In [22]:	<pre>from sklearn.impute import SimpleImputer from sklearn.base import TransformerMixin import pandas as pd import numpy as np from impyute.imputation.cs import mice import seaborn as sns import matplotlib.pyplot as plotting import warnings warnings.filterwarnings("ignore")</pre>
	<pre>sns.set_palette("pastel")  pd.set_option('display.max_columns', None)  pd.set_option('max_colwidth', None)  class CustomImputer(TransformerMixin):     definit(self, cols=None, strategy='median'):         self.cols = cols         self.strategy = strategy</pre>
	<pre>def transform(self, df):     X = df.copy()     impute = SimpleImputer(strategy=self.strategy)     if self.cols == None:         self.cols = list(X.columns)     for col in self.cols:         if X[col].dtype == np.dtype('O'):             X[col].fillna(X[col].value_counts().index[0], inplace=True)         else :</pre>
	<pre>X[col] = impute.fit_transform(X[[col]])  return X  def fit(self, *_):     return self  def plottings(wines):</pre>
	<pre>with plotting.style.context('seaborn-bright'):     fig, (ax1, ax2) = plotting.subplots(nrows=2, ncols=1, sharex=False, figsize=({     heatmap1 = sns.heatmap(wines.isnull(),yticklabels=False,cbar=False,cmap='cividis',     heatmap1.set_title("Heatmap showing the missing values")  null_values = wines.isnull().sum(axis=0) null_values /= len(wines.index)  plotting1 = null_values.plot(kind='bar', color='darkorange', x=null_values.values,</pre>
	<pre>ticks = np.arange(0.5, len(labels)) ax2.xaxis.set(ticks=ticks, ticklabels=labels)  ax2.spines['top'].set_color('black') ax2.spines['right'].set_color('black')  na_ticks = ticks[(null_values &gt; 0) &amp; (null_values &lt; 0.05)] if (len(na_ticks) &gt; 0):     ax2.plot(na_ticks, [0,]*len(na_ticks), 's', c='darkorange', markersize=10,</pre>
	label='Very few missing values')  ax2.legend() plotting.show()  I have taken the Wine review dataset from kaggle. This dataset has lot of missing values which can be imputated. Out of the 11 columns, I have chose 4 variables/columns for data imputation.
In [23]:	<pre>df = pd.read_csv('wine-data.csv') print(df.head()) print("\n\nThe four variables to be used for imputation are") print("One numerical variable - Price") print("Three categorical variables - Country, Designation and Province")  Unnamed: 0 country \ 0 0 Italy 1 Portugal</pre>
	description \  description \  Aromas include tropical fruit, broom, brimstone and dried herb. The palate isn't overly expre ssive, offering unripened apple, citrus and dried sage alongside brisk acidity.  This is ripe and fruity, a wine that is smooth while still st ructured. Firm tannins are filled out with juicy red berry fruits and freshened with a cidity. It's already drinkable, although it will certainly be better from 2016.  Tart and snappy, the flavors of lime flesh and rind dominate. Some green pineapple pokes through, with cris p acidity underscoring the flavors. The wine was all stainless-steel fermented.  Pineapple rind, lemon pith and or ange blossom start off the aromas. The palate is a bit more opulent, with notes of hon ey-drizzled guava and mango giving way to a slightly astringent, semidry finish.  Much like the regular bottling from 2012, this comes across as rather rough and tan nic, with rustic, earthy, herbal characteristics. Nonetheless, if you think of it as a pleasantly unfussy country wine, it's a good companion to a hearty winter stew.  designation points price province \  Vulkà Bianco 87 NaN Sicily & Sardinia  Avidagos 87 15.0 Douro  Vulkà Bianco 87 NaN Sicily & Sardinia  Avidagos 87 15.0 Douro  NaN 87 14.0 Oregon  Reserve Late Harvest 87 13.0 Michigan  Vintner's Reserve Wild Child Block 87 65.0 Oregon
	region_1 region_2 taster_name \ 0 Etna NaN Kerin O'Keefe 1 NaN NaN Roger Voss 2 Willamette Valley Willamette Valley Paul Gregutt 3 Lake Michigan Shore NaN Alexander Peartree 4 Willamette Valley Willamette Valley Paul Gregutt  taster_twitter_handle \ 0 @kerinokeefe 1 @vossroger 2 @paulgwine 3 NaN 4 @paulgwine  title
	Nicosia 2013 Vulkà Bianco (Etna)  Quinta dos Avidagos 2011 Avidagos Red (Douro)  Rainstorm 2013 Pinot Gris (Willamette Valley)  St. Julian 2013 Reserve Late Harvest Riesling (Lake Michigan Shore)  Sweet Cheeks 2012 Vintner's Reserve Wild Child Block Pinot Noir (Willamette Valley)  variety winery  White Blend Nicosia  Portuguese Red Quinta dos Avidagos  Pinot Gris Rainstorm  Riesling St. Julian  Prinet Noir Cheeks
In [24]:	The four variables to be used for imputation are One numerical variable - Price Three categorical variables - Country, Designation and Province  wines = df.drop(columns=['Unnamed: 0','description','points','region_1','region_2','taprint("\nThe number of missing values are") print(wines.isnull().sum())  The number of missing values are country 63 designation 37465 price 8996 province 63
In [25]:	<pre>dtype: int64  print("\n1.MEDIAN IMPUTATION\n\nThe unfilled head of dataset is shown below") print(wines.head()) print("\n\nBefore the median imputation, the heatmap and bar plots look likes this") plottings(wines) wines.price.fillna(wines.price.dropna().median(),inplace =True) columnsList = list(wines.columns) columnsList.remove('price') cci = CustomImputer(columnsList) wines = cci.transform(wines) print("\nAfter the median imputation, the heatmap and bar plots look likes this") plottings(wines) print("\nThe number of null values is reduced to zero after the median imputation") print(wines.isnull().sum())</pre>
	print("\n\nThe filled head of dataset is shown below") print(wines.head())  1.MEDIAN IMPUTATION  The unfilled head of dataset is shown below country designation price province 0 Italy Vulkà Bianco NaN Sicily & Sardinia 1 Portugal Avidagos 15.0 Douro 2 US NaN 14.0 Oregon
	3 US Reserve Late Harvest 13.0 Michigan 4 US Vintner's Reserve Wild Child Block 65.0 Oregon  Before the median imputation, the heatmap and bar plots look likes this  Heatmap showing the missing values
	country designation price province  Null value rate per column  Very few missing values
	0.8 - 0.6 - 0.4 -
	After the median imputation, the heatmap and bar plots look likes this
	Heatmap showing the missing values
	country designation price province  Null value rate per column  Null value rate  Null value rate  0.8 -
	The number of null values is reduced to zero after the median imputation country 0 designation 0
	price 0 province 0 dtype: int64  The filled head of dataset is shown below
In [26]:	print("\n2.MOST FREQUENT VALUES IMPUTATION") wines1 = df.drop(columns=['Unnamed: 0','description','points','region_1','region_2',' print("\nThe number of missing values are") print(wines1.isnull().sum()) print("\n\nThe unfilled head of dataset is shown below.") print("\n\nBefore the most frequent values imputation, the heatmap and bar plots look plottings(wines1) imp_mean = SimpleImputer(strategy='most_frequent') imp_mean.fit(wines1) imputed_train_df = imp_mean.transform(wines1) resultant_df = pd.DataFrame(imputed_train_df, columns =['country','designation','price print("\nAfter the most frequent values imputation, the heatmap and bar plots look lil plottings(resultant_df) print("\nThe number of null values is reduced to zero after the most frequent values : print(resultant_df.isnull().sum()) print("\n\nThe filled head of dataset is shown below") print(resultant_df.head())  2.MOST FREQUENT VALUES IMPUTATION
	The number of missing values are country 63 designation 37465 price 8996 province 63 dtype: int64  The unfilled head of dataset is shown below. country designation price province 0 Italy Vulkà Bianco NaN Sicily & Sardinia
	Avidagos 15.0 Douro  US NaN 14.0 Oregon  US Reserve Late Harvest 13.0 Michigan  US Vintner's Reserve Wild Child Block 65.0 Oregon  Before the most frequent values imputation, the heatmap and bar plots look likes this  Heatmap showing the missing values
	country designation price province  Null value rate per column  Very few missing values Null value rate  Null value rate
	0.6 - 0.4 - 0.2 -
	After the most frequent values imputation, the heatmap and bar plots look likes this  Heatmap showing the missing values
	country designation price province  Null value rate per column  Null value rate
	0.6 - 0.4 -
	The number of null values is reduced to zero after the most frequent values imputation
	country 0 designation 0 price 0 province 0 dtype: int64  The filled head of dataset is shown below country designation price province 0 Italy Vulkà Bianco 20 Sicily & Sardinia
In [28]:	1 Portugal 2 US Reserve 14 Oregon 3 US Reserve Late Harvest 13 Michigan 4 US Vintner's Reserve Wild Child Block 65 Oregon  print("\n3.MULTIVARIATE IMPUTATION BY CHAINED EQUATION(MICE)") wines2 = df.drop(columns=['Unnamed: 0','description','points','region_1','region_2','tprint("\nThe number of missing values are") print(wines2.isnull().sum()) print("\nNbefore the MICE imputation, the heatmap and bar plots look likes this") plottings(wines2)  countryUnique = wines2.country.unique() uniqueCountries = list(countryUnique) del uniqueCountries[18]  designationUnique = wines2.designation.unique() uniqueDesignations = list(designationUnique) del uniqueDesignations[2]  provinceUnique = wines2.province.unique() uniqueProvinces = list(provinceUnique) del uniqueProvinces = list(provinceUnique) for i in uniqueCountries:     dict_obj[i] = float(count)     count=0  for i in uniqueCountries:     dict_obj[i] = float(count)     count=0  for i in uniqueProvinces:
	<pre>dict_obj3[i] = float(count)     count+=1  dict_obj2 = {} count=0  for i in uniqueDesignations:     dict_obj2[i] = float(count)     count+=1  wines2['countryMap'] = wines2.country.map(dict_obj) wines2['designationMap'] = wines2.designation.map(dict_obj2) wines2['provinceMap'] = wines2.province.map(dict_obj3) wines2 = wines2.drop(columns=['country', 'designation', 'province']) imputed_training=mice(wines2.values) wines3 = pd.DataFrame(imputed_training, columns =['price', 'countryMap', 'designationMap'</pre>
	print("\n\nAfter the MICE imputation, the heatmap and bar plots look likes this") plottings(wines3) print("\nThe number of null values is reduced to zero after the MICE imputation") print(wines3.isnull().sum())  3.MULTIVARIATE IMPUTATION BY CHAINED EQUATION(MICE)  The number of missing values are country 63 designation 37465 price 8996
	province 63 dtype: int64  Before the MICE imputation, the heatmap and bar plots look likes this  Heatmap showing the missing values
	country designation price province
	Null value rate per column  Very few missing values Null value rate  0.8 -  0.6 -  0.4 -
	0.2 - During all and a signature of the
	After the MICE imputation, the heatmap and bar plots look likes this  Heatmap showing the missing values
	price countryMap designationMap provinceMap  Null value rate per column  Null value rate  Null value rate
	0.6 - 0.4 - 0.2 -
	The number of null values is reduced to zero after the MICE imputation price 0 countryMap 0 designation 0 designation 0
	designationMap 0 provinceMap 0 dtype: int64