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CLUSTERING - product segmentation for marketing

I. Define & Scope

The Brief

```
 Based on internal RS corporate data on best-selling products we carry, use
clustering algorithm (k-means) to group them together into clusters, using
multiple features available in the dataset, so that our online marketing team
can customize their ad campaigns to promote key product groups more
effectively. Then create a visualization of the resulting analysis. Draw
conclusions, if findings allow it.
```

i) Intro

In this notebook I'm going to apply clustering method(s) of Machine Learning to our best-selling products in RS Components product catalogue. While clustering algorithms consist of a number of algorithms available to be used, from hierarchical, through Fuzzy C-means to GMM (Gaussian Mixed Models), none of those is perfect. i'm going to utilize probably most commonly used clustering algorithm, namely k-means to mine for commonalities among those top selling products, trying to determine how they can be best split into a number of clusters and grouped into them, hoping to find some hidden patterns or shared characteristics.

ii) Background

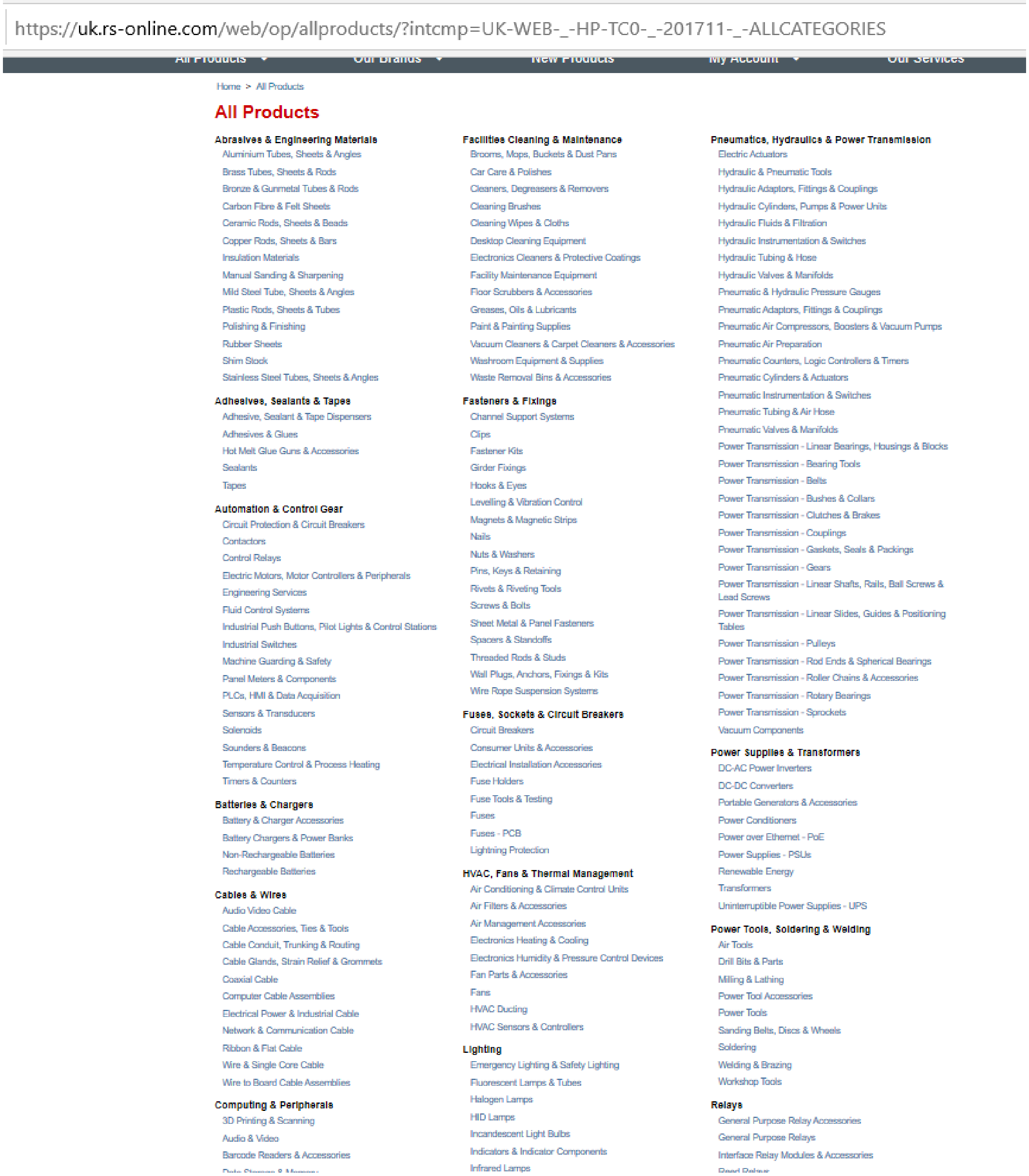
RS Components is a publicly listed corporation and trades on LSE (London Stock Exchange) under Electrocomponents PLC trade name. We have significant trading presence in each of the top economically most active regions - EMEA, APAC and Americas. Due to wildly varying standards across any number of electronic products specifications that have local requirements, whether voltage, number of prongs/holes in a electric socket, certification standards or just local engineer's preferences, standarization is a challenge for RS and thus we need to stock very large range of products. As it stands RS currently has over 500,000 SKU's (over 0.5 million product in stock) and over 2.5 million non-stock products which we can drop-ship for our clients from our global supplier base. That means that while most of online stores would be content with coming up with a Top 100 best selling products, out Best Sellers list features slightly over 10,000 products. Some of the products on that best-sellers' list vary only slightly from their "cousins", e.g. by different AC/DC output or electrical resistance (in Ohms).

To make matters even more complicated we carry a number of distinct categories of products, e.g. BLE (Board Level Electronics) - something a computer maker like Asus or Dell would need, or IA&C (Undustrial Automation & Control) - e.g. assembly line sensors monitoring health of a conveyor belt, or PPE (Personal Protection Equipment) - e.g. gloves or protective masks engineers or doctors can cover their faces with.

iii) Problem statement and potential business application

With such huge range or products covering a number of distinct categories and sourced from over 2500 unique suppliers across different geographies, it's little wonder that our investory management function is 3-digit strong when it comes to headcount and inventory planners are always playing a catch-up game. Whether it comes to updating ERP system with up-to-date stock counts from a number of out trade counters (brick and mortar store locations), keeping track what's about to run out in our warehouses located in key countries globally or even trying to assign priorities correctly across several different team within Inventory Management, while RS as a company noticeably improved our approach to managing stock, we are surely in need of further improvements. Those will be difficult to come by and even more so - to implement - unless we manage to identify signicant patterns in underlying data.

Grouping best-selling products based on features such as number of web page views, additions to cars, revenue generated, number of customers who backed out of buying it - who knows what nuggets of knowledge are hidden from our eyes. It's my hope that perhaps k-means will help shine some light onto those hidden shared characteristics and perhaps those will be of significant enough importance that it will warrant changes in the way inventory mgmt teams operate. More importantly, our Marketing function has been observing a steady cost creep to their online ad campaigns, yet effectiveness of those campaigns seem to be declining over time (as evidence by conversion rate metric). It's our hope, here at Machine Learning team, that regrouping key product categories via clustering model, key reveal a better way to group our products and thus arm our marketing team with more efficient way to promote those key product groups.



iv) Data

The dataset has been sourced internally, with a help of a product analyst, who is a part of inventory management function and looks after best-selling products, making sure they are in stock with maximum availability. The Excel files utilized here has over 11,000 rows with multiple columns providing information such as Category, Technology type, number of orders, etc.

	Article	Description	FSTD Global	Category	Cell	Technology	Visit	Product Views	In Stock Views	Cart Additions	Orde	Conversion Rate	Revenue
26	9092061	PCM INTERFACE PAD FOR HS300, 128X72.5MM	12/31/9999	II&T	EMECH	Thermal Management	98	101	0.713	6	2	0.0204	135.68
27	291717	NYLON 6.6 HOSE CLIP,26.5-29.5MM	12/31/9999	TCFM	Consumables & Safety	Fasteners	281	256	0.835	43	17	0.0605	182.56
28	5217528	DELRIN SPUR GEAR - 1.0 MODULE 25 TEETH	12/31/9999	IA&C	Mech & Flu Pwr	Pow Tran & Struc	226	247	0.781	36	15	0.0664	205.26
29	9225141	SOLID STATE RELAY	12/31/9999	IA&C	Sensors & Switches	Ctrl & Ind Relay	274	312	0.254	16	1	0.0036	211.08
30	2664268	MEDIUM DISPOSABLE CO-POLYMER GLOVES	12/31/9999	TCFM	Consumables & Safety	PPE	274	264	0.989	41	6	0.0219	213.6

v) Data protection

The dataset used doesn't contain any customer-related info (other than number of orders and views in our online store) so there is no personally-identifiable information available. Thus there is no risk of any GDPR violation. As far as corporate data is concerned, there is no strictly confidential data being used. Almost all of the data used is publicaly available on our web store. The only potentially sensitive data in there is revenue generated by each of the top selling products. If accessed in its entirety, one could imagine a potential risk of a competitor being able to peek behind the curtain and try to replicate - say - our Top 1000 selling products and undercutting our pricing. To avoid that, I have sorted revenue in ascending order and never show the column content - only few rows at a time.

Loading libraries

In [1]:

```
# pandas for dataframe manipulation
import pandas as pd

# Seaborn and matplotlib for plotting results
import seaborn as sns
import matplotlib.pyplot as plt

# import function to scale our data so that we can perform sensible clusteri
from sklearn.preprocessing import MinMaxScaler

# KMeans to provide the implementation of our clustering algorithm
from sklearn.cluster import KMeans
```

Sourcing data

In [2]:

```
topsells = pd.read_excel("..\Top Sellers Digital Data_KP.xlsx")
```

In [3]:
```
topsells.tail()
```

Out[3]:

	Article	Description	FSTD Global	Category	Cell	Technology	Visits	Product Views	Sto Viev
11453	7609005	ALUMINIUM PAINT ENCLOSURE 160X160X90MM	9999-12-31 00:00:00	IA&C	Mach Guard & Enc	Enclosures	390	383	0.7
11454	4992470	PIPE CLEANING BRUSH FOR 15MM DIA PIPE	9999-12-31 00:00:00	TCFM	Tools Storage & FM	Hand Tools	1194	1125	0.9
11455	1257961	INDUSTRIAL CABLE 10MM2 10M	9999-12-31 00:00:00	II&T	Cable, Anti-Vib & Ac	Elec & Data Cable	291	335	0.2
11456	3971315	MINERAL INSULATED PT 100 SENSOR,3X150MM	9999-12-31 00:00:00	IA&C	Sensors & Switches	Proc Auto Sen	392	408	0.9
11457	2414782	ADHESIVE BASE MICRO WIRE SADDLE,9X7.3MM	9999-12-31 00:00:00	II&T	Cable, Anti-Vib & Ac	Cable Accs	591	561	0.9

Exploring, Cleaning & Transforming data

Exploring

Let's first have a quick look at what type data and its shape we are dealing with..

In [4]:
```
topsells.shape
```

Out[4]:
```
(11458, 13)
```

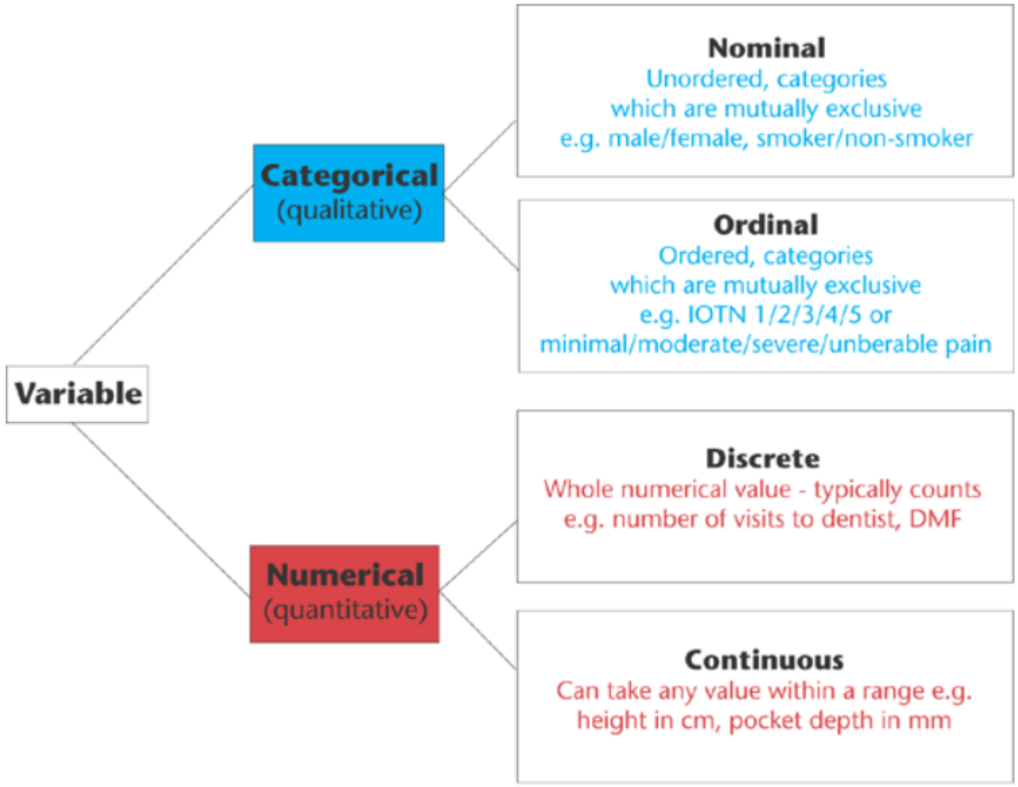
As we can see, our dataframe has almost 11,500 rows and 13 columns

In [5]:
```
topsells.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11458 entries, 0 to 11457
Data columns (total 13 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   Article          11458 non-null  int64  
 1   Description      11458 non-null  object 
 2   FSTD Global      11458 non-null  object 
 3   Category         11458 non-null  object 
 4   Cell             11458 non-null  object 
 5   Technology       11458 non-null  object 
 6   Visits           11458 non-null  int64  
 7   Product Views    11458 non-null  int64  
 8   In Stock Views   11458 non-null  float64
 9   Cart Additions   11458 non-null  int64  
 10  Orders           11458 non-null  int64  
 11  Conversion Rate  11458 non-null  float64
 12  Revenue          11458 non-null  float64
dtypes: float64(3), int64(5), object(5)
memory usage: 1.1+ MB
```

Good news - no null values in any of the rows - that doesn't happen often. I guess my colleague made sure the dataset has been of proper quality.

We can see that majority of the columns contain numerical values, while remaining 5 (column 2 - col 6) columns have categorical records.



As per above dichotomy, we can see that columns 2,4,5 and 6 contain nominal values, while column 3 (FSTD Global) appears to contain ordinal variables.

In [6]:
```
topsells.dtypes
```

Out[6]:
```
Article                int64
Description           object
FSTD Global           object
Category              object
Cell                  object
Technology            object
Visits                 int64
Product Views          int64
In Stock Views       float64
Cart Additions         int64
Orders                 int64
Conversion Rate      float64
Revenue              float64
dtype: object
```

We can further see that columns Visits, Product Views, cart additions and Orders contain whole numbers (aka integral = integers) while columns In Stock Views, Conversion rate and Revenue contain fractionals (in this case 64-bit floating point data types).

Interesting trivia - Nonintegral Numeric Types:

Nonintegral data types are those that represent numbers with both integer and fractional parts. The nonintegral numeric data types are Decimal (128-bit fixed point), Single Data Type (32-bit floating point), and Double Data Type (64-bit floating point). They are all signed types. If a variable can contain a fraction, declare it as one of these types. Decimal is not a floating-point data type. Decimal numbers have a binary integer value and an integer scaling factor that specifies what portion of the value is a decimal fraction. You can use Decimal variables for money values. The advantage is the precision of the values. The Double data type is faster and requires less memory, but it is subject to rounding errors. The Decimal data type retains complete accuracy to 28 decimal places. Floating-point (Single and Double) numbers have larger ranges than Decimal numbers but can be subject to rounding errors. Floating-point types support fewer significant digits than Decimal but can represent values of greater magnitude.

Cleaning

We are lucky - there doesn't seem to be a need for further data cleaning at this point. If that need arises, I'll do it on the fly.

Investigating

Let's see now what are the most commonly ordered products:

In [7]:
```
topsells.sort_values(by=['Orders'], ascending=False).head(1)
```

Out[7]:

	Article	Description	FSTD Global	Category	Cell	Technology	Visits	Product Views	In Stock Views	A
14	8660672	RS LITHIUM COIN CELL CR2032 5PK	9999-12-31 00:00:00	TCFM	Consumables & Safety	Battery	45475	28009	0.977	

Oh, the revenue... I'm going to hide it, as not to reveal too much at this stage:

In [8]:
```
topsellshider=topsells.drop(['Revenue'], axis=1)
```

In [9]:
```
topsellshider.head(7)
```

Out[9]:

	Article	Description	FSTD Global	Category	Cell	Technology	Visits	Product Views	I Stoc View
0	233487	BLACK CABLE TIE, 300X4.8MM, PACK 100	9999-12-31 00:00:00	II&T	Cable, Anti-Vib & Ac	Cable Accs	43371	28655	0.99
1	5375488	RS SEALED LEAD-ACID BATTERY,12V 7AH	9999-12-31 00:00:00	TCFM	Consumables & Safety	Battery	40171	41566	0.99
2	7348885	88PC 1/2IN. SOCKET & VDE TOOL KIT	9999-12-31 00:00:00	TCFM	Tools Storage & FM	Hand Tools	79286	89157	0.97
3	1681644	DUST REMOVER CLEANER 400ML	9999-12-31 00:00:00	TCFM	Consumables & Safety	Adhesives, Clean & M	8704	8340	0.93
4	6191506	SEALING STRIP,PVC,WIRE INSERT,1-2,9X6.	9999-12-31 00:00:00	TCFM	Consumables & Safety	Fasteners	9605	9731	0.99
5	8412518	ELECTRONIC CALIPER 150MM/6"	9999-12-31 00:00:00	TCFM	Tools Storage & FM	Measurement & Insp	35240	34067	0.99
6	100282	BRASS SLOT'D SCREW,NUT & WASHER KIT	9999-12-31 00:00:00	TCFM	Consumables & Safety	Fasteners	1609	1760	0.99

ok, now we can safely go back to seeing most frequently ordered products:

In [10]:
```
topsellshider.sort_values(by=['Orders'], ascending=False).head(10)
```

Out[10]:

	Article	Description	FSTD Global	Category	Cell	Technology	Visits	Product Views
14	8660672	RS LITHIUM COIN CELL CR2032 5PK	9999-12-31 00:00:00	TCFM	Consumables & Safety	Battery	45475	28009
89	7757233	LR44 ALKALINE COIN CELL 1.5V 158MAH	9999-12-31 00:00:00	TCFM	Consumables & Safety	Battery	51456	37928
0	233487	BLACK CABLE TIE, 300X4.8MM, PACK 100	9999-12-31 00:00:00	II&T	Cable, Anti-Vib & Ac	Cable Accs	43371	28655
29	512238	PTFE THREAD SEAL TAPE,12M L X 12MM W	9999-12-31 00:00:00	TCFM	Consumables & Safety	Adhesives, Clean & M	36293	26000
157	233455	CABLE TIE,100 X 2.5,BLACK,PACK 100	9999-12-31 00:00:00	II&T	Cable, Anti-Vib & Ac	Cable Accs	27824	17143
72	458702	RED INSUL BOOTLACE FERRULE,8MMPIN 1MMSQ.	9999-12-31 00:00:00	II&T	I-Conn	Crimp Term & Power	29405	19737
33	7442199	NON-RECHARGEABLE AA ALKALINE BATTERY	9999-12-31 00:00:00	TCFM	Consumables & Safety	Battery	22215	13742
36	458718	BLK INSUL BOOTLACE FERRULE,1.5MMSQ. WIRE	9999-12-31 00:00:00	II&T	I-Conn	Crimp Term & Power	29259	19750
26	593423	RS SR44 COIN CELL BATTERY, 1.55V	9999-12-31 00:00:00	TCFM	Consumables & Safety	Battery	23043	17434
138	467406	STANDARD TOP HAT PUNCHED DIN RAIL,0.5M	9999-12-31 00:00:00	IA&C	Mach Guard & Enc	Enclosures	32740	25221

It looks like batteries and cables are most popular among our customers.

Now let's find out which products got most eyeballs (but not necessarily most orders):

In [11]:
```
1 topsellshider.sort_values(by=['Product Views'], ascending=False).head(10)
```

Out[11]:

	Article	Description	FSTD Global	Category	Cell	Technology	Visits	Product Views
2	7348885	88PC 1/2IN. SOCKET & VDE TOOL KIT	9999-12-31 00:00:00	TCFM	Tools Storage & FM	Hand Tools	79286	89157
1293	8179236	55PC BIT AND SOCKET SET 1/4" DRIVE	9999-12-31 00:00:00	TCFM	Tools Storage & FM	Hand Tools	55287	58233
1	5375488	RS SEALED LEAD-ACID BATTERY,12V 7AH	9999-12-31 00:00:00	TCFM	Consumables & Safety	Battery	40171	41566
89	7757233	LR44 ALKALINE COIN CELL 1.5V 158MAH	9999-12-31 00:00:00	TCFM	Consumables & Safety	Battery	51456	37928
397	7613319	PROFILE 8 40X40 LIGHT 1M	9999-12-31 00:00:00	IA&C	Mech & Flu Pwr	Pow Tran & Struc	28691	37330
58	1231938	RS PRO COMPACT MULTIMETER AUTORANGING	9999-12-31 00:00:00	II&T	Test & Measurement	Electrical T&M	33038	36788
84	7348889	94PC MECHANICS TOOL KIT	9999-12-31 00:00:00	TCFM	Tools Storage & FM	Hand Tools	30977	34490
5	8412518	ELECTRONIC CALIPER 150MM/6"	9999-12-31 00:00:00	TCFM	Tools Storage & FM	Measurement & Insp	35240	34067
273	1251266	LI-POLYMER BATTERY 3.7V 2000MAH	9999-12-31 00:00:00	TCFM	Consumables & Safety	Battery	25953	30361
5372	7698736	CLEAR POLYCARBONATE SHEET, 305X625X3MM	9999-12-31 00:00:00	TCFM	Consumables & Safety	Engineering Mat	27735	30288

Pandas is telling us that it wasn't batteries or cables but, actually, sockets. Interesting. It would appear that conversion rate of sockets is noticeably lower than that of the 2 former groups. Perhaps it's driven by price. Either way - interesting fact...

Finally, let's learn which product was least often in stock, when viewed:

In [12]:
```
topsellshider.sort_values(by=['In Stock Views']).head(10)
```

Out[12]:

	Article	Description	FSTD Global	Category	Cell	Technology	Visits	Product Views
1622	6693677	THREE STEP MOBILE PLATFORM	9999-12-31 00:00:00	TCFM	Tools Storage & FM	Acc, Stor & Mat Hand	0	0
8995	1777087	OIL FILLED RADIATOR 2KW 9FIN UK PLUG	9999-12-31 00:00:00	TCFM	Tools Storage & FM	HVAC	8	0
6164	9076422	5/2 PILOT OPERATED SOLENOID VALVE, G1/2"	9999-12-31 00:00:00	IA&C	Mech & Flu Pwr	Pneumatics	190	222
10254	8938534	FUSE KIT 6.3X32 FAST AND SLOW GLASS 250V	9999-12-31 00:00:00	II&T	EMECH	Fuses	1921	1922
10273	7761989	ORANGE 3 CORE ARCTIC CABLE 2.5MM 100M	2024-12-19 00:00:00	II&T	Cable, Anti-Vib & Ac	Pwr & Ind Cable	520	542
6567	542093	30 PIECE ENGINEERS ZIPPED TOOL KIT	9999-12-31 00:00:00	TCFM	Tools Storage & FM	Hand Tools	2064	2264
362	9225141	SOLID STATE RELAY	9999-12-31 00:00:00	IA&C	Sensors & Switches	Ctrl & Ind Relay	274	312
3157	6211694	GENERAL STORAGE CAB 457X915X1830MM	9999-12-31 00:00:00	TCFM	Tools Storage & FM	Acc, Stor & Mat Hand	951	1116
7931	1615878	CABLE LOCKOUT SAFETY PADLOCK W/1FT CABLE	9999-12-31 00:00:00	TCFM	Consumables & Safety	Site Safety & Janit	1085	1170
11455	1257961	INDUSTRIAL CABLE 10MM2 10M	9999-12-31 00:00:00	II&T	Cable, Anti-Vib & Ac	Elec & Data Cable	291	335

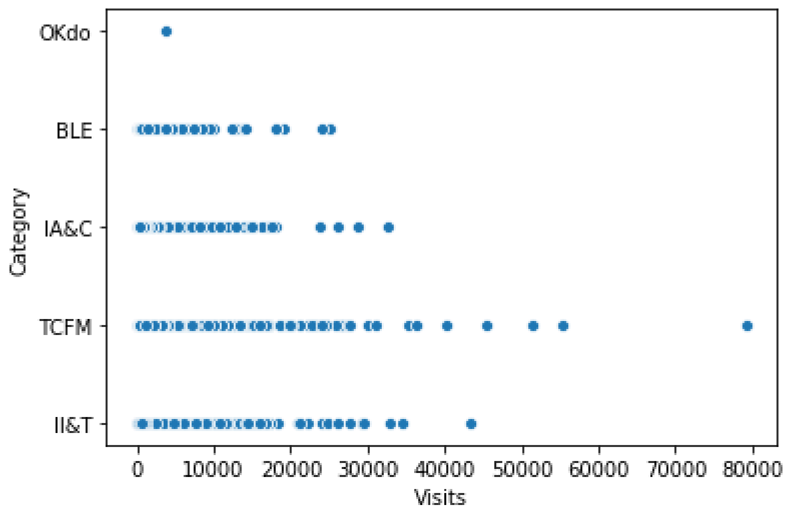
I won't pretend to be able to exlain what's so special about solenoid valve but it looks like it was viewed 222 times and was only in stock less than %1 of those times. And fuse kit was clicked on to view 1921 times and yet it was available for purchase only 5.1% of the time...

Visualizing the data

In [13]:
```
# create a scatter plot of Category vs. Visits using the scatterplot() funct
sns.scatterplot(x = topsellshider['Visits'], y = topsellshider['Category'])
```

Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x1d60c57ae88>

Out[13]:



In [14]:
```
#Learning what unique values exist in the Cell column:
topsellshider.Cell.unique()
```

Out[14]:
```
array(['Cable, Anti-Vib & Ac', 'Consumables & Safety',
       'Tools Storage & FM', 'I-Conn', 'Sensors & Switches',
       'Process Control', 'Mach Guard & Enc', 'E-Conn',
       'Test & Measurement', 'Passives', 'EMECH', 'Mech & Flu Pwr',
       'BLE E-Mech', 'Opto', 'Analog Disc Power', 'SBC & IOT'],
      dtype=object)
```

In [15]:
```
# Chehcking the amount of unique values in the Technology column:
topsellshider.Technology.value_counts()
```

Out[15]:
```
Fasteners               1376
Hand Tools               639
Acc, Stor & Mat Hand     562
Cable Accs               528
Pwr & Ind Cable          500
                        ...
Sensors                    4
LED                        4
Displays                   3
Power PCB                  3
SBC IOT Dev. Tools         1
Name: Technology, Length: 67, dtype: int64
```

In [16]:
```
#I'm going to drop some columns temporarily to be able to use heatmap type o
topsellshider2=topsellshider.filter(['Cell','Technology','Conversion Rate'])
```

In [17]:

```
topsellshider2.head(10)
```

Out[17]:

	Cell	Technology	Conversion Rate
0	Cable, Anti-Vib & Ac	Cable Accs	0.2227
1	Consumables & Safety	Battery	0.0899
2	Tools Storage & FM	Hand Tools	0.0100
3	Consumables & Safety	Adhesives, Clean & M	0.1743
4	Consumables & Safety	Fasteners	0.1620
5	Tools Storage & FM	Measurement & Insp	0.0852
6	Consumables & Safety	Fasteners	0.0298
7	I-Conn	Crimp Term & Power	0.1639
8	Tools Storage & FM	HVAC	0.0136
9	Tools Storage & FM	Hand Tools	0.1653

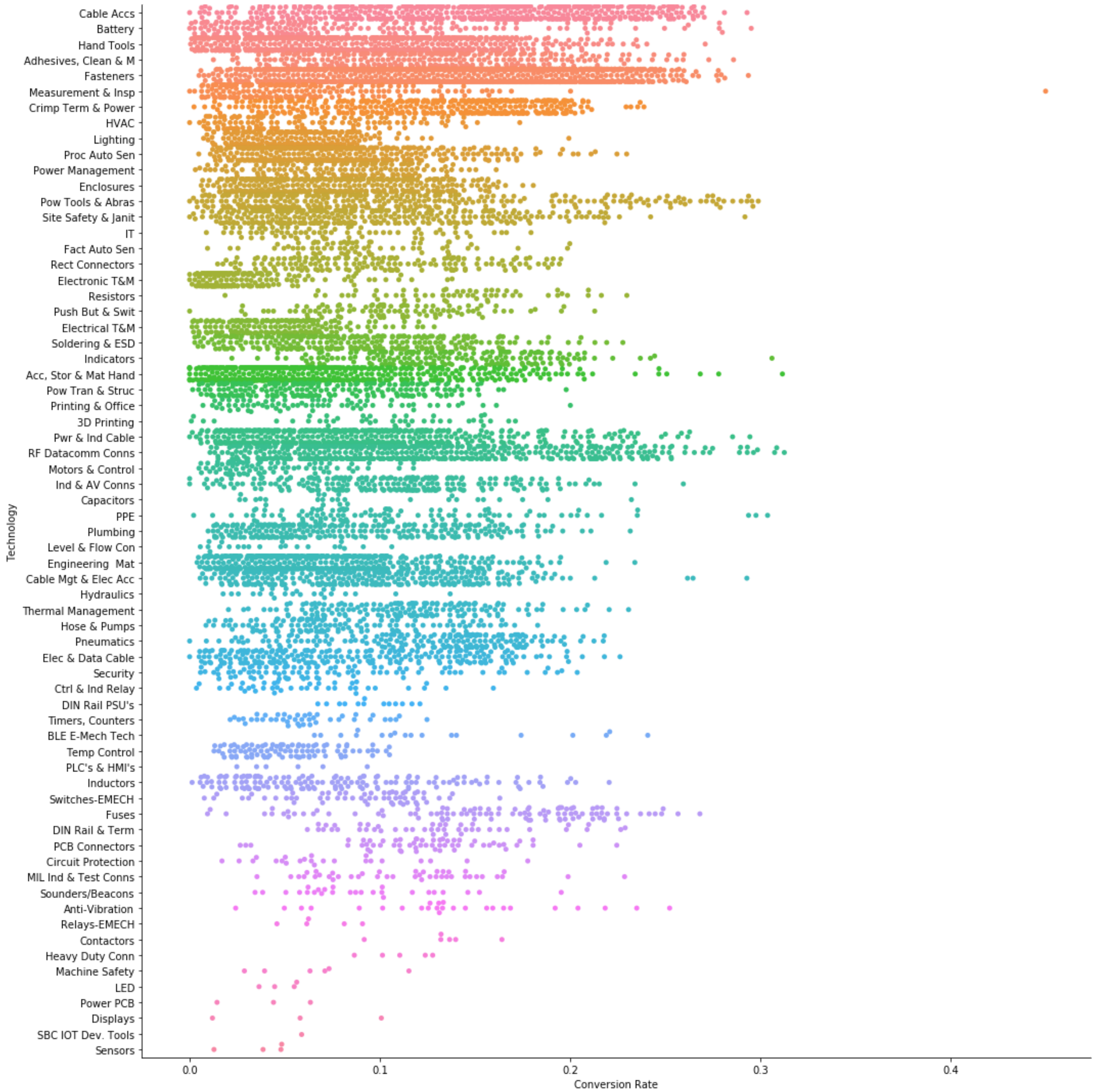
In [18]:

```
plt.figure(figsize=(8,35))
sns.catplot(data=topsellshider2, x="Conversion Rate", y="Technology", kind="
```

Out[18]: <seaborn.axisgrid.FacetGrid at 0x1d60c513d88>

Out[18]: <Figure size 576x2520 with 0 Axes>

Out[18]:



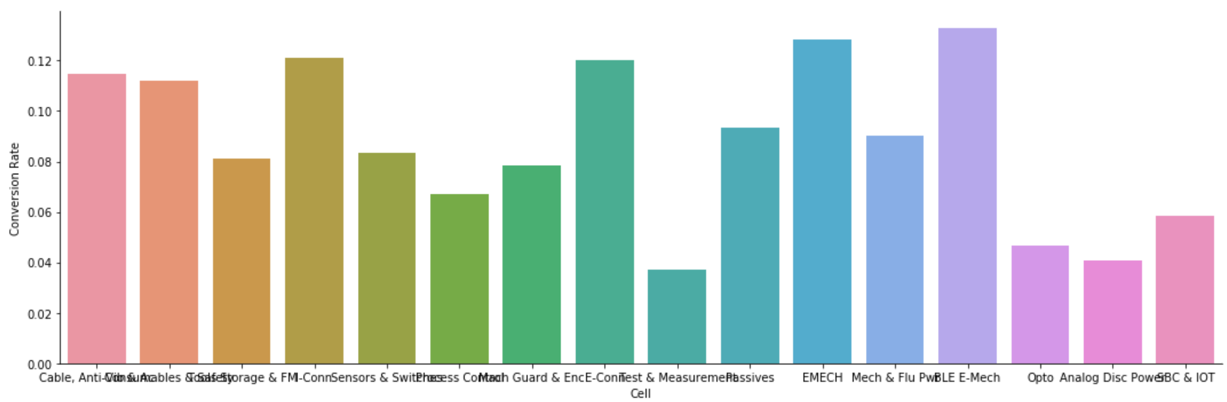
It would appear that Hand Tools and Hydration Ventilation Air Conditioning categories have the lowest conversion rates.

In [19]:
```
plt.figure(figsize=(32,8))
sns.catplot(data=topsellshider2, x="Cell", y="Conversion Rate", kind="bar",
```

Out[19]: <seaborn.axisgrid.FacetGrid at 0x1d60c892088>

Out[19]: <Figure size 2304x576 with 0 Axes>

Out[19]:

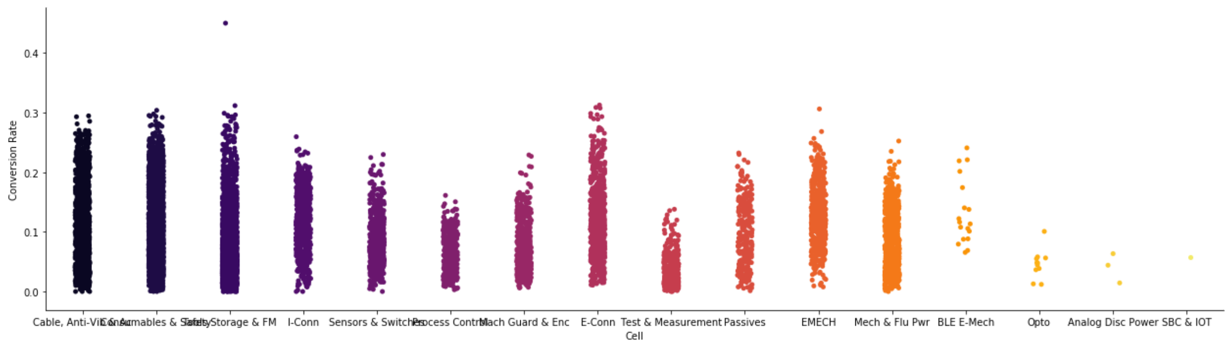


In [20]:

```
plt.figure(figsize=(18,7)) # default is inches
graph=sns.catplot(data=topsellshider2, x="Cell", y="Conversion Rate", palett
# pad is space under title
plt.box(on=1)
```

Out[20]: <Figure size 1296x504 with 0 Axes>

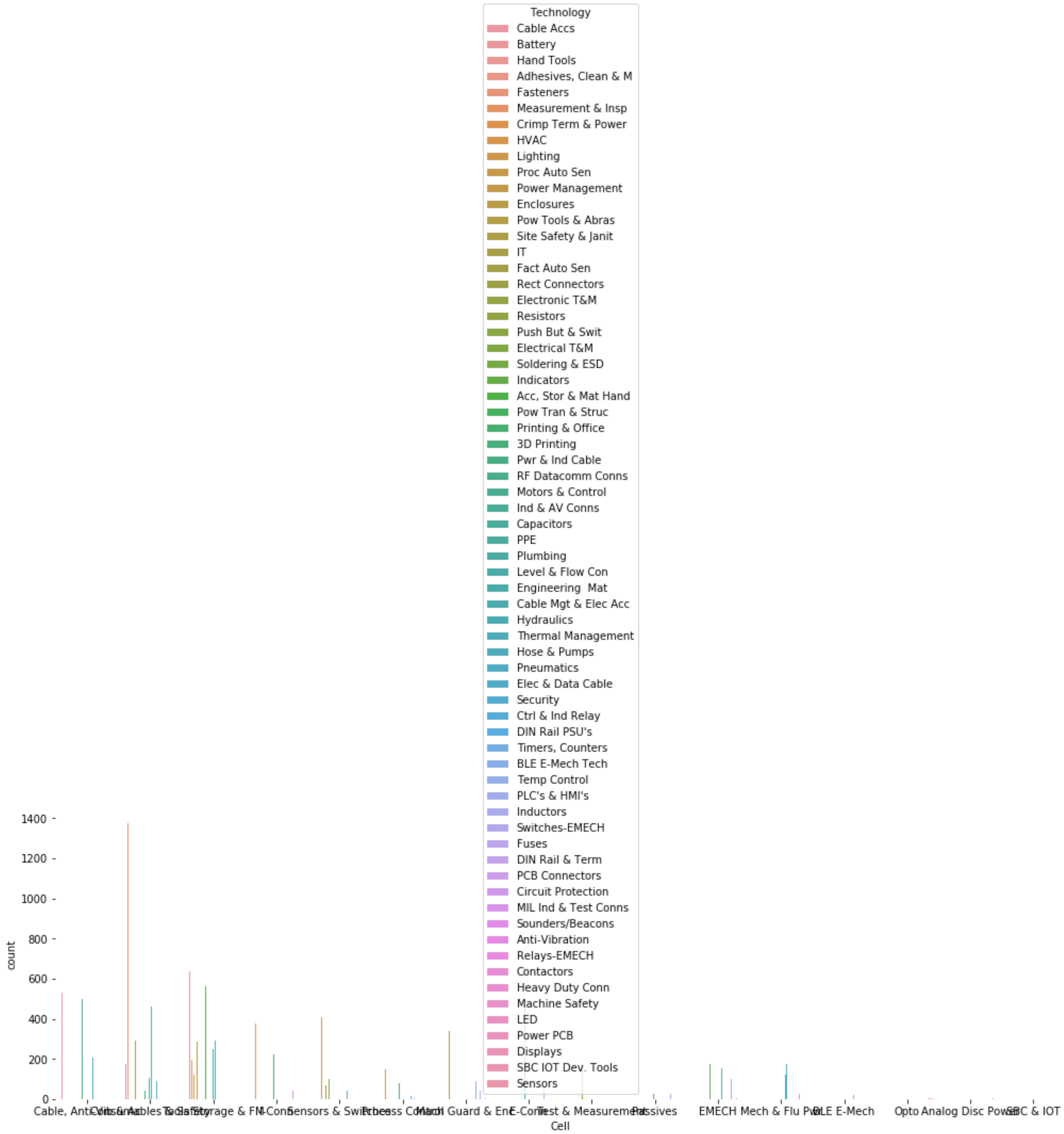
Out[20]:



In [21]:

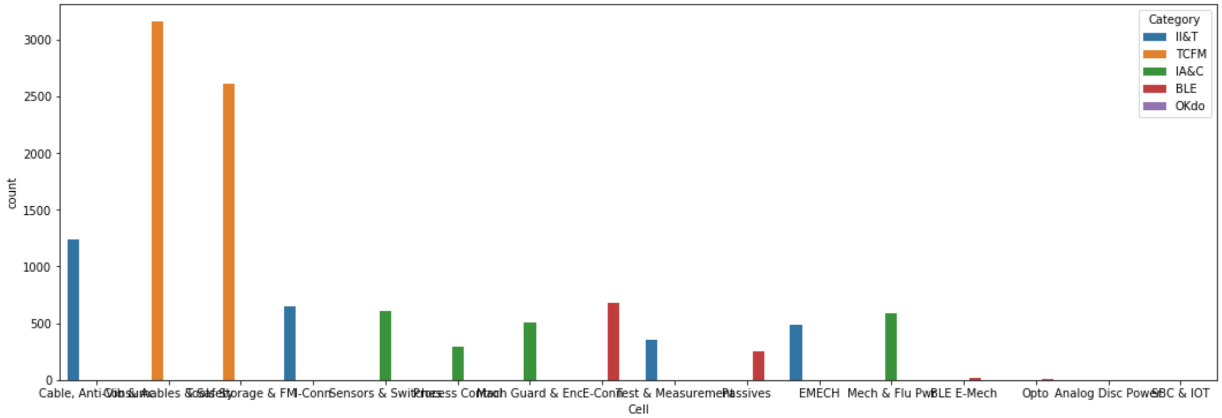
```
plt.figure(figsize=(17,5)) # default is inches
sns.countplot(data=topsellshider, x="Cell", hue="Technology")
plt.box()
```

Out[21]:



In [22]:
```
plt.figure(figsize=(18,6)) # default is inches
sns.countplot(data=topsellshider, x="Cell", hue="Category")
plt.show()
```

Out[22]:



Modelling with K-Means

Let's remind ourselves what the dataframe looks like:

In [23]:
```
topsellshider.head()
```

Out[23]:

	Article	Description	FSTD Global	Category	Cell	Technology	Visits	Product Views	In Stock Views
0	233487	BLACK CABLE TIE, 300X4.8MM, PACK 100	9999-12-31 00:00:00	II&T	Cable, Anti-Vib & Ac	Cable Accs	43371	28655	0.996
1	5375488	RS SEALED LEAD-ACID BATTERY,12V 7AH	9999-12-31 00:00:00	TCFM	Consumables & Safety	Battery	40171	41566	0.992
2	7348885	88PC 1/2IN. SOCKET & VDE TOOL KIT	9999-12-31 00:00:00	TCFM	Tools Storage & FM	Hand Tools	79286	89157	0.970
3	1681644	DUST REMOVER CLEANER 400ML	9999-12-31 00:00:00	TCFM	Consumables & Safety	Adhesives, Clean & M	8704	8340	0.933
4	6191506	SEALING STRIP,PVC,WIRE INSERT,1-2,9X6.	9999-12-31 00:00:00	TCFM	Consumables & Safety	Fasteners	9605	9731	0.997

In [24]:
```
1 topsellshider.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11458 entries, 0 to 11457
Data columns (total 12 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   Article          11458 non-null  int64  
 1   Description      11458 non-null  object 
 2   FSTD Global      11458 non-null  object 
 3   Category         11458 non-null  object 
 4   Cell             11458 non-null  object 
 5   Technology       11458 non-null  object 
 6   Visits           11458 non-null  int64  
 7   Product Views    11458 non-null  int64  
 8   In Stock Views   11458 non-null  float64
 9   Cart Additions   11458 non-null  int64  
 10  Orders           11458 non-null  int64  
 11  Conversion Rate  11458 non-null  float64
dtypes: float64(2), int64(5), object(5)
memory usage: 1.0+ MB
```

K-means only accepts numerical values in columns so we'll need to drop all the columns with categorical variables in them. I'll also drop Article column since while it has integral numbers in that column, it's just a way to indetify a product and we don't need it to pass it on to k-means.

In [25]:
```
1 topsellshider_nrs=topsellshider.filter(['Visits','Product Views','In Stock V
```

In [26]:
```
1 topsellshider_nrs.head(8)
```

Out[26]:

	Visits	Product Views	In Stock Views	Cart Additions	Orders	Conversion Rate
0	43371	28655	0.996	16065	9658	0.2227
1	40171	41566	0.992	6666	3611	0.0899
2	79286	89157	0.970	2373	789	0.0100
3	8704	8340	0.933	2245	1517	0.1743
4	9605	9731	0.997	2152	1556	0.1620
5	35240	34067	0.997	6000	3001	0.0852
6	1609	1760	0.998	106	48	0.0298
7	18232	17077	0.998	4412	2989	0.1639

Let's double-check:

In [27]:
```
topsellshider_nrs.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11458 entries, 0 to 11457
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   Visits           11458 non-null  int64  
 1   Product Views    11458 non-null  int64  
 2   In Stock Views   11458 non-null  float64
 3   Cart Additions   11458 non-null  int64  
 4   Orders           11458 non-null  int64  
 5   Conversion Rate  11458 non-null  float64
dtypes: float64(2), int64(4)
memory usage: 537.2 KB
```

OK. No numerical values anymore.

Scaling - standardize/normalize numbers:

First we need to make sure all variables are on the same scale, as currently In Stock Views and Conversion Rate are in % and thus in the order of magnitude of 0.01 and other columns are from 10's to being in the 4th order of magnitude (10000s). If we model the data as is, the Kmeans algorithm will skew away from % values and towards the variables with largest orders of magnitude, as any differences in distance will be more significant -- i.e. distance between Conversion Rate of 0.1743 and 0.1620 is only 0.0123 units, which on the Cart Additions axis would only equate to the distance between say, 10,000 and 10,000.0123! Hence, we need to scale to give variables equal weighting when clustering. There are two main ways to do this: Standardise: convert all to values in the range of 0-1 Normalise: convert all to values that have a mean of 0, and a standard deviation of 1 -- i.e. convert them such that they would lie on a normal distribution

For this situation we will stick to only standardising, as assuming a normal distribution gives too much weight to the mean of the data (which may not be relavant at all!).

In [28]:
```
# To standardise, we can use the MinMaxScaler functions from Sklearn
data_scaled = MinMaxScaler().fit_transform(topsellshider_nrs)

## If you would rather normalise the data, you could use the 'scale' functio
# data_scaled = scale(data)
```

In [29]:
```
data_scaled
```

Out[29]:
```
array([[5.47019650e-01, 3.21399329e-01, 9.96000000e-01, 8.14118482e-01,
        8.15847271e-01, 4.94778938e-01],
       [5.06659435e-01, 4.66211290e-01, 9.92000000e-01, 3.37809760e-01,
        3.05034634e-01, 1.99733393e-01],
       [1.00000000e+00, 1.00000000e+00, 9.70000000e-01, 1.20255410e-01,
        6.66497719e-02, 2.22172850e-02],
       ...,
       [3.67025704e-03, 3.75741669e-03, 2.89000000e-01, 1.57097248e-03,
        9.29211015e-04, 8.39813375e-02],
       [4.94412633e-03, 4.57619705e-03, 9.97000000e-01, 2.58450312e-03,
        2.19631695e-03, 1.47300600e-01],
       [7.45402719e-03, 6.29227094e-03, 9.96000000e-01, 4.91562357e-03,
        4.98394999e-03, 2.21728505e-01]])
```

It appears to have worked.

We can now proceed to the actual modelling:

In [30]:
```
# create the KMeans model object with a number of clusters k.
model = KMeans(n_clusters = 3, random_state= 123)
```

Note:

Machine learning algorithms (both supervised and unsupervised) are inherently stochastic (or probabilistic). This means they each have an element of randomness in them -- i.e. you can only estimate things with certain amounts of confidence, it's never deterministic. With kmeans, there's randomness associated with the initial positions of the centroids for instance. Different initial locations could potentially to lead to different results! Therefore to ensure reproducible results, we specify the random_state parameter -- if you set it to say, '123', and send the code over to someone else, provided they also specify the same state, you both should get the same clusters.

In [31]:
```
# fit the model to our scaled data.
model.fit(data_scaled)
```

Out[31]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=3, n_init=10, n_jobs=None, precompute_distances='auto',
       random_state=123, tol=0.0001, verbose=0)
```

In [32]:
```
# look at the cluster labels for the data points
model.labels_
```

Out[32]:
```
array([1, 1, 2, ..., 0, 2, 2])
```

In [33]:
```
# add a column to the dataframe called "Cluster" which tells us which cluste
topsellshider_nrs["Cluster"] = model.labels_.astype(int)
```

In [34]:
```
topsellshider_nrs.tail(10)
```

Out[34]:

	Visits	Product Views	In Stock Views	Cart Additions	Orders	Conversion Rate	Cluster
11448	433	485	0.996	16	4	0.0092	2
11449	220	226	0.522	41	9	0.0409	0
11450	804	819	0.939	159	86	0.1070	2
11451	777	697	0.960	167	108	0.1390	1
11452	143	153	0.773	11	2	0.0140	0
11453	390	383	0.713	63	38	0.0974	0
11454	1194	1125	0.998	224	131	0.1097	2
11455	291	335	0.289	31	11	0.0378	0
11456	392	408	0.997	51	26	0.0663	2
11457	591	561	0.996	97	59	0.0998	2

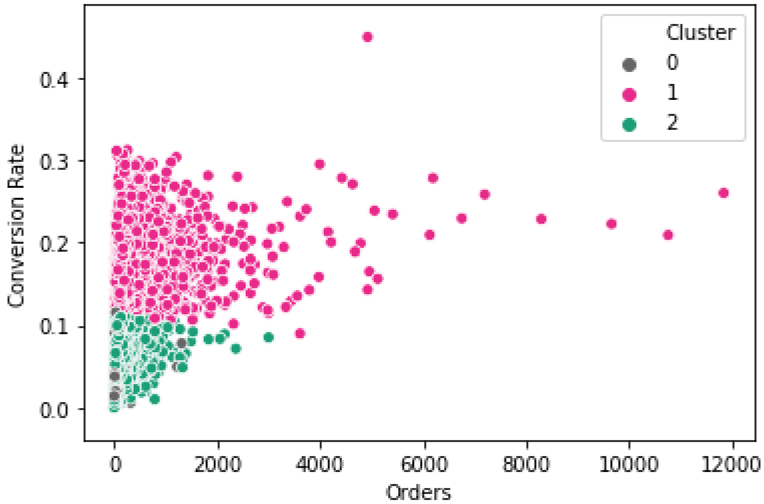
Visualizing the clusters

Now I would like to recreate the scatter plot above, but with the data points coloured according to cluster:

In [35]:
```
# I can do this by specifying the 'hue' parameter in the same scatterplot fu
sns.scatterplot(x = topsellshider_nrs['Orders'], y = topsellshider_nrs['Conv
                    hue = topsellshider_nrs['Cluster'],
                   palette= 'Dark2_r')
```

Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x1d60f0eab88>

Out[35]:



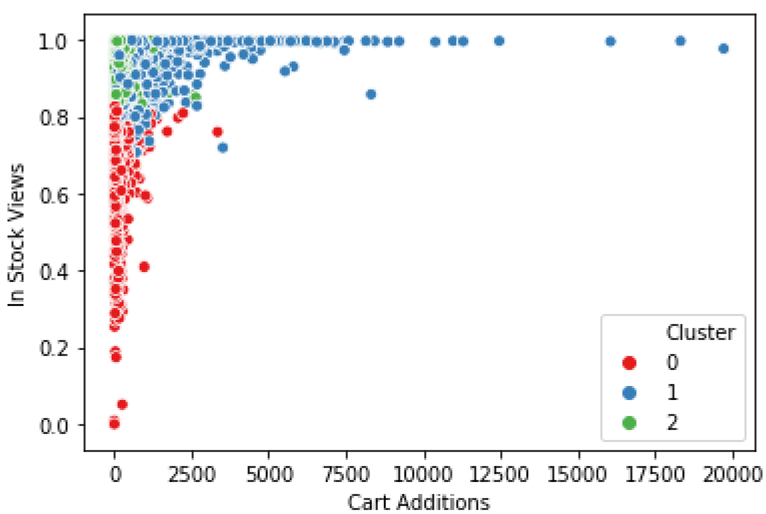
Looks like k-means separated variables rather neatly. and, looking closer, it seems that conversion rate slightly above 0.1 becomes a threshold between clusters 1 and 2.

Now let's have a look what it will look like if we change columns inspected - how will cluster distribution change:

In [36]:
```
sns.scatterplot(x = topsellshider_nrs['Cart Additions'], y = topsellshider_n
                    hue = topsellshider_nrs['Cluster'],
                   palette="Set1")
```

Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0x1d60f459dc8>

Out[36]:



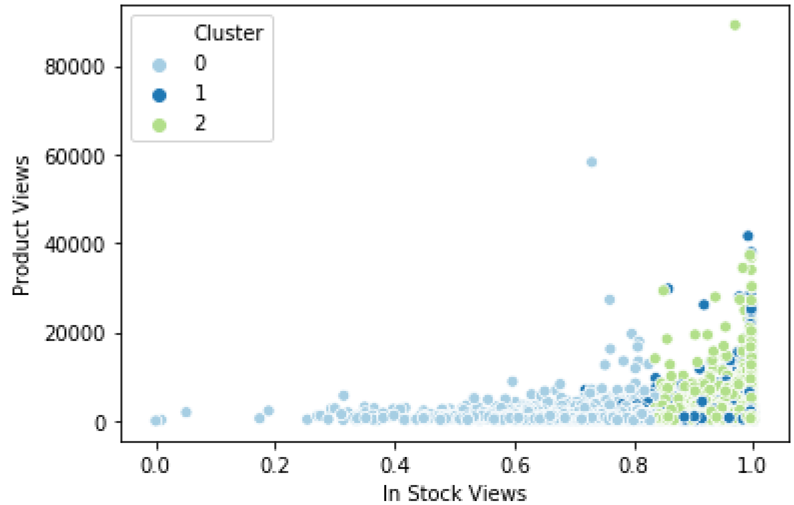
I have to say - it looks quite clear-cut as well - first cluster hugging the near 0 cart additions, while 3rd cluster having very high in stock views and larger amount of cart additions.

Let's inspect In Stock Views vs Product Views:

In [37]:
```
sns.scatterplot(x = topsellshider_nrs['In Stock Views'], y = topsellshider_n
                hue = topsellshider_nrs['Cluster'],
               palette="Paired")
```

Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x1d60fb3f308>

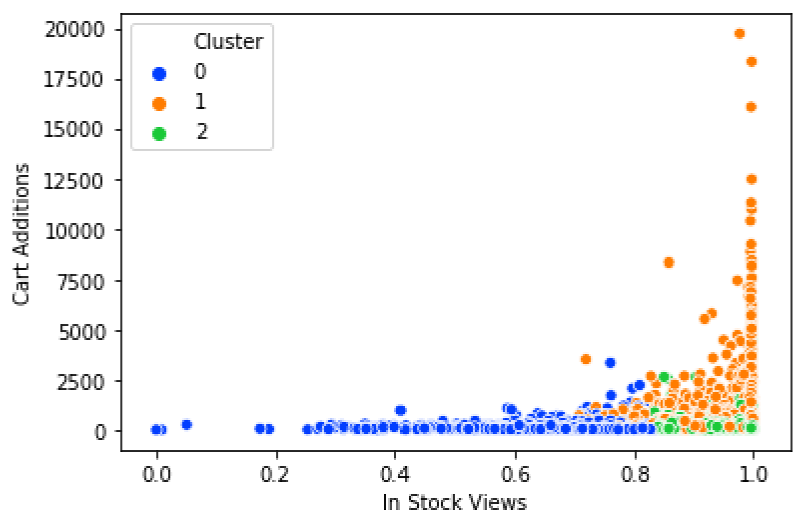
Out[37]:



In [38]:
```
#And finally let's look at cart additions vs in stock views:
sns.scatterplot(x = topsellshider_nrs['In Stock Views'], y = topsellshider_n
                hue = topsellshider_nrs['Cluster'],
               palette="bright")
```

Out[38]: <matplotlib.axes._subplots.AxesSubplot at 0x1d6110dadc8>

Out[38]:



Determine the optimal number of clusters k

Above, we arbitrarily chose to segment our data into three clusters (k = 3). However, this value of may not create the optimal clustering for our data.

Note on optimisation In order to optimise for anything in machine learning, we need a numerical metric (a number). In distance-based clustering like kmeans, there are are a few metrics we can choose to optimise. Most commonly, the ones used are:

- Within cluster distance: This is calculated by summing the squared distances between each point and its nearest cluster centroid (i.e. the centroid of the cluster to which it belongs).
- Silhouette coefficient: A metric that compares how close a data point is to all other points within the same cluster (on average) vs. how close it is to other points (on average) in the nearest cluster that the data point does not belong to.

For how the silhouette coefficient is calculated, [scikit-learn's documentation (https://scikit-learn.org/stable/modules/generated/sklearn.metrics.silhouette_score.html)](https://scikit-learn.org/stable/modules/generated/sklearn.metrics.silhouette_score.html) of the `silhouette_score` function is a great start.

However, for now we want to focus on within cluster sum-of-squares error (or WSS - within-cluster sum of squares) as our optimization metric. To do this we use what's called the 'elbow test' for different values of k.

In [39]:

```
# Idea: peform k-means clustering for various k, and compute the WSS each ti

# create a list of the different values of k to test. Could also use: list(r
num_clusters = [1,2,3,4,5,6,7,8,9,10]

# create a kmeans model for each value of k. Could use a regular for loop, b
kmeans_list = [KMeans(n_clusters = i) for i in num_clusters]

# For each value of k, fit the model with our data and use the "inertia" met
scores = [kmeans_list[i-1].fit(data_scaled).inertia_ for i in num_clusters]


# Optional
# We can choose to normalise the scores with respect to the score for k=1 (t
scores_normalised = scores/scores[0]
```

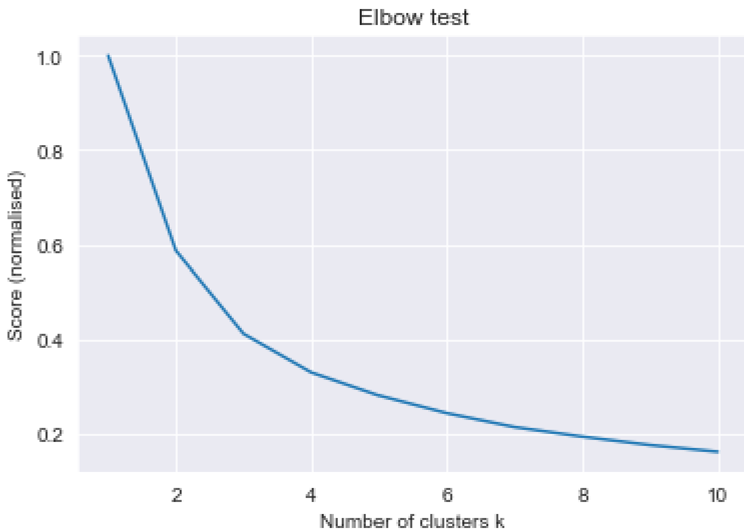
In [40]:
```
# We can choose to set a grid
sns.set_style('darkgrid')

# Use the lineplot function from seaborn
sns.lineplot(num_clusters, scores_normalised)


# Add a title and axis labels
plt.xlabel("Number of clusters k")
plt.ylabel("Score (normalised)")
plt.title("Elbow test")
```

Out[40]:
```
Text(0.5, 1.0, 'Elbow test')
```

Out[40]:



It would seem that optimal number k of cluster would be from 4 to 6. Once k is larger than 6 custers, RSS doesn't really drop off that much.

In [41]:
```
# create the KMeans model object with a number of clusters k = 6:
model2 = KMeans(n_clusters = 6, random_state= 123)
```

In [42]:
```
# fit the model to our scaled data.
model2.fit(data_scaled)
```

Out[42]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=6, n_init=10, n_jobs=None, precompute_distances='auto',
       random_state=123, tol=0.0001, verbose=0)
```

In [43]:
```
# Look at the cluster labels for the data points
model.labels_
```

Out[43]:
```
array([1, 1, 2, ..., 0, 2, 2])
```

In [44]:
```
# add a column to the dataframe called "Cluster" which tells us which cluste
topsellshider_nrs["ClusterK6"] = model2.labels_.astype(int)
```

In [45]:
```
topsellshider_nrs.head()
```

Out[45]:

	Visits	Product Views	In Stock Views	Cart Additions	Orders	Conversion Rate	Cluster	ClusterK6
0	43371	28655	0.996	16065	9658	0.2227	1	4
1	40171	41566	0.992	6666	3611	0.0899	1	4
2	79286	89157	0.970	2373	789	0.0100	2	4
3	8704	8340	0.933	2245	1517	0.1743	1	5
4	9605	9731	0.997	2152	1556	0.1620	1	5

In [46]:
```
plt.figure(figsize=(10,8))
sns.scatterplot(x = topsellshider_nrs['Orders'], y = topsellshider_nrs['Conv
                hue = topsellshider_nrs['ClusterK6'],
               palette= 'Dark2_r')
```

Out[46]: <matplotlib.axes._subplots.AxesSubplot at 0x1d60f4bfe08>

Out[46]:

In [47]:

```
plt.figure(figsize=(10,8))
sns.scatterplot(x = topsellshider_nrs['Orders'], y = topsellshider_nrs['Conv
                hue = topsellshider_nrs['ClusterK6'],
               palette= 'bright')
```

Out[47]: <matplotlib.axes._subplots.AxesSubplot at 0x1d60f09eb08>

Out[47]:

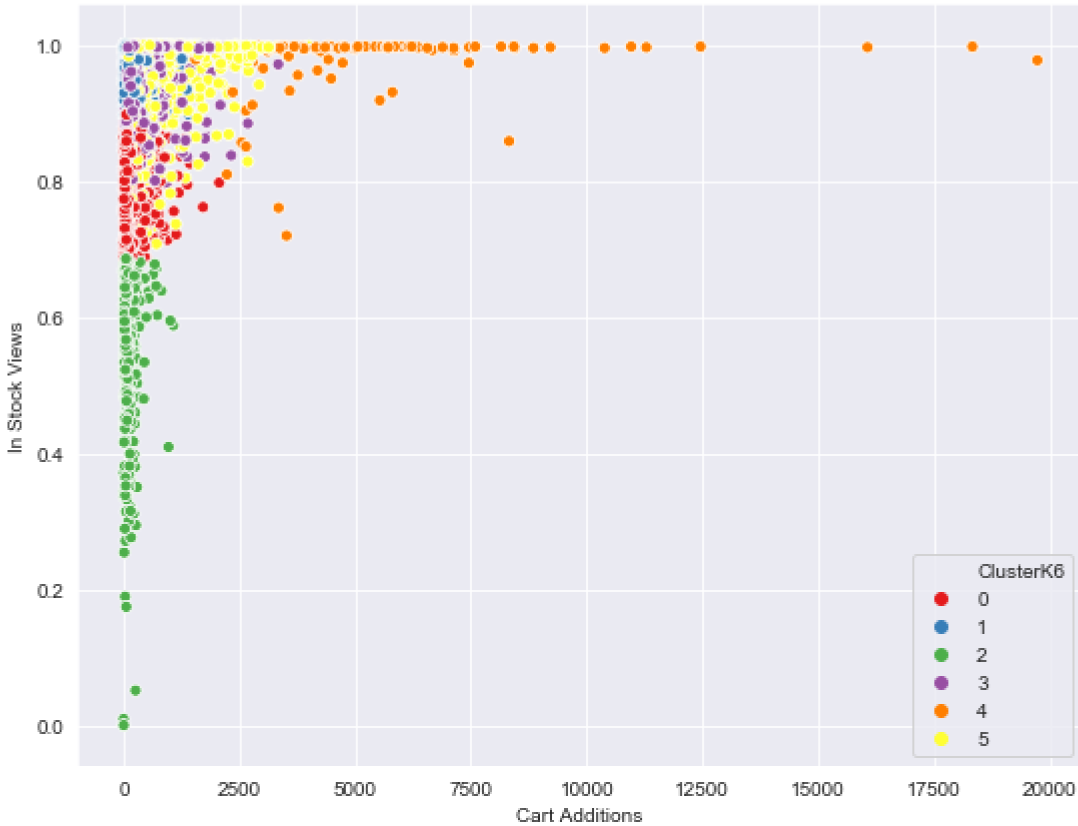
Hmm - it would appear that in this case k=3 resulted in neater clustering than with 6 clusters.

In [48]:

```
plt.figure(figsize=(9,7))
sns.scatterplot(x = topsellshider_nrs['Cart Additions'], y = topsellshider_n
                hue = topsellshider_nrs['ClusterK6'],
               palette="Set1")
```

Out[48]: <matplotlib.axes._subplots.AxesSubplot at 0x1d60ef2adc8>

Out[48]:

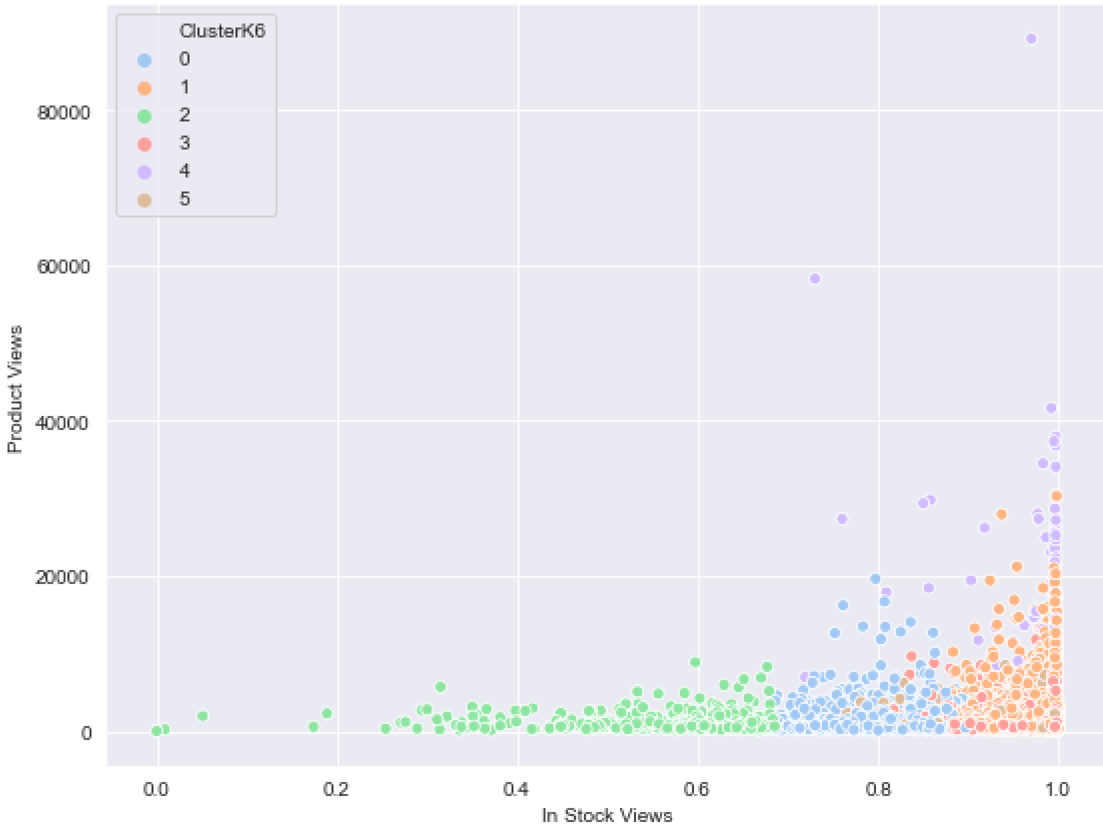


In the case above - Cart Additions vs In Stock Views - increasing k to 6 resulted in more refined clusters.

In [49]:
```
plt.figure(figsize=(9,7))
sns.scatterplot(x = topsellshider_nrs['In Stock Views'], y = topsellshider_n
                hue = topsellshider_nrs['ClusterK6'],
               palette="pastel")
```

Out[49]: <matplotlib.axes._subplots.AxesSubplot at 0x1d60ee4df88>

Out[49]:

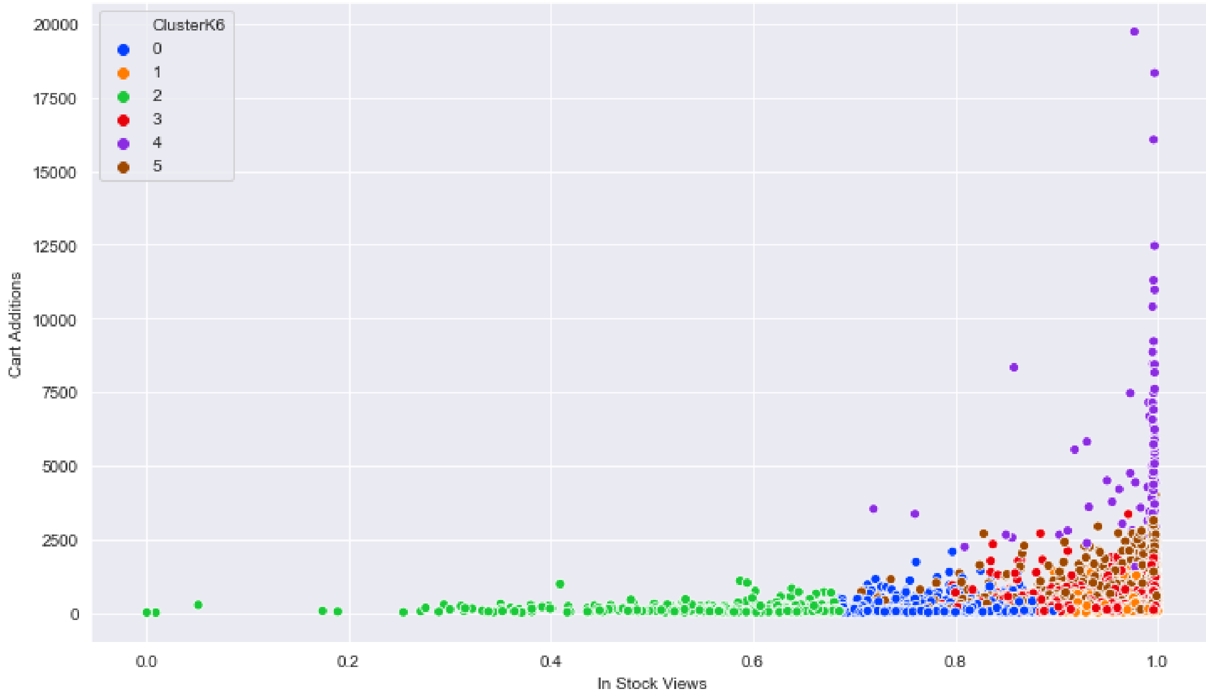


Also in the case of comparing Product Views with In Stock Views increasing numer of cluster yielded improvements (less outliers "invading" adjacent clusters)

In [50]:
```
#And finally let's look - again -  at cart additions vs in stock views:
plt.figure(figsize=(12,7))
sns.scatterplot(x = topsellshider_nrs['In Stock Views'], y = topsellshider_n
                hue = topsellshider_nrs['ClusterK6'],
               palette="bright")
```

Out[50]: <matplotlib.axes._subplots.AxesSubplot at 0x1d60c21d388>

Out[50]:



Mixed results here: while reds seems to competing with oranges and browns, k=6 delivered neater split of remaining values across green, purple and blue clusters.

Conclusions:

So far there isn't anything obvious popping up and begging for a deep dive. That could be due to multi-dimensional analysis performed above.

Reducing the dimensions:

How can we visualize the clustering differently? Well, we cannot do it directly if we have more than 3 columns (which we did - above). However, we can apply a Principal Component Analysis to reduce the space into 2 columns and visualize this instead.

In order to do that, we'll need to run PCA (Principal Component Analysis) on the data and reduce the dimensions in pca_num_components dimensions:

In [51]:
```
#First we need to import PCA component:
from sklearn.decomposition import PCA
```

In [52]:
```
topsellshider_nrs.head()
```

Out[52]:

	Visits	Product Views	In Stock Views	Cart Additions	Orders	Conversion Rate	Cluster	ClusterK6
0	43371	28655	0.996	16065	9658	0.2227	1	4
1	40171	41566	0.992	6666	3611	0.0899	1	4
2	79286	89157	0.970	2373	789	0.0100	2	4
3	8704	8340	0.933	2245	1517	0.1743	1	5
4	9605	9731	0.997	2152	1556	0.1620	1	5

In [53]:
```
topsellshider_nrs2 = topsellshider_nrs.drop(['Cluster', 'ClusterK6'], axis=1
```

In [54]:
```
topsellshider_nrs2.head()
```

Out[54]:

	Visits	Product Views	In Stock Views	Cart Additions	Orders	Conversion Rate
0	43371	28655	0.996	16065	9658	0.2227
1	40171	41566	0.992	6666	3611	0.0899
2	79286	89157	0.970	2373	789	0.0100
3	8704	8340	0.933	2245	1517	0.1743
4	9605	9731	0.997	2152	1556	0.1620

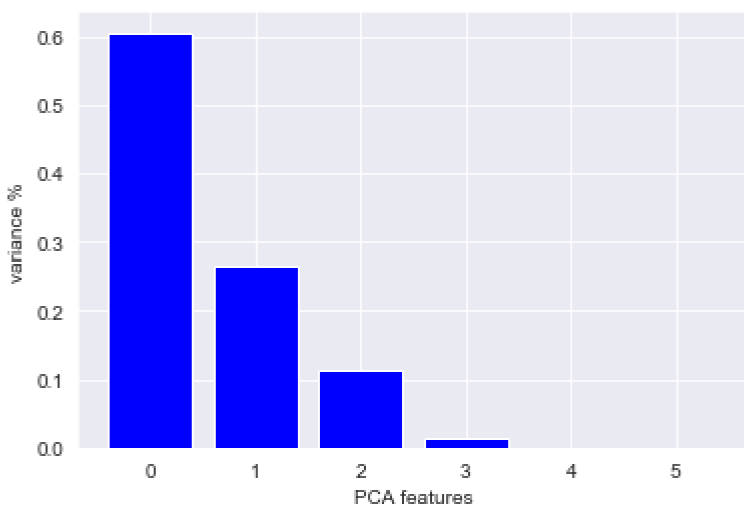
In [55]:
```
pca = PCA(n_components=6)
```

In [56]:
```
principalComponents = pca.fit_transform(data_scaled)
```

In [57]:
```
# Plot the explained variances
features = range(pca.n_components_)
plt.bar(features, pca.explained_variance_ratio_,color='blue' )
plt.xlabel('PCA features')
plt.ylabel('variance %')
plt.xticks(features)
```

Out[57]:
```
([<matplotlib.axis.XTick at 0x1d60f111708>,
  <matplotlib.axis.XTick at 0x1d60f2bed08>,
  <matplotlib.axis.XTick at 0x1d60ee33088>,
  <matplotlib.axis.XTick at 0x1d60ee13b08>,
  <matplotlib.axis.XTick at 0x1d60edf4208>,
  <matplotlib.axis.XTick at 0x1d60edf4688>],
 <a list of 6 Text xticklabel objects>)
```

Out[57]:



We can see that only 3 main features (0,1,2) will be enough to explain the majority of the variance in our data. After feature 2, the variance in data drops significantly and feature 3 (4th feature) won't add much depth to our dataset.

In [58]:
```
# Save components to a DataFrame
PCA_components = pd.DataFrame(principalComponents)
```

To help visualize this, i'll quickly plot just the first 2 features. That's in order to observe if there are any clear clusters:

In [59]:
```
plt.scatter(PCA_components[0], PCA_components[1], alpha=.1, color='green')
plt.xlabel('PCA 1')
plt.ylabel('PCA 2')
```

Out[59]: Text(0, 0.5, 'PCA 2')

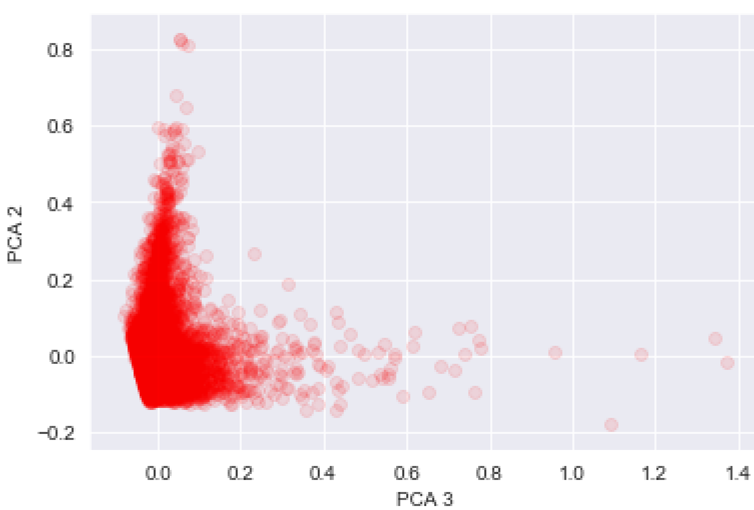
Out[59]:

Let's do the same - only this time for 2nd and 3rd feature of our dataset (so PCA feature 1 and 2 in the blue bar graph above):

In [60]:
```
plt.scatter(PCA_components[2], PCA_components[1], alpha=.1, color='red')
plt.xlabel('PCA 3')
plt.ylabel('PCA 2')
```

Out[60]: Text(0, 0.5, 'PCA 2')

Out[60]:



Here I can see that there is a concetration of observations clvstered tiahtlv toaether towards lower left corner of the graph.

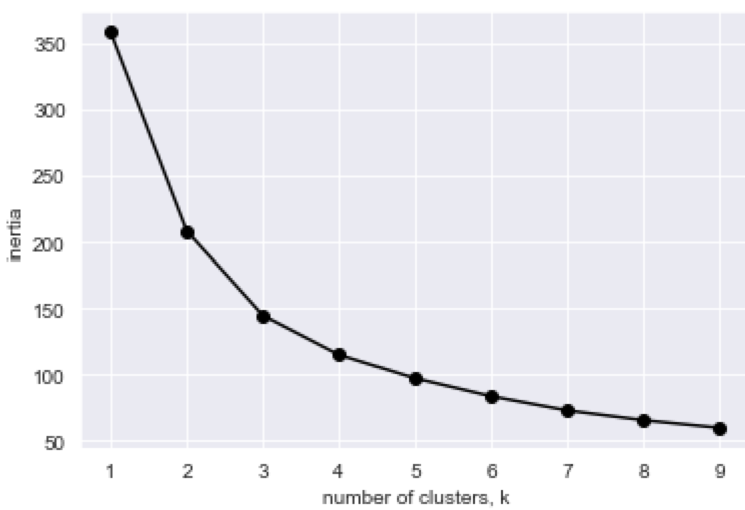
As as next step, I'll fit these principal components to the k-means algorithm and determine the best number of clusters. Arriving at the perfect number of clusters for our k-means model can be accomplished by measuring the sum of the squared distances to the nearest cluster center - also known as **inertia**. Much like the bar plot for variance in PCA features, the k-means line plot below will indicate % (the percentage) of variance explained, but in somewhat different terms, as a function of the number of clusters:

In [61]:

```
ks = range(1, 10)
inertias = []
for k in ks:
    # Create a KMeans instance with k clusters: model
    model3 = KMeans(n_clusters=k)

    # Fit model to samples
    model3.fit(PCA_components.iloc[:,:3])
  # Append the inertia to the list of inertias
    inertias.append(model3.inertia_)
#blank
plt.plot(ks, inertias, '-o', color='black')
plt.xlabel('number of clusters, k')
plt.ylabel('inertia')
plt.xticks(ks)
plt.show()
```

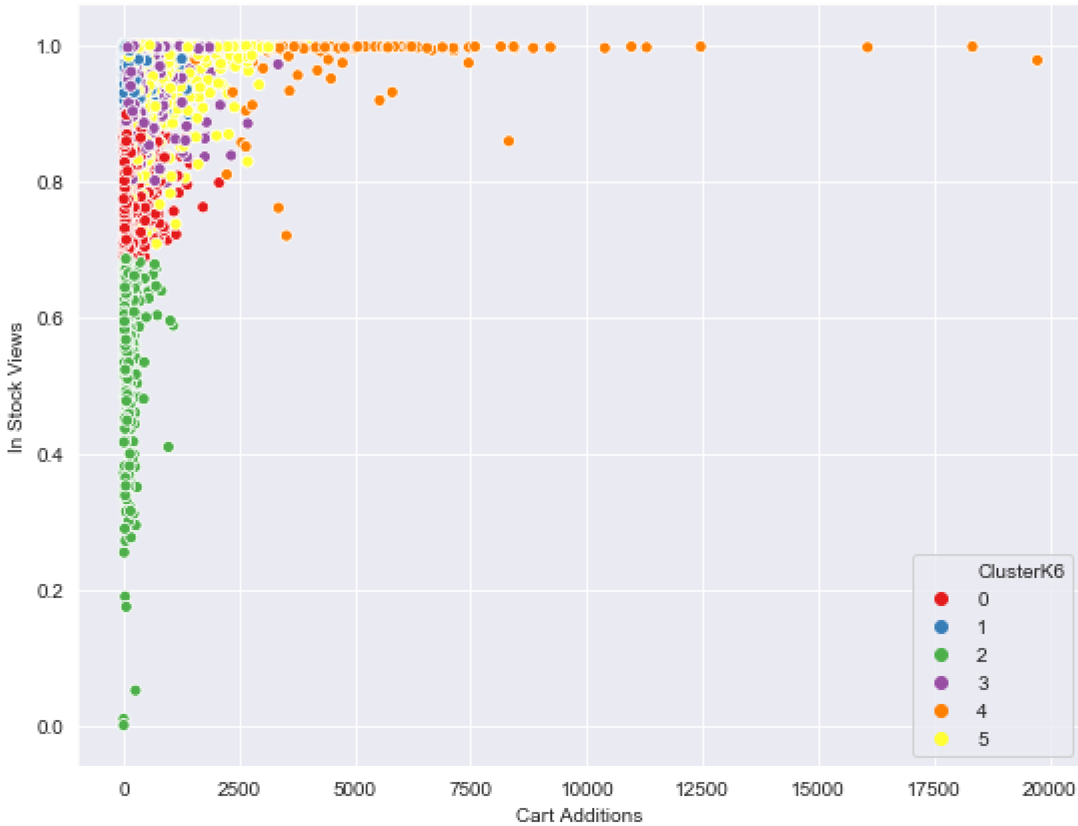
Out[61]:



In [62]:
```
plt.figure(figsize=(9,7))
sns.scatterplot(x = topsellshider_nrs['Cart Additions'], y = topsellshider_n
                 hue = topsellshider_nrs['ClusterK6'],
                palette="Set1")
```

Out[62]: <matplotlib.axes._subplots.AxesSubplot at 0x1d60efba508>

Out[62]:



In [63]:
```
# create the KMeans model object with a number of clusters k = 6:
model4 = KMeans(n_clusters = 4, random_state= 321)
```

In [64]:
```
model4.fit(PCA_components)
```

Out[64]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=4, n_init=10, n_jobs=None, precompute_distances='auto',
       random_state=321, tol=0.0001, verbose=0)
```

In [65]:
```
model4.labels_
```

Out[65]:
```
array([2, 0, 3, ..., 1, 3, 0])
```

In [66]:
```
PCA_components["Clusters4"] = model4.labels_.astype(int)
```

In [67]:
```
PCA_components.sample(12)
```

Out[67]:

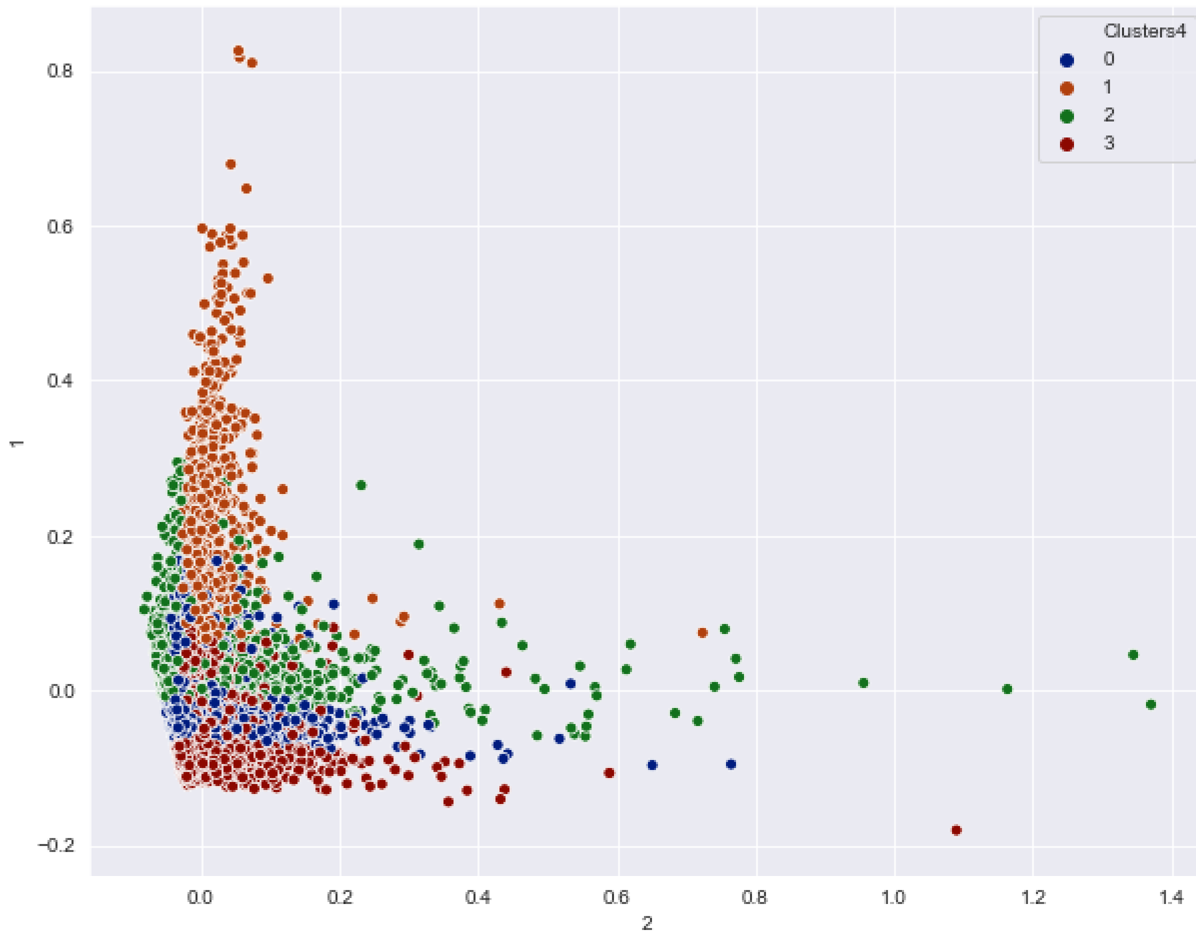
	0	1	2	3	4	5	Clusters4
3123	-0.188280	0.135084	0.005901	-0.004904	-0.000424	-0.000036	1
11012	-0.122557	0.046328	-0.000951	-0.002632	0.000540	-0.000230	3
7823	-0.166323	0.022846	-0.004841	-0.007608	0.000936	0.000138	3
7450	0.194961	0.007522	-0.032692	0.006240	0.000465	0.001276	2
945	0.238817	0.104038	0.145325	-0.034117	0.006297	0.001353	2
1138	0.040766	-0.038636	-0.009965	-0.000776	-0.000785	-0.000014	0
8634	-0.090266	-0.081805	-0.020006	-0.009027	0.001076	0.000630	3
6004	0.321200	0.056449	-0.034283	0.013119	0.000669	-0.000997	2
3282	-0.048669	0.251773	-0.021336	0.004132	0.000227	-0.000148	1
3293	0.142055	0.038566	-0.018279	0.005517	0.000062	-0.001176	2
2341	-0.073131	-0.075175	-0.031048	-0.012278	0.000227	0.000106	3
6905	0.006019	-0.053280	-0.009493	-0.000837	0.000870	0.001017	0

In [68]:

```
plt.figure(figsize=(10,8))
sns.scatterplot(x = PCA_components[2], y = PCA_components[1],
                hue = PCA_components['Clusters4'],
               palette= 'dark')
```

Out[68]: <matplotlib.axes._subplots.AxesSubplot at 0x1d60ee88c88>

Out[68]:



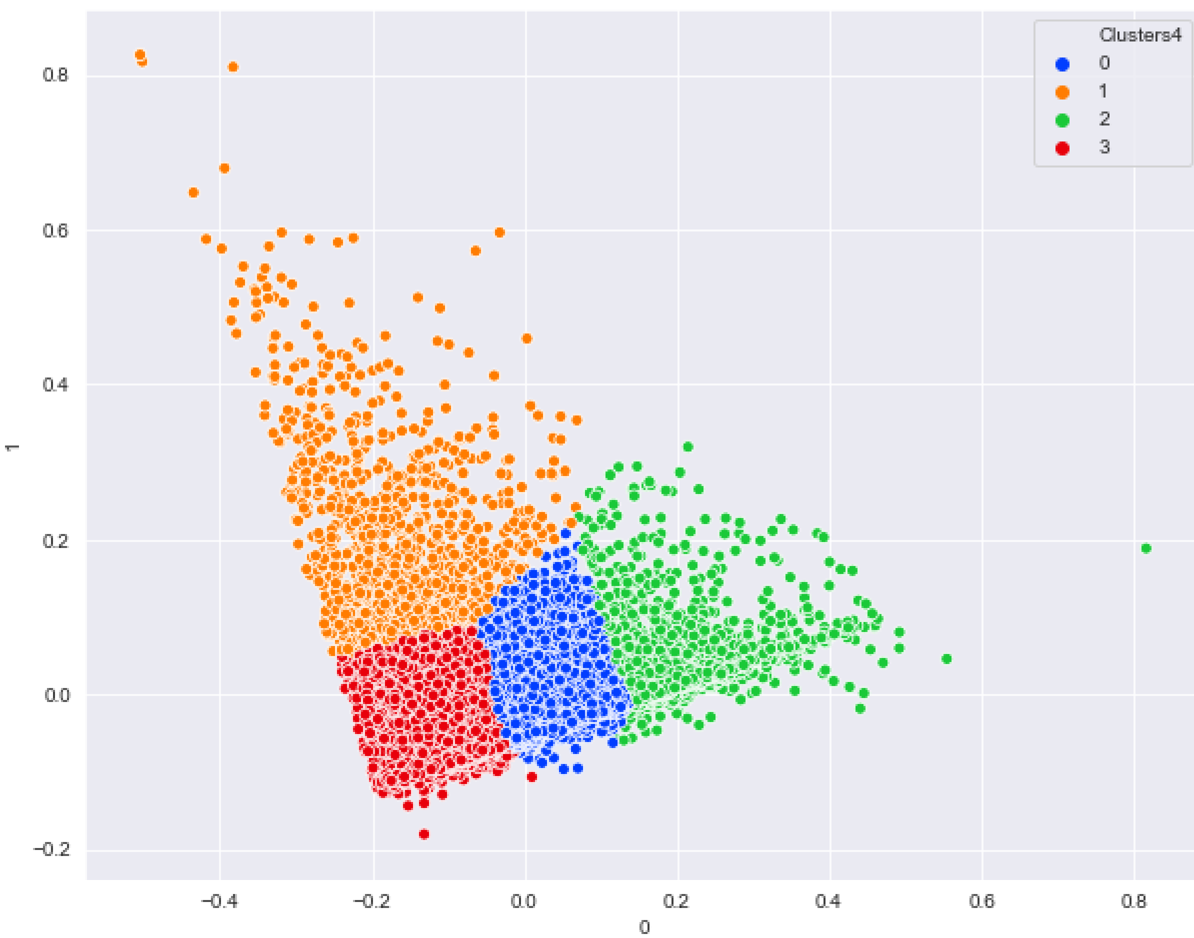
We are getting more homogeneity and therefore more order but it's still not what I'd like to see.

Let's try it one more time. This time let's try to juxtapose feature 1 and feature 2 with the most variance from our reduced dimensionality featurees (PCA 0 and PCA 1 on the same graph):

In [69]:
```
plt.figure(figsize=(10,8))
sns.scatterplot(x = PCA_components[0], y = PCA_components[1],
                hue = PCA_components['Clusters4'],
               palette= 'bright')
```

Out[69]: <matplotlib.axes._subplots.AxesSubplot at 0x1d60ef29308>

Out[69]:



BINGO!

That's what I was hoping to see. We can observe very neatly ordered clustered with virtually no intrusion of cluster elements into the border of a neighboring cluster. Not sure how to call this state but it resembles a child with OCD who organized lego blocks in a very tidy manner-)

Summary:

As we can see above, that wasn't a straight line journey. Against better judgement, I have decided against making a discretionary call of choosing 2 or 3 at most columns with different product features, instead opting to include all 6 columns with numerical values. At first I have started with 3 clusters but that didn't lead me to where I wanted. I have then conducted k number optimization exercise and determined that 6 clusters could be a better idea.While that yielded largely better separation of clusters, it still wasn't what I wanted to see. Then,I have decided to apply the concept of dimension reduction, drawing upon PCA method in sklearn decomposition module. After determining where the variance drop off in features lies, I have run PCA and reduced dimensionality of our dataset and settled for 4 clusters. That finally did the trick.

I haven't labeled the dataset, so we do not know the names of the clusters. This does not mean that one couldn’t go back and label these groupings, though.

Now that we know how many clusters there are in our data, we have a better sense of how many groups we can label the products with. It’s possible now to come up with a model that grades importance of a product to have in stock in 4 grades. Similarly, there could be 4 categories of impact on sales numbers. Introducing these labels back into the reduced dataset on the unique id of each sample would allow us to visualize them by cluster.

Next Steps:
To implement this into production and to apply it effectively so that Marketing team could adjust their campaign budget and promote those 4 key product categories better, not to mention to arm Inventory Management function with ability to improve our product stocking levels, it next requires somewhat major exercise of manually labeling data points). As it happens, I've been approached recently by couple of organizations that offer mas labeling services to enterprises so I am happy to engage them in the dialogue about commercial terms of such exercise.

In [0]:

```
1
```