In [16]:
```
import numpy as np
import pandas as pd
import random
from kmodes.kprototypes import KPrototypes
import matplotlib.pyplot as plt
from matplotlib import style
import seaborn as sb
import seaborn as sns
import warnings
import math
from math import isnan
warnings.filterwarnings("ignore")
```

In [56]:
```
Data = pd.read_csv('C:/Users/mia.kong/OneDrive - Canadian Tire/Desktop/Survey Ana
Data.head()
```

Out[56]:

	Respondent ID	Collector ID	Start Date	End Date	IP Address	NPS	Detractors feedback	Passives feedback	Pro fe
0	12246985268	263245465	12/10/2020 16:32	12/10/2020 16:32	99.252.69.113	9	NaN	NaN	
1	12179406900	263245465	11/17/2020 20:48	11/17/2020 20:49	99.240.132.190	7	NaN	NaN	
2	12043039162	263245465	10/02/2020 23:04	10/02/2020 23:05	99.246.167.93	8	NaN	NaN	
3	12011013117	263245465	09/22/2020 17:43	09/22/2020 17:43	170.52.68.9	8	NaN	NaN	
4	11973635491	263245465	09/09/2020 15:50	09/09/2020 15:50	172.97.250.147	9	NaN	NaN	

In [57]:
```
def f(NPS):
    if NPS <= 6:
        return "Detractor"
    elif NPS >6 and NPS<=8:
        return "Passive"
    elif NPS >=9 and NPS <=10:
        return "Promoter"
```

In [58]:
```
Data['NPS Type']=Data['NPS'].apply(f)
Data.head()
```

Out[58]:

	Respondent ID	Collector ID	Start Date	End Date	IP Address	NPS	Detractors feedback	Passives feedback	Pro fe
0	12246985268	263245465	12/10/2020 16:32	12/10/2020 16:32	99.252.69.113	9	NaN	NaN	
1	12179406900	263245465	11/17/2020 20:48	11/17/2020 20:49	99.240.132.190	7	NaN	NaN	
2	12043039162	263245465	10/02/2020 23:04	10/02/2020 23:05	99.246.167.93	8	NaN	NaN	
3	12011013117	263245465	09/22/2020 17:43	09/22/2020 17:43	170.52.68.9	8	NaN	NaN	
4	11973635491	263245465	09/09/2020 15:50	09/09/2020 15:50	172.97.250.147	9	NaN	NaN	

Data Cleanning

In [59]:
```
#Value counts, check Typo!!!!
for col in ['Division',
 'Role',
 'Course Name',
 'Course Type']:
        print(Data[col].value_counts())
```

```
Automotive - General Merch    40
Living                        36
Playing                       33
Seasonal & Gardening          26
Fixing                        22
Automotive - Parts            13
Automotive - Hard Parts        8
Name: Division, dtype: int64
Category Business Analyst         99
CBA                               61
Forecasting Analyst               47
Pricing Specialist                10
Category Business Manager/ACBM     6
CBP                                4
Name: Role, dtype: int64
CBA Onboarding                   35
Fundamentals of Analytics        30
CBM Assortment Decision          23
Tools of Analytics               23
Advanced Product Execution       22
FA Onboarding                    16
Data Vault                       16
Assortment Forecasting           12
Promo season forecasting         11
Build RFQ                        11
Category Management Framework     6
Inventory Management Basics       6
Forecasting Promo Late Deal       5
PS Onboarding                     5
CBP Onboarding                    4
Assortment Update                 2
Name: Course Name, dtype: int64
Onboarding       140
JIT               62
Self-directed     25
Name: Course Type, dtype: int64
```

In [60]:
```
Data['Division']=Data['Division'].replace("Automotive - Parts","Automotive - Har
```

In [61]:
```
Data['Role']=Data['Role'].replace("CBA","Category Business Analyst")
Data['Role']=Data['Role'].replace("CBP","Category Business Planning")
```

In [62]:
```
#Value counts, check Typo!!!!
for col in ['Division',
 'Role','First time']:
        print(Data[col].value_counts())
```

```
Automotive - General Merch    40
Living                        36
Playing                       33
Seasonal & Gardening          26
Fixing                        22
Automotive - Hard Parts       21
Name: Division, dtype: int64
Category Business Analyst         160
Forecasting Analyst                47
Pricing Specialist                 10
Category Business Manager/ACBM      6
Category Business Planning          4
Name: Role, dtype: int64
Yes    85
No     26
Name: First time, dtype: int64
```

Deal with missing value

In [63]:
```
Data.isna().sum()
```

Out[63]:
```
Respondent ID               0
Collector ID                0
Start Date                  0
End Date                    0
IP Address                  0
NPS                         0
Detractors feedback       222
Passives feedback         182
Promoters feedback         85
Prior course knowledge    166
After course knowledge    166
Division                   49
Role                        0
Course Name                 0
Course Type                 0
First time                116
NPS Type                    0
dtype: int64
```

imputing missing value as a new group

In [64]:

```
Data['Division'] = Data['Division'].fillna("Unkonwn")
Data['First time'] = Data['First time'].fillna("Unkonwn")
Data['Prior course knowledge'] = Data['Prior course knowledge'].fillna("Unkonwn"
Data['After course knowledge'] = Data['After course knowledge'].fillna("Unkonwn"
Data['Detractors feedback'] = Data['Detractors feedback'].fillna("")
Data['Passives feedback'] = Data['Passives feedback'].fillna("")
Data['Promoters feedback'] = Data['Promoters feedback'].fillna("")
Data
```

Out[64]:

	Respondent ID	Collector ID	Start Date	End Date	IP Address	NPS	Detractors feedback	Passives feedback	F
0	12246985268	263245465	12/10/2020 16:32	12/10/2020 16:32	99.252.69.113	9			
1	12179406900	263245465	11/17/2020 20:48	11/17/2020 20:49	99.240.132.190	7			
2	12043039162	263245465	10/02/2020 23:04	10/02/2020 23:05	99.246.167.93	8			
3	12011013117	263245465	09/22/2020 17:43	09/22/2020 17:43	170.52.68.9	8			
4	11973635491	263245465	09/09/2020 15:50	09/09/2020 15:50	172.97.250.147	9			
...	...	...	...	...	...	...	...	...	
222	11709822976	262172241	06/18/2020 11:27	06/18/2020 11:27	184.145.69.133	10			
223	11709822068	262172241	06/18/2020 11:26	06/18/2020 11:28	24.114.99.0	10			
224	11702461458	262172241	06/16/2020 11:53	06/16/2020 15:19	99.234.138.51	10			
225	11926202861	253298738	08/23/2020 13:39	08/23/2020 13:41	99.224.71.94	10			
226	11529014619	253298738	04/22/2020 17:11	04/22/2020 17:12	99.237.186.247	8		More details on where to locate certain docume...	

227 rows × 17 columns

Imputing missing value by most frequency words

In [65]:
```
#Data['Division'] = Data['Division'].fillna(Data['Division'].value_counts().inde>
```

In [66]:
```
#Data.isna().sum()
```

In [67]:
```
#Data
```

In [192]:
```
#Value counts, check Typo!!!!
#for col in ['Division']:
#       print(Data[col].value_counts())
```

```
Living                          85
Automotive - General Merch      40
Playing                         33
Seasonal & Gardening            26
Fixing                          22
Automotive - Hard Parts         21
Name: Division, dtype: int64
```

imputing missing number by KNN

In [88]:
```
# from sklearn.impute import KNNImputer
```

In [106]:
```
#cat_variables = Data[['Division', 'Role','Course Name','Course Type','NPS Type'_
#cat_dummies = pd.get_dummies(cat_variables)
#cat_dummies.loc[cat_variables.Division.isnull(), cat_dummies.columns.str.startsw
#cat_dummies
```

Out[106]:

	Division_Automotive - General Merch	Division_Automotive - Hard Parts	Division_Fixing	Division_Living	Division_Playing	D
0	NaN	NaN	NaN	NaN	NaN	
1	NaN	NaN	NaN	NaN	NaN	
2	NaN	NaN	NaN	NaN	NaN	
3	NaN	NaN	NaN	NaN	NaN	
4	NaN	NaN	NaN	NaN	NaN	
...	...	...	...	...	...	
222	0.0	0.0	0.0	0.0	0.0	
223	0.0	0.0	0.0	1.0	0.0	
224	0.0	0.0	0.0	0.0	0.0	
225	0.0	0.0	0.0	1.0	0.0	
226	1.0	0.0	0.0	0.0	0.0	

227 rows × 33 columns

In [107]:
```
#cat_dummies.isna().sum()
```

Out[107]:
```
Division_Automotive - General Merch          49
Division_Automotive - Hard Parts             49
Division_Fixing                              49
Division_Living                              49
Division_Playing                             49
Division_Seasonal & Gardening                49
Role_Category Business Analyst                0
Role_Category Business Manager/ACBM           0
Role_Category Business Planning               0
Role_Forecasting Analyst                      0
Role_Pricing Specialist                       0
Course Name_Advanced Product Execution        0
Course Name_Assortment Forecasting            0
Course Name_Assortment Update                 0
Course Name_Build RFQ                         0
Course Name_CBA Onboarding                    0
Course Name_CBM Assortment Decision           0
Course Name_CBP Onboarding                    0
Course Name_Category Management Framework     0
Course Name_Data Vault                        0
Course Name_FA Onboarding                     0
Course Name_Forecasting Promo Late Deal       0
Course Name_Fundamentals of Analytics         0
Course Name_Inventory Management Basics       0
Course Name_PS Onboarding                     0
Course Name_Promo season forecasting          0
Course Name_Tools of Analytics                0
Course Type_JIT                               0
Course Type_Onboarding                        0
Course Type_Self-directed                     0
NPS Type_Detractor                            0
NPS Type_Passive                              0
NPS Type_Promoter                             0
dtype: int64
```

In [108]:

```
#Data = Data.drop(['Division', 'Role','Course Name','Course Type','NPS Type'], ax
#Data_KNN = pd.concat([Data['NPS'], cat_dummies], axis=1)
#Data_KNN.head()
```

Out[108]:

	NPS	Division_Automotive - General Merch	Division_Automotive - Hard Parts	Division_Fixing	Division_Living	Division_Playin
0	9	NaN	NaN	NaN	NaN	Nal
1	7	NaN	NaN	NaN	NaN	Nal
2	8	NaN	NaN	NaN	NaN	Nal
3	8	NaN	NaN	NaN	NaN	Nal
4	9	NaN	NaN	NaN	NaN	Nal

5 rows × 34 columns

In [109]:

```
#from sklearn.preprocessing import MinMaxScaler
#scaler = MinMaxScaler()
#Data_KNN = pd.DataFrame(scaler.fit_transform(Data_KNN), columns = Data_KNN.colu
#Data_KNN.head()
```

Out[109]:

	NPS	Division_Automotive - General Merch	Division_Automotive - Hard Parts	Division_Fixing	Division_Living	Division_Pl
0	0.833333	NaN	NaN	NaN	NaN	
1	0.500000	NaN	NaN	NaN	NaN	
2	0.666667	NaN	NaN	NaN	NaN	
3	0.666667	NaN	NaN	NaN	NaN	
4	0.833333	NaN	NaN	NaN	NaN	

5 rows × 34 columns

In [111]:

```
#from sklearn.impute import KNNImputer
#imputer = KNNImputer(n_neighbors=5)
#Data_KNN = pd.DataFrame(imputer.fit_transform(Data_KNN),columns = Data_KNN.colu
```

In [112]:
```
#Data_KNN
```

Out[112]:

	NPS	Division_Automotive - General Merch	Division_Automotive - Hard Parts	Division_Fixing	Division_Living	Division_
0	0.833333	0.0	0.0	0.4	0.0	
1	0.500000	0.4	0.2	0.0	0.2	
2	0.666667	0.4	0.4	0.0	0.0	
3	0.666667	0.2	0.2	0.0	0.2	
4	0.833333	0.0	0.2	0.2	0.6	
...	...	...	...	...	...	
222	1.000000	0.0	0.0	0.0	0.0	
223	1.000000	0.0	0.0	0.0	1.0	
224	1.000000	0.0	0.0	0.0	0.0	
225	1.000000	0.0	0.0	0.0	1.0	
226	0.666667	1.0	0.0	0.0	0.0	

227 rows × 34 columns

In [113]:

```
#Data_KNN.isna().sum()
```

Out[113]:

```
NPS                                          0
Division_Automotive - General Merch          0
Division_Automotive - Hard Parts             0
Division_Fixing                              0
Division_Living                              0
Division_Playing                             0
Division_Seasonal & Gardening                0
Role_Category Business Analyst               0
Role_Category Business Manager/ACBM          0
Role_Category Business Planning              0
Role_Forecasting Analyst                     0
Role_Pricing Specialist                      0
Course Name_Advanced Product Execution       0
Course Name_Assortment Forecasting           0
Course Name_Assortment Update                0
Course Name_Build RFQ                        0
Course Name_CBA Onboarding                   0
Course Name_CBM Assortment Decision          0
Course Name_CBP Onboarding                   0
Course Name_Category Management Framework    0
Course Name_Data Vault                       0
Course Name_FA Onboarding                    0
Course Name_Forecasting Promo Late Deal      0
Course Name_Fundamentals of Analytics        0
Course Name_Inventory Management Basics      0
Course Name_PS Onboarding                    0
Course Name_Promo season forecasting         0
Course Name_Tools of Analytics               0
Course Type_JIT                              0
Course Type_Onboarding                       0
Course Type_Self-directed                    0
NPS Type_Detractor                           0
NPS Type_Passive                             0
NPS Type_Promoter                            0
dtype: int64
```

In [68]:
```
Data.isna().sum()
```

Out[68]:
```
Respondent ID             0
Collector ID              0
Start Date                0
End Date                  0
IP Address                0
NPS                       0
Detractors feedback       0
Passives feedback         0
Promoters feedback        0
Prior course knowledge    0
After course knowledge    0
Division                  0
Role                      0
Course Name               0
Course Type               0
First time                0
NPS Type                  0
dtype: int64
```

Sentiment Analysis

In [69]:
```
import textblob
from textblob import TextBlob
```

In [70]:
```
Data['Feedback']=Data['Detractors feedback']+Data['Passives feedback']+Data['Pro
```

In [71]:
```
def getPolarity(text):
    return TextBlob(text).sentiment.polarity
def getSubjectivity(text):
    return TextBlob(text).sentiment.subjectivity

Data['polarity'] = Data['Feedback'].apply(getPolarity)
Data['Subjectivity'] = Data['Feedback'].apply(getSubjectivity)
```

In [72]:
```python
def getAnalysis(score):
    if score < 0:
        return 'Negative'
    elif score == 0:
        return 'Neutral'
    else:
        return 'Positive'

Data['Sentiment_Analysis'] = Data['polarity'].apply(getAnalysis)

Data.head(10)
```

Out[72]:

	Respondent ID	Collector ID	Start Date	End Date	IP Address	NPS	Detractors feedback	Passives feedback	Pr f
0	12246985268	263245465	12/10/2020 16:32	12/10/2020 16:32	99.252.69.113	9			
1	12179406900	263245465	11/17/2020 20:48	11/17/2020 20:49	99.240.132.190	7			
2	12043039162	263245465	10/02/2020 23:04	10/02/2020 23:05	99.246.167.93	8			
3	12011013117	263245465	09/22/2020 17:43	09/22/2020 17:43	170.52.68.9	8			
4	11973635491	263245465	09/09/2020 15:50	09/09/2020 15:50	172.97.250.147	9			
5	11973515355	263245465	09/09/2020 15:09	09/09/2020 15:09	198.52.172.141	7		More audio, less reading	
6	12238243891	253305724	12/08/2020 10:42	12/08/2020 10:42	104.249.225.115	8			
7	12210690194	253305724	11/29/2020 13:47	11/29/2020 13:49	99.240.132.190	10			A c b
8	12006288111	253305724	09/21/2020 12:08	09/21/2020 12:09	172.97.240.78	8			
9	11987105767	253305724	09/14/2020 15:37	09/14/2020 15:38	70.52.142.63	9			

10 rows × 21 columns

Exploratory Analysis

Understand Employee's Behaviour

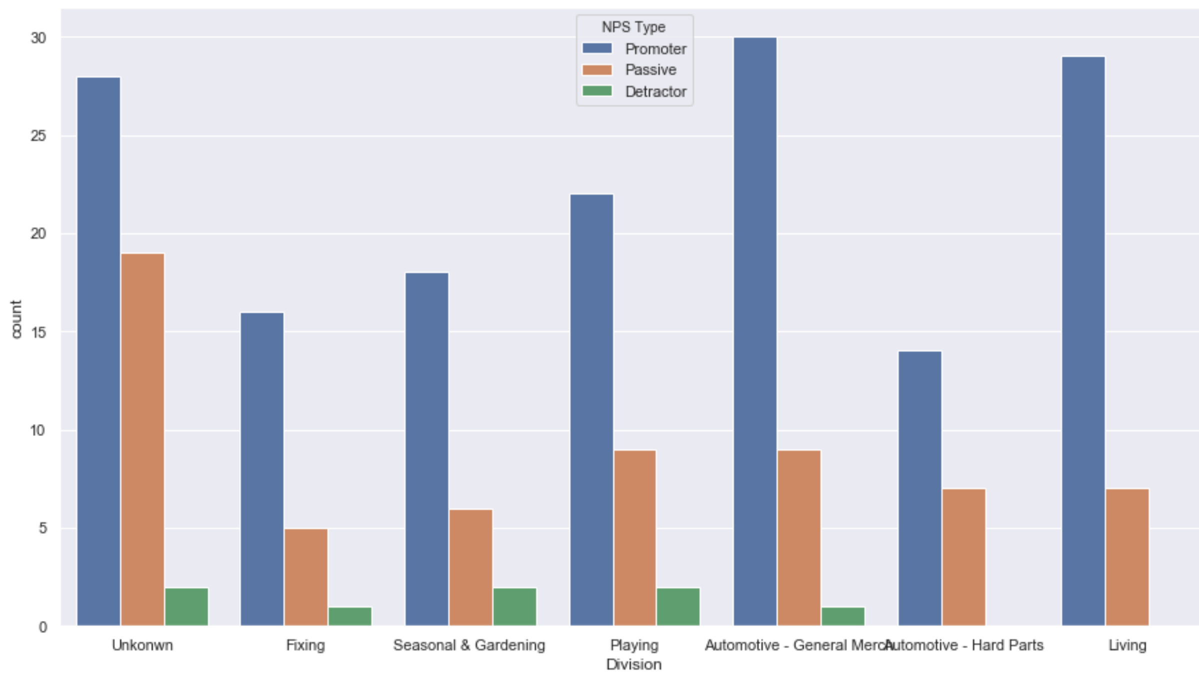
Question: What is the relation between Division and NPS's classification?

In [211]:
```python
Data.groupby(['NPS Type'])['Division'].value_counts(normalize=True)
```

Out[211]:
```
NPS Type   Division
Detractor  Playing                          0.250000
           Seasonal & Gardening             0.250000
           Unkonwn                          0.250000
           Automotive - General Merch       0.125000
           Fixing                           0.125000
Passive    Unkonwn                          0.306452
           Automotive - General Merch       0.145161
           Playing                          0.145161
           Automotive - Hard Parts          0.112903
           Living                           0.112903
           Seasonal & Gardening             0.096774
           Fixing                           0.080645
Promoter   Automotive - General Merch       0.191083
           Living                           0.184713
           Unkonwn                          0.178344
           Playing                          0.140127
           Seasonal & Gardening             0.114650
           Fixing                           0.101911
           Automotive - Hard Parts          0.089172
Name: Division, dtype: float64
```

In [242]:
```
sns.set(rc={'figure.figsize':(15,8.27)})
sns.countplot(x ='Division', hue = "NPS Type", data = Data)

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



Auto-GM is the division which is the most frequency to give promoter NPS, the next one is living. the most frequency privided detractor division is playing and season&garden

Question: What is the relation between Role and NPS's classification?

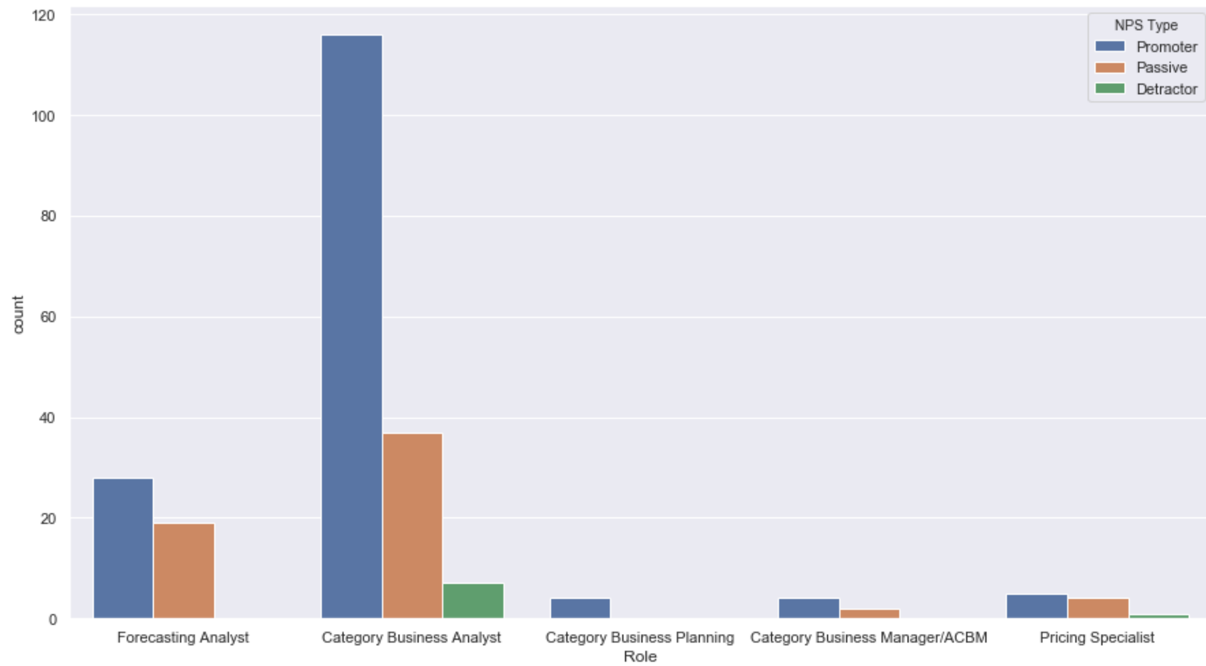
In [213]:
```
Data.groupby(['Role'])['NPS Type'].value_counts(normalize=True)
```

Out[213]:
```
Role                           NPS Type
Category Business Analyst      Promoter     0.725000
                               Passive      0.231250
                               Detractor    0.043750
Category Business Manager/ACBM Promoter     0.666667
                               Passive      0.333333
Category Business Planning     Promoter     1.000000
Forecasting Analyst            Promoter     0.595745
                               Passive      0.404255
Pricing Specialist             Promoter     0.500000
                               Passive      0.400000
                               Detractor    0.100000
Name: NPS Type, dtype: float64
```

CBA is the group who is easilest to become promoter. the next groups are CBM, FA and PS. Since we have less sample data of CBP, we cannot draw the conclusion now.

In [18]:
```
sns.set(rc={'figure.figsize':(15,8.27)})
sns.countplot(x ='Role', hue = "NPS Type", data = Data)

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



Understand Course's Performance

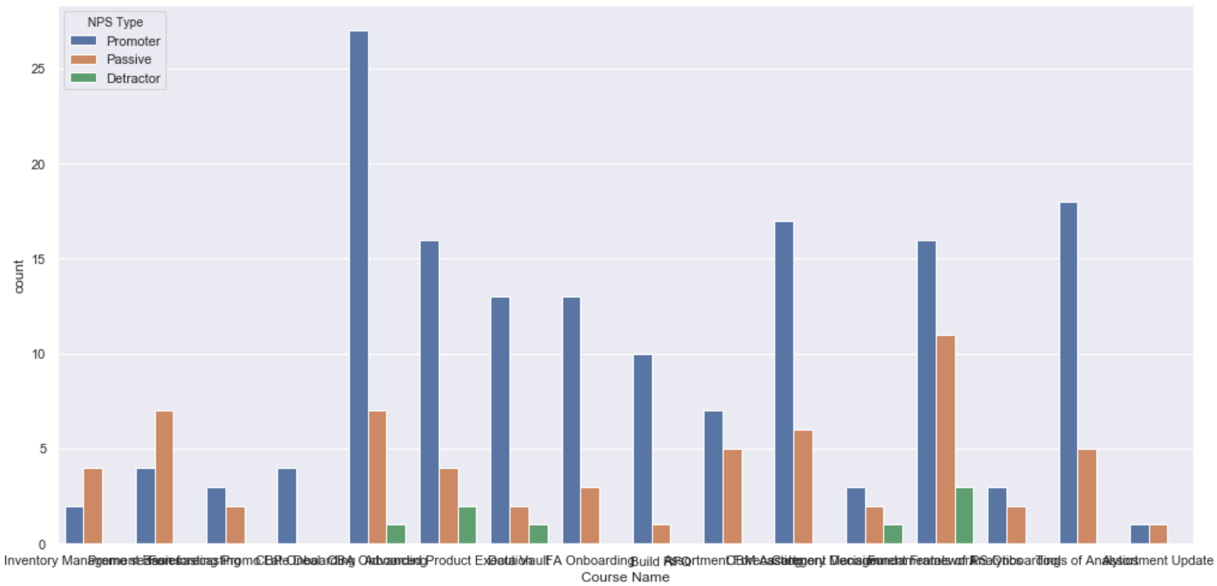
Question: What is the relation between course and NPS's classification?

In [217]:
```
Data.groupby(['Course Name'])['NPS Type'].value_counts(normalize=True)
```

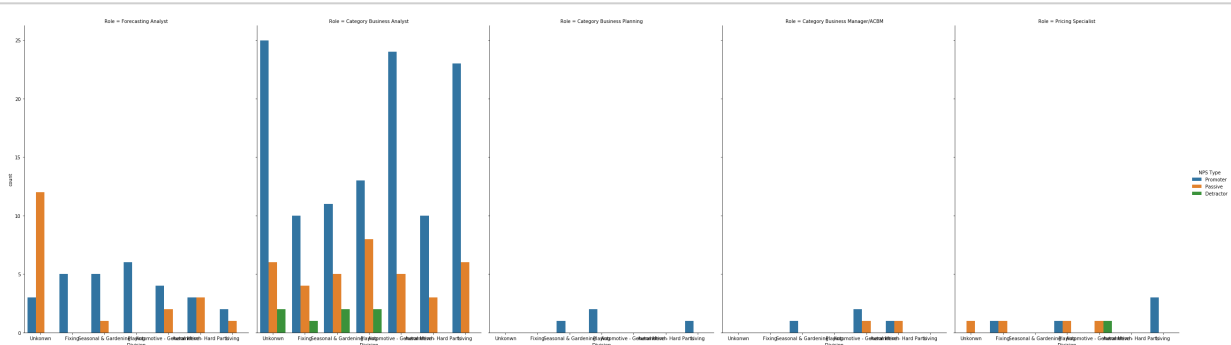
Out[217]:
```
Course Name                      NPS Type
Advanced Product Execution       Promoter     0.727273
                                 Passive      0.181818
                                 Detractor    0.090909
Assortment Forecasting           Promoter     0.583333
                                 Passive      0.416667
Assortment Update                Passive      0.500000
                                 Promoter     0.500000
Build RFQ                        Promoter     0.909091
                                 Passive      0.090909
CBA Onboarding                   Promoter     0.771429
                                 Passive      0.200000
                                 Detractor    0.028571
CBM Assortment Decision          Promoter     0.739130
                                 Passive      0.260870
CBP Onboarding                   Promoter     1.000000
Category Management Framework    Promoter     0.500000
                                 Passive      0.333333
                                 Detractor    0.166667
Data Vault                       Promoter     0.812500
                                 Passive      0.125000
                                 Detractor    0.062500
FA Onboarding                    Promoter     0.812500
                                 Passive      0.187500
Forecasting Promo Late Deal      Promoter     0.600000
                                 Passive      0.400000
Fundamentals of Analytics        Promoter     0.533333
                                 Passive      0.366667
                                 Detractor    0.100000
Inventory Management Basics      Passive      0.666667
                                 Promoter     0.333333
PS Onboarding                    Promoter     0.600000
                                 Passive      0.400000
Promo season forecasting         Passive      0.636364
                                 Promoter     0.363636
Tools of Analytics               Promoter     0.782609
                                 Passive      0.217391
Name: NPS Type, dtype: float64
```

In [20]:
```python
sns.set(rc={'figure.figsize':(17,8.27)})
sns.countplot(x ='Course Name', hue = "NPS Type", data = Data)

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



In [13]:
```python
sns.catplot(x="Division", hue="NPS Type", col="Role",
                data=Data, kind="count",
                height=10, aspect=0.7);
```



Question: What is the relation between course type and NPS's classification?

Question: What is the relation between course type and NPS's classification?

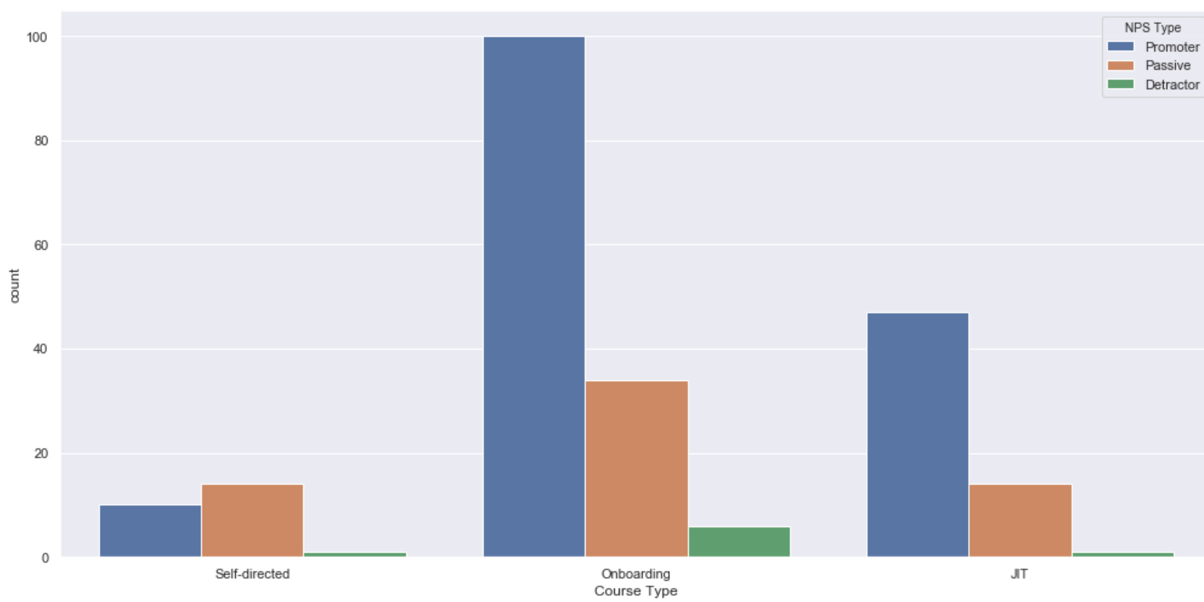
In [14]:
```
Data.groupby(['Course Type'])['NPS Type'].value_counts(normalize=True)
```

Out[14]:
```
Course Type    NPS Type
JIT            Promoter     0.758065
               Passive      0.225806
               Detractor    0.016129
Onboarding     Promoter     0.714286
               Passive      0.242857
               Detractor    0.042857
Self-directed  Passive      0.560000
               Promoter     0.400000
               Detractor    0.040000
Name: NPS Type, dtype: float64
```

JIT is the type of course which is the easiest to get the promoter and the lowest probability to get detractor. the next one is onboarding. Self-directed course is easiest to get passive. the probability to get detractor is similar with onboarding course.

In [21]:
```
sns.set(rc={'figure.figsize':(17,8.27)})
sns.countplot(x ='Course Type', hue = "NPS Type", data = Data)

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



Question: What is the relation between prior course knowledge and NPS's classification?

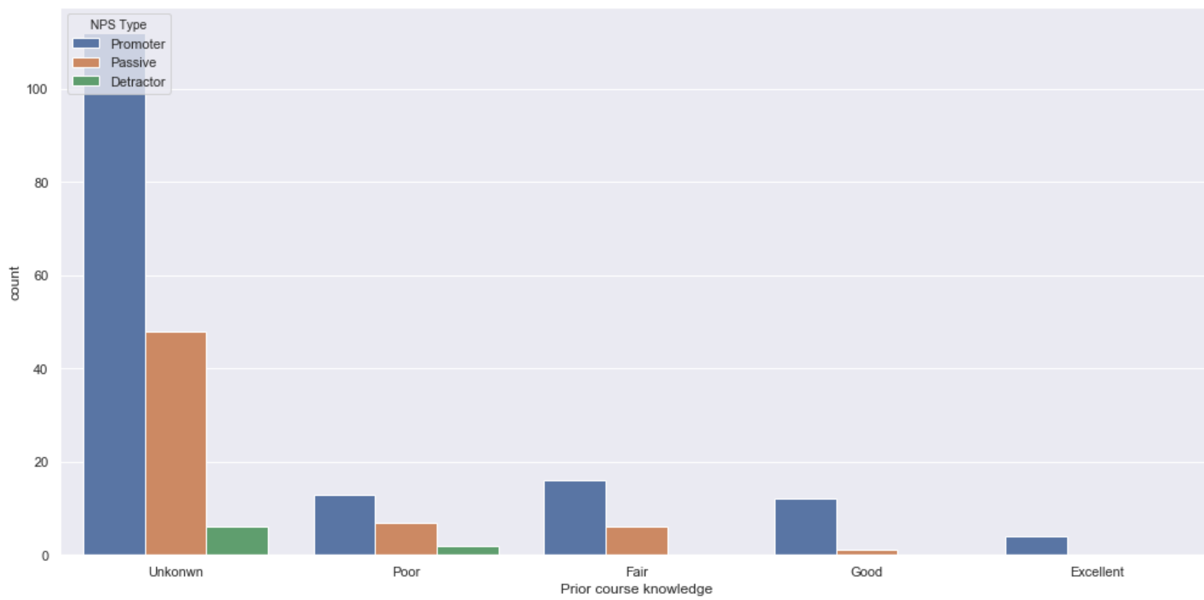
In [23]:
```
Data.groupby(['Prior course knowledge'])['NPS Type'].value_counts(normalize=True
```

Out[23]:
```
Prior course knowledge  NPS Type 
Excellent               Promoter     1.000000
Fair                    Promoter     0.727273
                        Passive      0.272727
Good                    Promoter     0.923077
                        Passive      0.076923
Poor                    Promoter     0.590909
                        Passive      0.318182
                        Detractor    0.090909
Unkonwn                 Promoter     0.674699
                        Passive      0.289157
                        Detractor    0.036145
Name: NPS Type, dtype: float64
```

The probability of promoter is the highest for all options. In other words, this ferature is not a significant feature to our model.

In [24]:
```
sns.set(rc={'figure.figsize':(17,8.27)})
sns.countplot(x ='Prior course knowledge', hue = "NPS Type", data = Data)

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



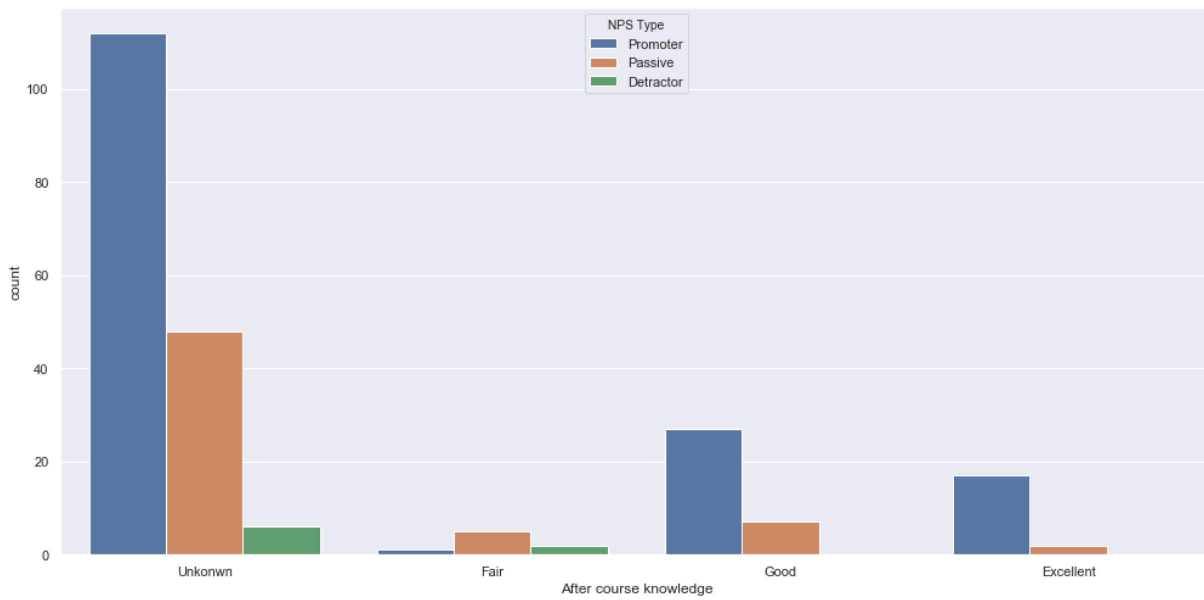
Question: What is the relation between after course knowledge and NPS's classification?

In [25]:
```
Data.groupby(['After course knowledge'])['NPS Type'].value_counts(normalize=True
```

Out[25]:
```
After course knowledge  NPS Type
Excellent               Promoter     0.894737
                        Passive      0.105263
Fair                    Passive      0.625000
                        Detractor    0.250000
                        Promoter     0.125000
Good                    Promoter     0.794118
                        Passive      0.205882
Unkonwn                 Promoter     0.674699
                        Passive      0.289157
                        Detractor    0.036145
Name: NPS Type, dtype: float64
```

In [26]:
```
sns.set(rc={'figure.figsize':(17,8.27)})
sns.countplot(x ='After course knowledge', hue = "NPS Type", data = Data)

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



Question: What is the relation between first time to the task/take the courses and NPS's classification?

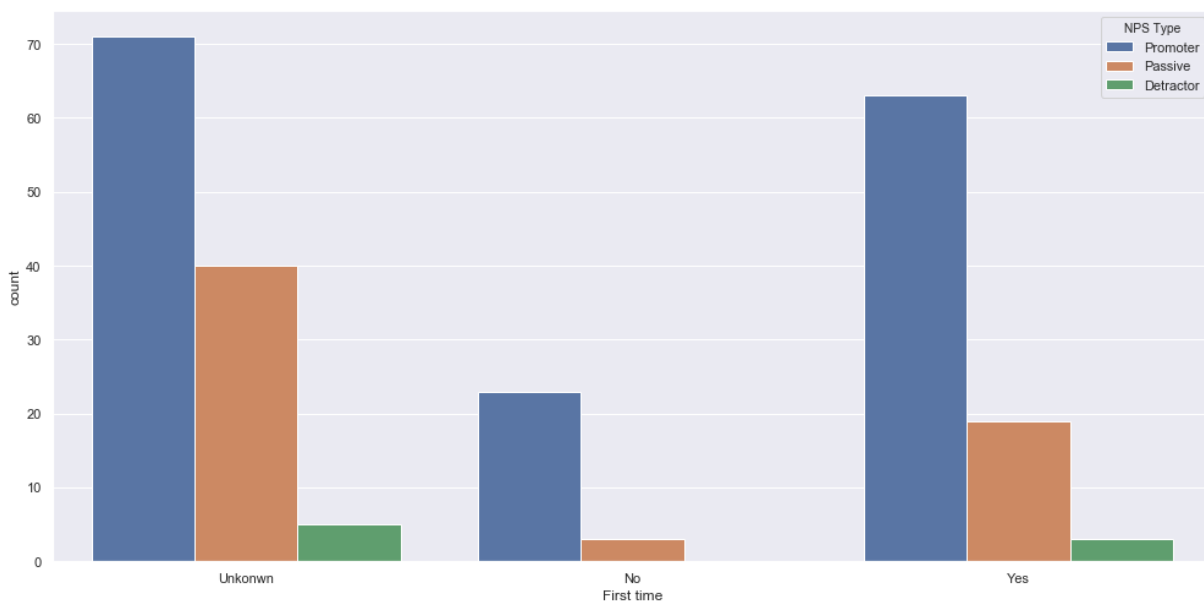
In [27]:
```
Data.groupby(['First time'])['NPS Type'].value_counts(normalize=True)
```

Out[27]:
```
First time  NPS Type
No          Promoter     0.884615
            Passive      0.115385
Unkonwn     Promoter     0.612069
            Passive      0.344828
            Detractor    0.043103
Yes         Promoter     0.741176
            Passive      0.223529
            Detractor    0.035294
Name: NPS Type, dtype: float64
```

the learner who took the course before or they finish the task before, they likely provide higher NPS. The reason maybe because they know what they are going to learn/what they want to learn and the course match their requirement. For the learner who are the first time to do the task/attend this course, they don't have the correct expectation about what they need to know. If they expect more and we don't think they need these knowledge, they would provide lower NPS.

In [28]:
```
sns.set(rc={'figure.figsize':(17,8.27)})
sns.countplot(x ='First time', hue = "NPS Type", data = Data)

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



Question: What is the relation between Sentiment_Analysis and NPS's classification?

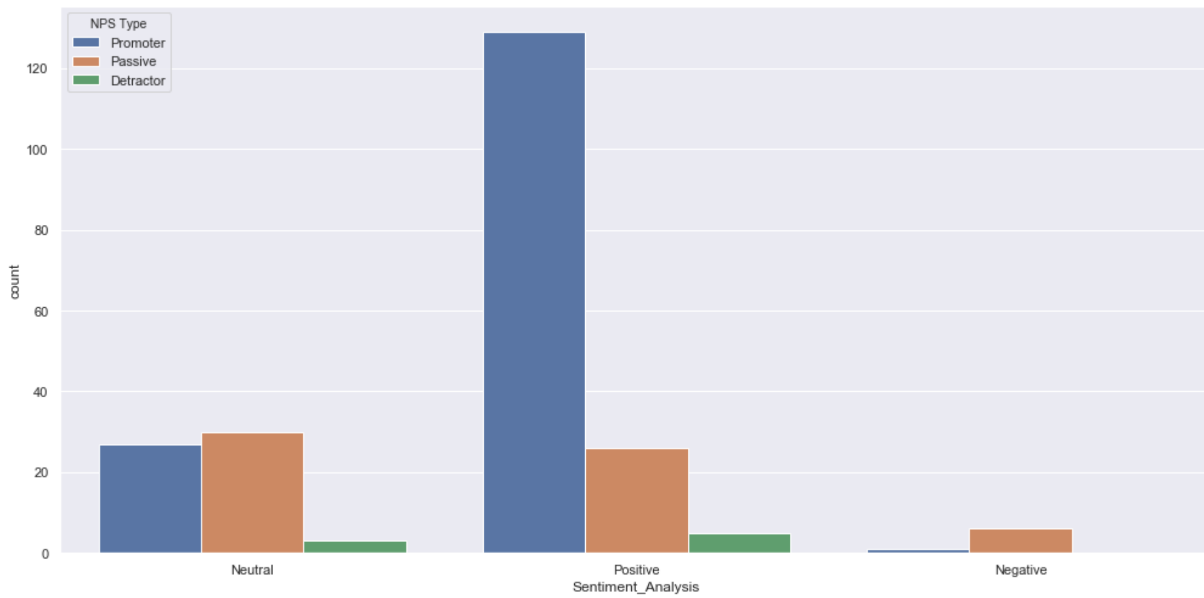
In [73]:
```
Data.groupby(['Sentiment_Analysis'])['NPS Type'].value_counts(normalize=True)
```

Out[73]:
```
Sentiment_Analysis  NPS Type
Negative            Passive      0.857143
                    Promoter     0.142857
Neutral             Passive      0.500000
                    Promoter     0.450000
                    Detractor    0.050000
Positive            Promoter     0.806250
                    Passive      0.162500
                    Detractor    0.031250
Name: NPS Type, dtype: float64
```

positive feedback most likely come from a promoter. negative and netural feedback most likely come from a passive.

In [74]:
```
sns.set(rc={'figure.figsize':(17,8.27)})
sns.countplot(x ='Sentiment_Analysis', hue = "NPS Type", data = Data)

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



Build Cluster Model with K-Mode

Choice clustering dataset

In [75]:
```
df2 = Data[['NPS Type','After course knowledge','Division', 'Role','Course Type'
df2.head()
```

Out[75]:

	NPS Type	After course knowledge	Division	Role	Course Type	First time	Sentiment_Analysis
0	Promoter	Unkonwn	Unkonwn	Forecasting Analyst	Self-directed	Unkonwn	Neutral
1	Passive	Unkonwn	Unkonwn	Forecasting Analyst	Self-directed	Unkonwn	Neutral
2	Passive	Unkonwn	Unkonwn	Forecasting Analyst	Self-directed	Unkonwn	Neutral
3	Passive	Unkonwn	Unkonwn	Category Business Analyst	Self-directed	Unkonwn	Neutral
4	Promoter	Unkonwn	Unkonwn	Category Business Analyst	Self-directed	Unkonwn	Neutral

Lable the catagory variables

In [76]:
```
import pandas as pd
from sklearn.preprocessing import LabelEncoder
from sklearn.pipeline import Pipeline

class MultiColumnLabelEncoder:
    def __init__(self,columns = None):
        self.columns = columns # array of column names to encode

    def fit(self,X,y=None):
        return self # not relevant here

    def transform(self,X):
        '''
        Transforms columns of X specified in self.columns using
        LabelEncoder(). If no columns specified, transforms all
        columns in X.
        '''
        output = X.copy()
        if self.columns is not None:
            for col in self.columns:
                output[col] = LabelEncoder().fit_transform(output[col])
        else:
            for colname,col in output.iteritems():
                output[colname] = LabelEncoder().fit_transform(col)
        return output

    def fit_transform(self,X,y=None):
        return self.fit(X,y).transform(X)
```

In [79]:
```
df3=MultiColumnLabelEncoder(columns = ['NPS Type','After course knowledge','Divi
df3.head()
```

Out[79]:

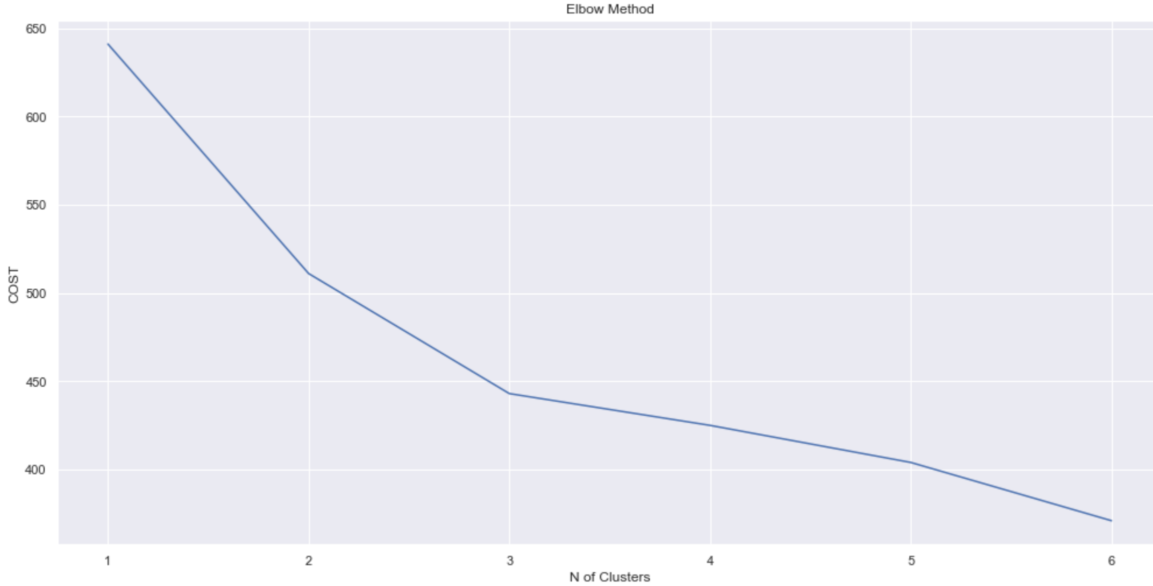
	NPS Type	After course knowledge	Division	Role	Course Type	First time	Sentiment_Analysis
0	2	3	6	3	2	1	1
1	1	3	6	3	2	1	1
2	1	3	6	3	2	1	1
3	1	3	6	0	2	1	1
4	2	3	6	0	2	1	1

Using the Elbow Method to find the best K for K-mode based on our data

In [81]:
```
from kmodes.kmodes import KModes
```

In [87]:
```
cost = []
for num_clusters in list(range(1,7)):
    kmode = KModes(n_clusters=num_clusters, init = "Cao", n_init = 1, verbose=1)
    kmode.fit_predict(df3)
    cost.append(kmode.cost_)
plt.plot(range(1, 7), cost)
plt.title('Elbow Method')
plt.xlabel('N of Clusters')
plt.ylabel('COST') #within cluster sum of squares
plt.show()
```

```
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 0, cost: 641.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 8, cost: 511.0
Run 1, iteration: 2/100, moves: 0, cost: 511.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 21, cost: 443.0
Run 1, iteration: 2/100, moves: 0, cost: 443.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 24, cost: 425.0
Run 1, iteration: 2/100, moves: 0, cost: 425.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 24, cost: 404.0
Run 1, iteration: 2/100, moves: 0, cost: 404.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 43, cost: 371.0
Run 1, iteration: 2/100, moves: 0, cost: 371.0
```



We chose K=3

In [91]:
```
km_cao = KModes(n_clusters=3, init = "Cao", n_init = 1, verbose=1)
df2['fitClusters_cao'] = km_cao.fit_predict(df3)
```

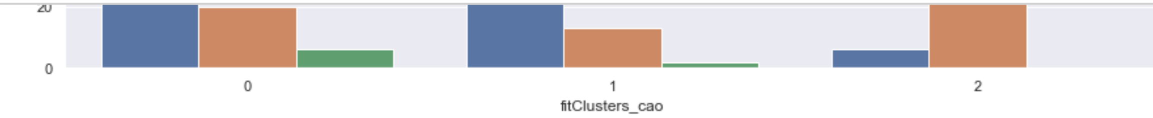
```
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 21, cost: 443.0
Run 1, iteration: 2/100, moves: 0, cost: 443.0
```

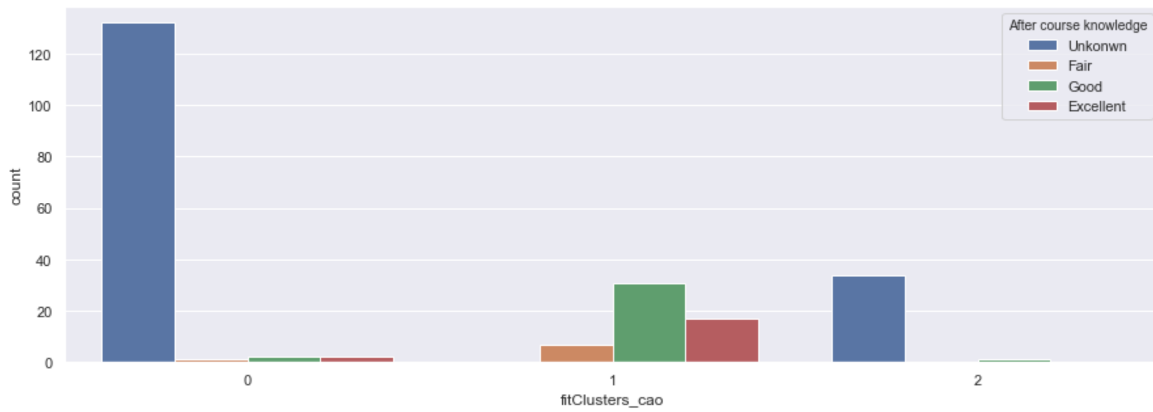
In [92]:
```
df2.head()
```

Out[92]:

	NPS Type	After course knowledge	Division	Role	Course Type	First time	Sentiment_Analysis	fitClusters_ca
0	Promoter	Unkonwn	Unkonwn	Forecasting Analyst	Self-directed	Unkonwn	Neutral	
1	Passive	Unkonwn	Unkonwn	Forecasting Analyst	Self-directed	Unkonwn	Neutral	
2	Passive	Unkonwn	Unkonwn	Forecasting Analyst	Self-directed	Unkonwn	Neutral	
3	Passive	Unkonwn	Unkonwn	Category Business Analyst	Self-directed	Unkonwn	Neutral	
4	Promoter	Unkonwn	Unkonwn	Category Business Analyst	Self-directed	Unkonwn	Neutral	

In [93]:
```
for col in 'NPS Type','After course knowledge','Division', 'Role','Course Type',
    plt.subplots(figsize = (15,5))
    sns.countplot(x='fitClusters_cao',hue=col, data = df2)
    plt.show()
```





In [ ]: