)	(Mountain Bottle Cage)	0.112979	0.074983	0.064896	0.574405	7.66(

In [151]:
```
# Filter the results and set the lift to 6 or more and confidence t
o 0.8 or more
rules[ (rules['lift'] >=6) &
       (rules['confidence'] >= 0.8)
     ]
```

Out[151]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	
0	(Mountain Bottle Cage)	(Water Bottle - 30 oz.)	0.074983	0.112979	0.064896	0.865471	7.660

In [152]:
```
# When we sell 223 Road Bottle Cage, 336 Water Bottles were sold
basket_us['Mountain Bottle Cage'].sum()
```

Out[152]: 223.0

In [153]:
```
basket_us['Water Bottle - 30 oz.'].sum()
```

Out[153]: 336.0

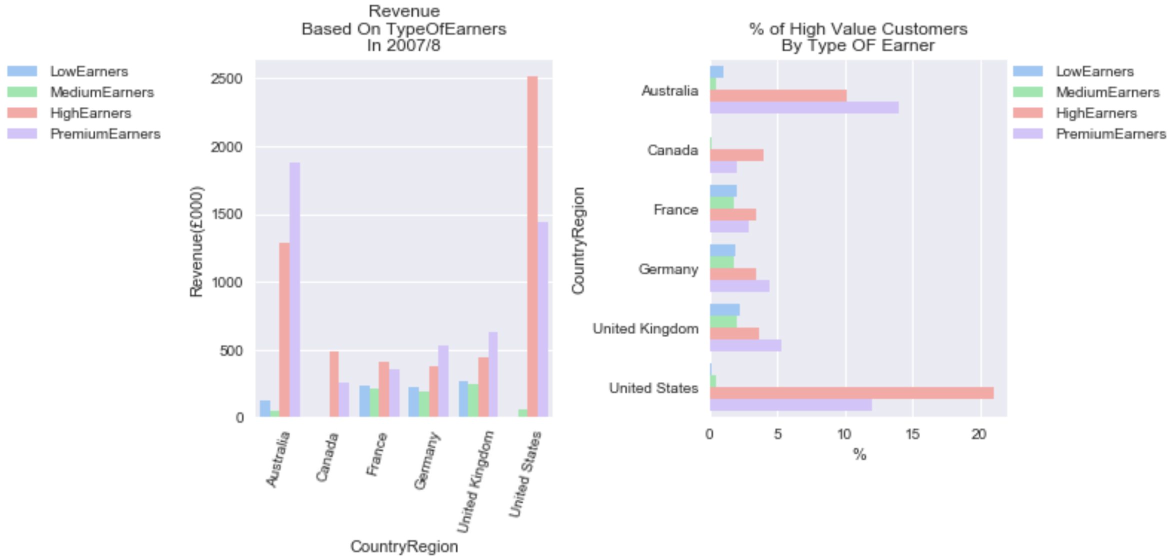
According to the Market Basket Analysis results, customers normally buy bottle cages along with water bottles. Road bottle cages and water bottles prove to be the best combination in most countries and mountain bottle cages and water bottles are the popular items to be bought together in Canada.

Top 3 Interesting Plots

Plot One

In [154]:
```
# High Value Customers By Income
# First plot
plt.subplot(1,2,1)
# Create a groupby that list the total sum of unit price for each T
ypeOfEarner for every country region
hv_earner_groupby = (high_cust.groupby(['CountryRegion','TypeOfEarn
er'])['UnitPrice'].sum())
# Divide by 1,000 to make visualisation easier to read
hv_earner_groupby = hv_earner_groupby/1000
# Convert variable to an integer
hv_earner_groupby = hv_earner_groupby.astype(int)

# Create a hue order of 4 different types of earners
hue_order  = ['LowEarners','MediumEarners','HighEarners','PremiumEa
```

```
rners']

# Add pipeline to use the above groupby function and create a bar c
hart with an x axis of 'CountryRegion'
# and a y axis of 'UnitPrice' in the order of the 4 TypeOfEarner gr
oups
ax = hv_earner_groupby.reset_index().pipe((sns.barplot, 'data'),
x='CountryRegion', y='UnitPrice', palette='pastel', hue='TypeOfEarn
er', hue_order=hue_order)
plt.xticks(rotation=75)
plt.xlabel('CountryRegion')
plt.ylabel('Revenue(£000)')
plt.title('Revenue'+ '\n' + 'Based On TypeOfEarners' + '\n' +'In 20
07/8')
# To locate and position the legend box
handles, labels = ax.get_legend_handles_labels()
l = plt.legend(handles[0:4], labels[0:4], bbox_to_anchor=(-0.85,1),
loc=2, borderaxespad=0.)

# Second plot
plt.subplot(1,2,2)
# Create a groupby that counts the number of customers for each Typ
eOfEarner group for every country region
groupby_earner = (high_cust.groupby(['CountryRegion','TypeOfEarner'
])['CustomerKey'].count())
# Sum the total number of customers as a denominator
total_earner = groupby_earner.sum()
# Divide each TypeOfEarner group by the denominator and times by 10
0 to create a percentage
# and round it by one decimal place
hv_earner = round(groupby_earner/total_earner*100,1)

# Add pipeline to use the above groupby function and create a bar c
hart with an x axis of 'CustomerKey'
# and a y axis of 'CountryRegion' in the order of the 4 TypeOfEarne
r groups
ax = hv_earner.reset_index().pipe((sns.barplot, 'data'),
y='CountryRegion', x='CustomerKey', palette='pastel', hue='TypeOfEa
rner', hue_order=hue_order)
plt.xlabel('%')
plt.ylabel('CountryRegion')
plt.title('% of High Value Customers' + '\n' + 'By Type OF Earner')
# To locate and position the legend box
handles, labels = ax.get_legend_handles_labels()
l = plt.legend(handles[0:4], labels[0:4], bbox_to_anchor=(1,1), loc
=2, borderaxespad=0.)

plt.tight_layout()
plt.show()
```



Description One

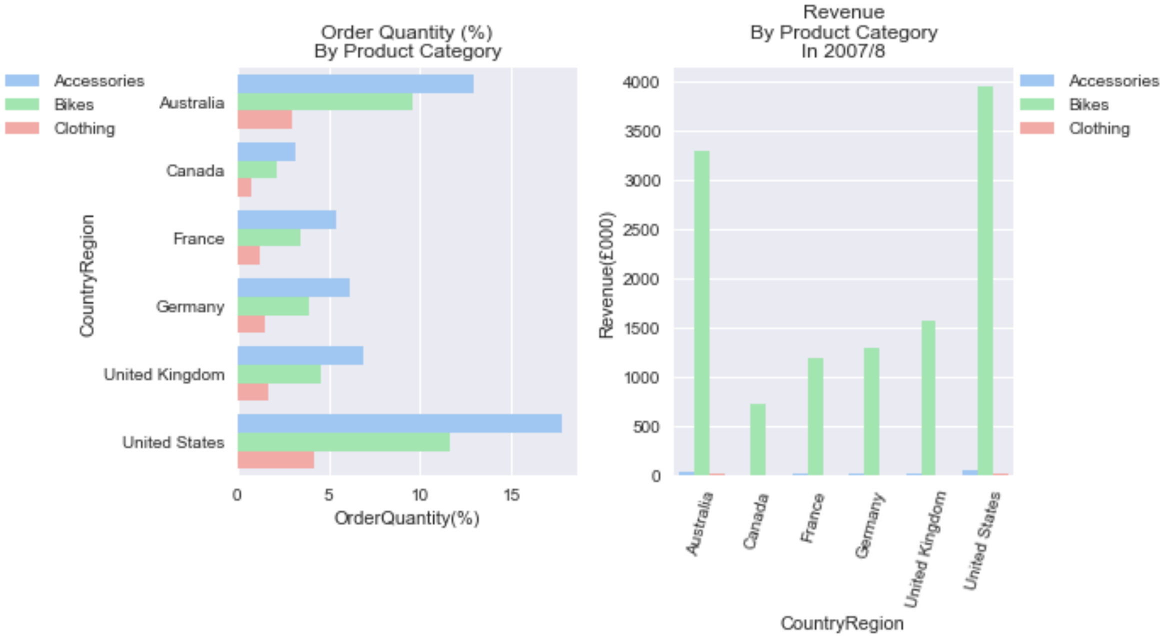
For the countries, the High Earners are the most significant customers particularly in United States which contirbuted to nearly £5m. However, the Premium Earners in Australia, Germany and United Kingdom are the dominant players in terms of revenue.

Plot Two

In [155]:

```
# What They Buy by Product Category
# First plot
plt.subplot(1,2,1)
# Create a groupby that list the total number of Order Quantity for
each Product Category for every country region
groupby_product = high_cust.groupby(['CountryRegion','ProductCatego
ry'])['OrderQuantity'].sum()
# Sum the total number of Order Quantity as a denominator
total_product = groupby_product.sum()
# Divide each Product Category group by the denominator and times b
y 100 to create a percentage
# and round it by one decimal place
product = round(groupby_product/total_product*100,1)

# Add pipeline to use the above groupby function and create a bar c
hart with an x axis of 'OrderQuantity'
# and a y axis of 'CountryRegion' in the order of the Product Categ
ory groups
ax = product.reset_index().pipe((sns.barplot, 'data'),
y='CountryRegion', x='OrderQuantity', palette='pastel', hue='Produc
tCategory')
plt.xlabel('OrderQuantity(%)')
```

```
plt.ylabel('CountryRegion')
plt.title('Order Quantity (%)' + '\n' + 'By Product Category')
# To locate and position the legend box
handles, labels = ax.get_legend_handles_labels()
l = plt.legend(handles[0:4], labels[0:4], bbox_to_anchor=(-0.7,1),
loc=2, borderaxespad=0.)

# Second plot
plt.subplot(1,2,2)
# Create a groupby that list the total sum of unit price for each P
roduct Category for every country region
hv_product_groupby = high_cust.groupby(['CountryRegion','ProductCat
egory'])['UnitPrice'].sum()
# Divide by 1,000 to make visualisation easier to read
hv_product_groupby = hv_product_groupby/1000
# Convert variable to an integer
hv_product_groupby = hv_product_groupby.astype(int)
# Add pipeline to use the above groupby function and create a bar c
hart with an x axis of 'CountryRegion'
# and a y axis of 'UnitPrice' in the order of the three Product Cat
egories
ax = hv_product_groupby.reset_index().pipe((sns.barplot, 'data'),
x='CountryRegion', y='UnitPrice', palette='pastel', hue='ProductCat
egory')
plt.xticks(rotation=75)
plt.ylabel('Revenue(£000)')
plt.title('Revenue'+'\n' + 'By Product Category' + '\n' +'In 2007/8
')
# To locate and position the legend box
handles, labels = ax.get_legend_handles_labels()
l = plt.legend(handles[0:4], labels[0:4], bbox_to_anchor=(1,1), loc
=2, borderaxespad=0.)

plt.tight_layout()
plt.show()
```

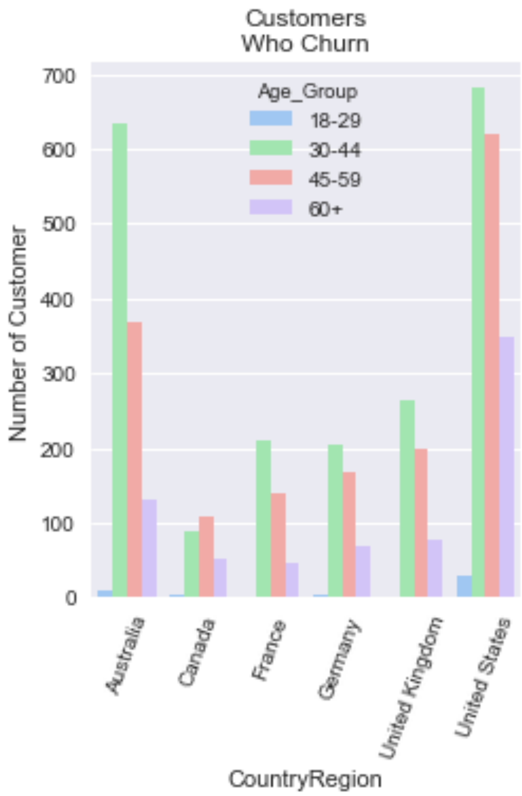


Description Two

The plot shows a majority of the sales are predominately Bikes. Many of the high value customers especially in Australia and United States each contributed to more than £7m in revenue. It is clear to say that Bikes will continue to be Kernal Ltd's main source of income.

Plot Three

In [156]:
```
# Customer Churn
# Create a groupby that list the total number of customer churns fo
r each age group for every country region
churn_groupby = (churn_cust_1.groupby(['CountryRegion','Age_Group']
)['Churn_Flag'].count())

plt.subplot(1,2,1)
# Add pipeline to use the above groupby function and create a bar c
hart with an x axis of 'CountryRegion'
# and a y axis of 'UnitPrice' in the order of the 4 age groups
ax = churn_groupby.reset_index().pipe((sns.barplot, 'data'),
x='CountryRegion', y='Churn_Flag', palette='pastel', hue='Age_Group
')
plt.xticks(rotation=70)
plt.xlabel('CountryRegion')
plt.ylabel('Number of Customer')
plt.title('Customers' + '\n' +  'Who Churn')

plt.subplot(1,2,2)
# Sum the total number of customers as a denominator
total_churn = churn_groupby.sum()
# Divide each age group by the denominator and times by 100 to crea
te a percentage and round it by one decimal place
age_earner = round(churn_groupby/total_churn*100,1)

# Add pipeline to use the above groupby function and create a bar c
hart with an x axis of 'Churn_Flag'
# and a y axis of 'CountryRegion' in the order of the 4 Age groups
ax = age_earner.reset_index().pipe((sns.barplot, 'data'),
x='Churn_Flag', y='CountryRegion', palette='pastel', hue='Age_Group
')
plt.xlabel('% Customer Churn')

plt.ylabel('CountryRegion')
plt.title('% of Customers' + '\n' + 'Who Churn')

plt.tight_layout()
plt.show()
```



Description Three

As customer churn is when an existing customer ends the business relationship meaning he/she no longer trades with Kernal Ltd. According to the plots above we can see that a majority of the customers are mainly from the age of 30-44 in green and 45-59 in pink. In United States over 15% of customers aged 30-44 never came back. For this reason, it is important that Kernal Ltd reduce the number customer churn in order to increase revenue such as reaching out to the customers, improving customer service, adding value to products etc.

Reflection

I finalised Kernal Ltd's dataset to 60,398 observations and 33 variables from 2007-2008. In order to prepare for this project I had to spend a lot of time planning as there are many different datasets that needed to be joined together. I also had to carefully pick and choose the variables as many of them are not relevant and useful for my analysis. After learning more about the dataset I managed to think of interesting questions as I carried on analysing.

Here are a list of interesting insights after completing my exploratory data analysis:

- Bikes bring in the most revenue even though Accessories were sold the most

- Road bikes are the most popular except for Mountain bikes which sells better in United States
- Sales demand in Australia decreases in December and also the weekend in general
- A high number of customers in Australia do not have any children
- Customers aged 30-44 contributed the most revenue in Australia, France and United States. However, customers aged 45-59 in Canada, Germany and United Kingdom are more profitable.
- Customers who work in Clerical are the most profitable in France, Germany and United Kingdom
- Tires and Tubes in United States, Australia and Canada are the most popular whereas customers in United Kingdom, Germany and France tend to buy Bottles and Cages the most.
- Jerseys are customers' favourite in United States, Australia, France and Canada. However, Caps are the number one favourite in United Kingdom and Germany.
- Customers commute shorter distance (0-1 Mile) in all countries and customers in Australia commute longer distance the most (10+ miles).
- Customers tend to purchase Road Cottle Cages and Water Bottles together whereas in Canada customers buy Mountain Bottle Cages and Water Bottles instead

According to the above findings I was able to create a customer profile based on what type of customers that Kernal Ltd should aim as their target market for each region. Although there will be other factors that might affect and change the customers' profiles externally and internally.

Current Issues after my analysis:

- Low Awareness
- Lack of events
- Not family friendly
- No Social Media

Actionable Recommendations:

- Market on younger people (18-29 years of age) as less sales were made by them
- Hold competitions/charity events to inspire the young community to get into biking
- Sell family friendly packages to encourage young parents to go biking and also those with children.
- Advertise on social media for summer sales especially during July and August
- Promote more on touring bikes during summer sales and sell old stocks to boost revenue and more room for new stocks
- Offer last minute offers on Fridays and weekends.
- Offer tailored advice, servicing and support to fellow bike enthusiasts