

```
In [2]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```
In [3]: df = pd.read_csv('DSE.csv')
```

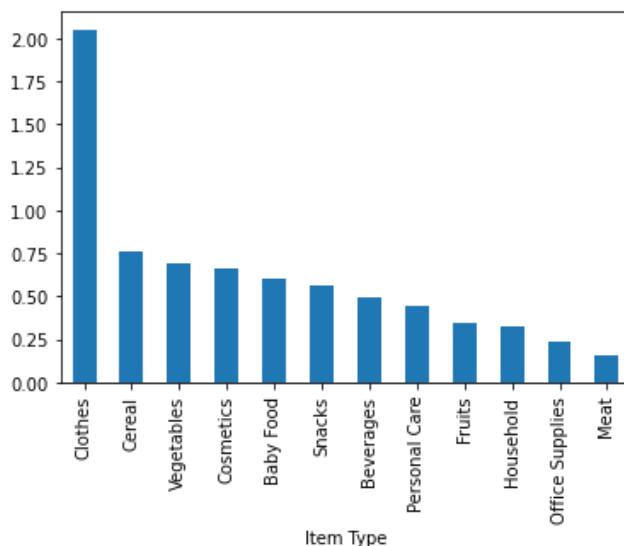
Question:

Which products should be dropped from selling in the next year moving forward and which products should be sold more?

To understand which products should be dropped from selling in the next year moving forward and which products should be sold more we can look at the profitability of each of the item type:

```
In [4]: item_list = df.groupby('Item Type')['Profit as % of Cost'].mean()
item_list.sort_values(ascending = False, inplace = True)
item_list.plot(kind = 'bar')
```

```
Out[4]: <AxesSubplot:xlabel='Item Type'>
```



We can see that Clothes are the most profitable item types in the given data with profit margins considerably higher than the other item types like cereal, vegetables, etc.

On the other hand, Meat products have the least profit margin.

Let's look at the region-wise profitability of each of the item types to comment on which of the products should be focussed on and which products can be dropped due to low profitability.

```
In [5]: item_region_list = df.groupby(['Region', 'Item Type'])['Profit as % of Cost'].mean()
item_region_list.to_frame()
item_region_list.sort_values()
```

```
Out[5]: Region      Item Type      Profit as % of Cost
Australia and Oceania  Meat      0.156846
North America          Meat      0.156846
Central America and the Caribbean  Meat      0.156846
Middle East and North Africa      Meat      0.156846
Asia                    Meat      0.156846
...
Central America and the Caribbean  Clothes  2.049107
North America                    Clothes  2.049107
Sub-Saharan Africa                Clothes  2.049107
```

```
Europe          Clothes    2.049107
Australia and Oceania  Clothes    2.049107
Name: Profit as % of Cost, Length: 84, dtype: float64
```

As we can see the overall trend is continued in our region-wise analysis as well, with Meat products being the least profitable and Clothes being the most profitable across all regions.

This makes sense intuitively as well because clothes are not perishable items and thus the shipping and storage costs associated with clothes will be much less than the costs associated with the meat products.

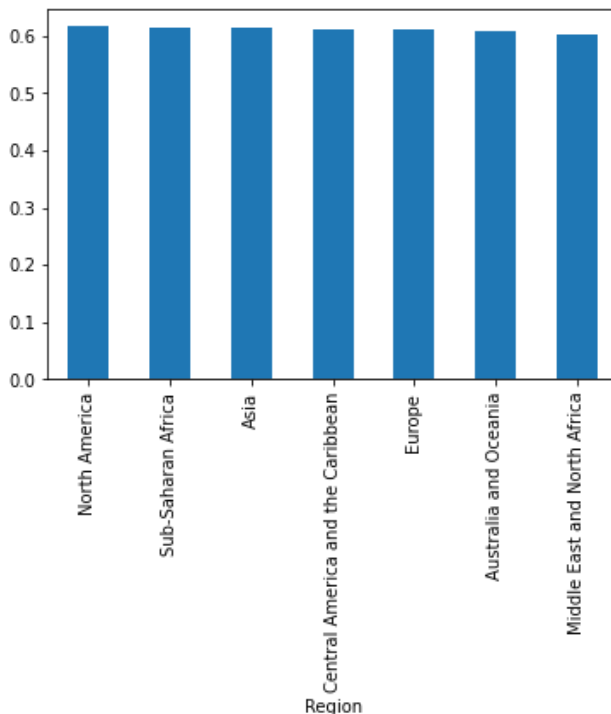
Thus, looking at the data, we can say that clothes should be given preference while meat can be dropped from the item list for the next year.

Question:

Should any region be given preference over the other?

```
In [6]: region_list = df.groupby('Region')['Profit as % of Cost'].mean()
region_list.sort_values(ascending = False, inplace = True)
region_list.plot(kind = 'bar')
```

```
Out[6]: <AxesSubplot:xlabel='Region'>
```



```
In [7]: region_list
```

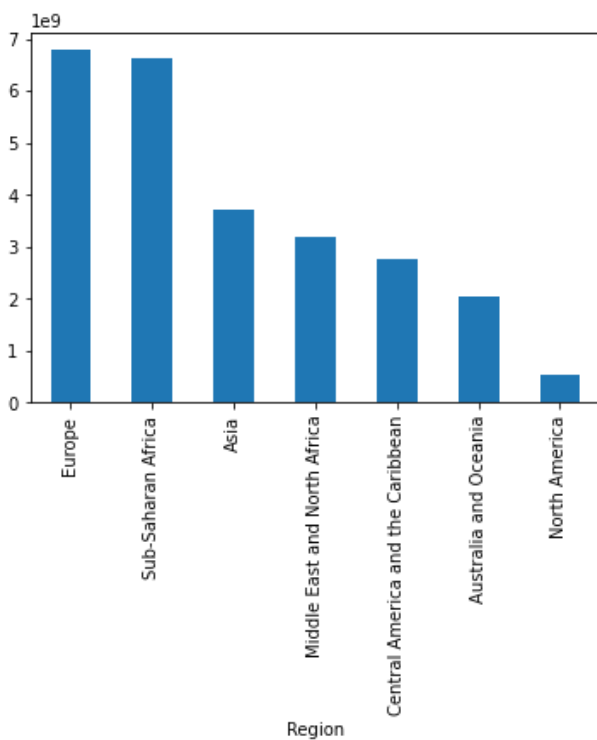
```
Out[7]: Region
North America          0.616335
Sub-Saharan Africa     0.613292
Asia                   0.613162
Central America and the Caribbean  0.611853
Europe                 0.610915
Australia and Oceania  0.606901
Middle East and North Africa  0.602093
Name: Profit as % of Cost, dtype: float64
```

While the average profit percentage on items sold is similar across all the regions, we can look at the total profit in each of the regions to find out which regions are the major sources of profit for the company.

```
In [8]: region_profit_list = df.groupby('Region')['Total Profit'].sum()
region_profit_list.sort_values(ascending = False, inplace = True)
```

```
region_profit_list.plot(kind = 'bar')
```

```
Out[8]: <AxesSubplot:xlabel='Region'>
```



We can see that Europe and Sub-Saharan Africa are the biggest sources of profit, whereas North America contributes least to the profits of the company.

To further analyze if there is a trend in profit distribution across the years, we can look at the profit percentages for every region across the 8 year period.

```
In [9]: region_yearly_list = df.groupby(['Region', 'Fiscal Year'])['Profit as % of Cost'].mean()
region_yearly_list
```

```
Out[9]: Region
Asia
2010    0.612257
2011    0.623655
2012    0.599875
2013    0.626162
2014    0.612539
2015    0.607315
2016    0.608798
2017    0.616189
Australia and Oceania
2010    0.625979
2011    0.595503
2012    0.635246
2013    0.586141
2014    0.582620
2015    0.616889
2016    0.597974
2017    0.621769
Central America and the Caribbean
2010    0.607194
2011    0.599154
2012    0.639289
2013    0.626914
2014    0.612037
2015    0.585143
2016    0.619679
2017    0.602543
Europe
2010    0.621562
2011    0.625333
2012    0.603423
2013    0.598143
2014    0.608834
```

	2015	0.608770
	2016	0.615124
	2017	0.602414
Middle East and North Africa	2010	0.590051
	2011	0.614410
	2012	0.603965
	2013	0.604804
	2014	0.588489
	2015	0.595654
	2016	0.612567
	2017	0.609953
North America	2010	0.639299
	2011	0.597680
	2012	0.607406
	2013	0.615505
	2014	0.690964
	2015	0.594264
	2016	0.559533
	2017	0.635224
Sub-Saharan Africa	2010	0.595902
	2011	0.609518
	2012	0.598528
	2013	0.618638
	2014	0.611330
	2015	0.613838
	2016	0.634590
	2017	0.632564

Name: Profit as % of Cost, dtype: float64

Looking at the profit percentages over the 8 year period, we can observe the following:

1. The profit percentage in Europe has seen a decline over the time period falling from 0.62% in 2010 to 0.60% in 2017.
2. In the same time period, Sub-Saharan Africa has shown an increase in profit percentage from 0.59% in 2010 to 0.63% in 2017.
3. All other regions have shown no significant increase or decrease in the profit percentage numbers.

Thus, looking at the total profit and profit as a % of cost numbers, the Sub-Saharan Africa region stands out as it has not only shown increase in profitability in the time period but is also one of the top regions by the amount of profit it generates.

Hence, the Sub-Saharan Africa region should be given preference over the other regions.

Question:

Which products are the easiest to sell?

```
In [10]: df['Order Date'] = pd.to_datetime(df['Order Date'])
df['Ship Date'] = pd.to_datetime(df['Ship Date'])
df['Time_to_ship'] = df['Ship Date'] - df['Order Date']
df.sort_values(by = ['Time_to_ship'])
```

	Region	Country	Item Type	Fiscal Year	Sales Channel	Order Priority	Order Date	Order ID	Ship Date	Units Sold	Unit Price	Unit Cost
32067	Sub-Saharan Africa	Chad	Cereal	2012	Offline	H	2012-12-23	524854934	2012-12-23	5093	205.70	117.11
18430	Sub-Saharan Africa	Guinea	Meat	2013	Offline	L	2013-05-22	300411117	2013-05-22	7180	421.89	364.69
47580	Asia	Sri Lanka	Cosmetics	2012	Offline	M	2012-09-22	793228185	2012-09-22	2702	437.20	263.33

	Region	Country	Item Type	Fiscal Year	Sales Channel	Order Priority	Order Date	Order ID	Ship Date	Units Sold	Unit Price	Unit Cost
8635	Sub-Saharan Africa	Mozambique	Baby Food	2013	Offline	H	2013-06-18	587924182	2013-06-18	8685	255.28	159.42
18447	Europe	Malta	Beverages	2010	Offline	C	2010-11-06	604477488	2010-11-06	7177	47.45	31.79
...
57210	Middle East and North Africa	Israel	Office Supplies	2013	Offline	L	2013-12-20	726482808	2014-02-08	1262	651.21	524.96
32931	Sub-Saharan Africa	Gabon	Beverages	2012	Online	M	2012-08-23	737139976	2012-10-12	4954	47.45	31.79
32928	Central America and the Caribbean	Jamaica	Cereal	2016	Offline	M	2016-12-24	189394700	2017-02-12	4955	205.70	117.11
28287	Europe	Austria	Personal Care	2010	Offline	H	2010-07-24	584669911	2010-09-12	5674	81.73	56.67
12403	Europe	Norway	Household	2011	Offline	H	2011-07-26	853836667	2011-09-14	8099	668.27	502.54

65535 rows × 17 columns

Looking at the dataframe, we can see some of the products are shipped within the same day, whereas some products take as much as 50 days to ship. However, we cannot see any specific relationship between the type of product and the days it is taking to get shipped. Let us check if we can find any relationship between different regions and the time for products to get shipped according to the item type and region.

```
In [ ]: df['Time_to_ship'] = df['Time_to_ship'].astype(str)
df["Time_to_ship"] = df["Time_to_ship"].str.split(" ", n = 1, expand = True)
df['Time_to_ship'] = df['Time_to_ship'].astype(int)
```

```
In [16]: shipping_list = df.groupby(by = ['Region', 'Item Type'])['Time_to_ship'].mean()
```

```
In [17]: shipping_list.to_frame()
shipping_list.sort_values()
```

```
Out[17]: Region      Item Type      22.933180
Australia and Oceania  Fruits
North America         Cereal      22.946903
Central America and the Caribbean  Cosmetics  23.968284
Australia and Oceania  Cosmetics  24.000000
Middle East and North Africa  Office Supplies  24.091822
...
Australia and Oceania  Vegetables  26.161731
Europe                Office Supplies  26.169410
North America         Personal Care  26.240602
                     Baby Food      26.434426
                     Meat           27.085271

Name: Time_to_ship, Length: 84, dtype: float64
```

Here too, we cannot see any specific relationship between the type of product, the regions and the days the item is taking to get shipped.