Assignment 3

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In [29]:
```
import pandas as pd, numpy as np, os, warnings, seaborn as sns, matplotlib.pyp
lot as plt, matplotlib
from datetime import datetime

warnings.simplefilter(action='ignore', category=FutureWarning)
pd.options.mode.chained_assignment = None
get_ipython().run_line_magic('matplotlib', 'inline')
plt.style.use('seaborn')
sns.set_color_codes('colorblind')
matplotlib.rcParams.update({'font.size': 14})
matplotlib.rcParams.update({'xtick.labelsize':16})
matplotlib.rcParams.update({'ytick.labelsize':16})
matplotlib.rcParams.update({'axes.labelsize':16})
matplotlib.rcParams.update({'axes.titlesize':20})
matplotlib.rcParams.update({'legend.fontsize': 16})
sns.set_style('white')
```

In [30]:
```
df = pd.read_csv('Winters-Attribution-PS3.csv', index_col=0)
```

In [31]:
```
df.head(5)
```

Out[31]:

	Orderid	Orderdatetime	Saleamount	Newcustomer	Position	Positiondatetime	Groupname
1	11634052	2012-05-01 4:24	341.5	Y	1	2012-05-01 3:49	BUZZ AFFILIATE
2	11634052	2012-05-01 4:24	341.5	Y	0	2012-05-01 3:47	SEARCH GOOGLE BRAND
3	11634059	2012-05-01 4:08	339.0	Y	2	2012-04-29 21:01	PRINT - MAGAZINES
4	11634059	2012-05-01 4:08	339.0	Y	1	2012-04-24 5:29	CPM
5	11634059	2012-05-01 4:08	339.0	Y	0	2012-04-23 2:46	PRINT - MAGAZINES

In [32]:
```
df.shape
```

Out[32]:
```
(7624, 12)
```

In [33]:
```
print('Time range: ', df['Orderdatetime'].min(), 'to', df['Orderdatetime'].max
())
print('Number of touchpoints:', len(df))
print('Number of orders:', len(df['Orderid'].unique()))
print('Number of touchpoints per order:', np.round(len(df)/len(df['Orderid'].u
nique()), 2))
```

```
Time range:  2012-05-01 10:04 to 2012-06-01 3:45
Number of touchpoints: 7624
Number of orders: 1627
Number of touchpoints per order: 4.69
```

In [34]:
```
df.Positionname.unique()
```

Out[34]:
```
array(['CONVERTER', 'ORIGINATOR', 'ASSIST', 'ROSTER'], dtype=object)
```

Q1. (30 pts) Compare first-touch vs. last-touch attribution models

a) (10 pts) What is the number of orders attributed to each channel using a last-touch model? What about the number of orders attributed to each channel using a first-touch model? What is the corresponding share of credit from the two attribution models?

In [35]:
```
# calculating the count per channel by last touch
num_order = len(df['Orderid'].unique())
T_last_count = pd.DataFrame(df.loc[df['Positionname']=='CONVERTER',
                            'Groupname'].value_counts()).reset_index().sort_va
lues('index')
# calculating the percentage per channel by last touch
T_last_percent = pd.DataFrame((df.loc[df['Positionname']=='CONVERTER',
                            'Groupname'].value_counts()/
                            num_order)*100).reset_index().sort_values('index')
# calculating the count per channel by first touch
T_first_count = pd.DataFrame(df.loc[df['Positionname']=='ORIGINATOR',
                             'Groupname'].value_counts()).reset_index().sort_v
alues('index')
# calculating the percentage per channel by first touch
T_first_percent = pd.DataFrame(df.loc[df['Positionname']=='ORIGINATOR',
                             'Groupname'].value_counts()/
                             num_order*100).reset_index().sort_values('index')
```

In [36]:
```
# merging all 4 tables
merge_1 = np.round(pd.merge(T_last_count, T_first_count, how = 'outer', on =
'index').fillna(0).rename(
    columns={"Groupname_x": "Converter", "Groupname_y": "Originator"}), 3)
merge_2= np.round(pd.merge(T_last_percent, T_first_percent, how = 'outer', on
= 'index').fillna(0).rename(
    columns={"Groupname_x": "Converter %", "Groupname_y": "Originator %"}), 3)
first_last = np.round(pd.merge(merge_1, merge_2, how = 'outer', on = 'index').
fillna(0), 3)

new_row = {'index': 'TOTAL', 'Converter': first_last.Converter.sum(), 'Origina
tor': first_last.Originator.sum(), 'Converter %': first_last['Converter %'].su
m(), 'Originator %': first_last['Originator %'].sum()}
first_last = first_last.append(new_row, ignore_index=True)
first_last = np.round(first_last, decimals=2)
first_last['Converter'] = first_last['Converter'].astype('int64')
first_last['Originator'] = first_last['Originator'].astype('int64')
```

The table below displays the number of orders and corresponding share of credit from the two attribution (first and last touch) models.

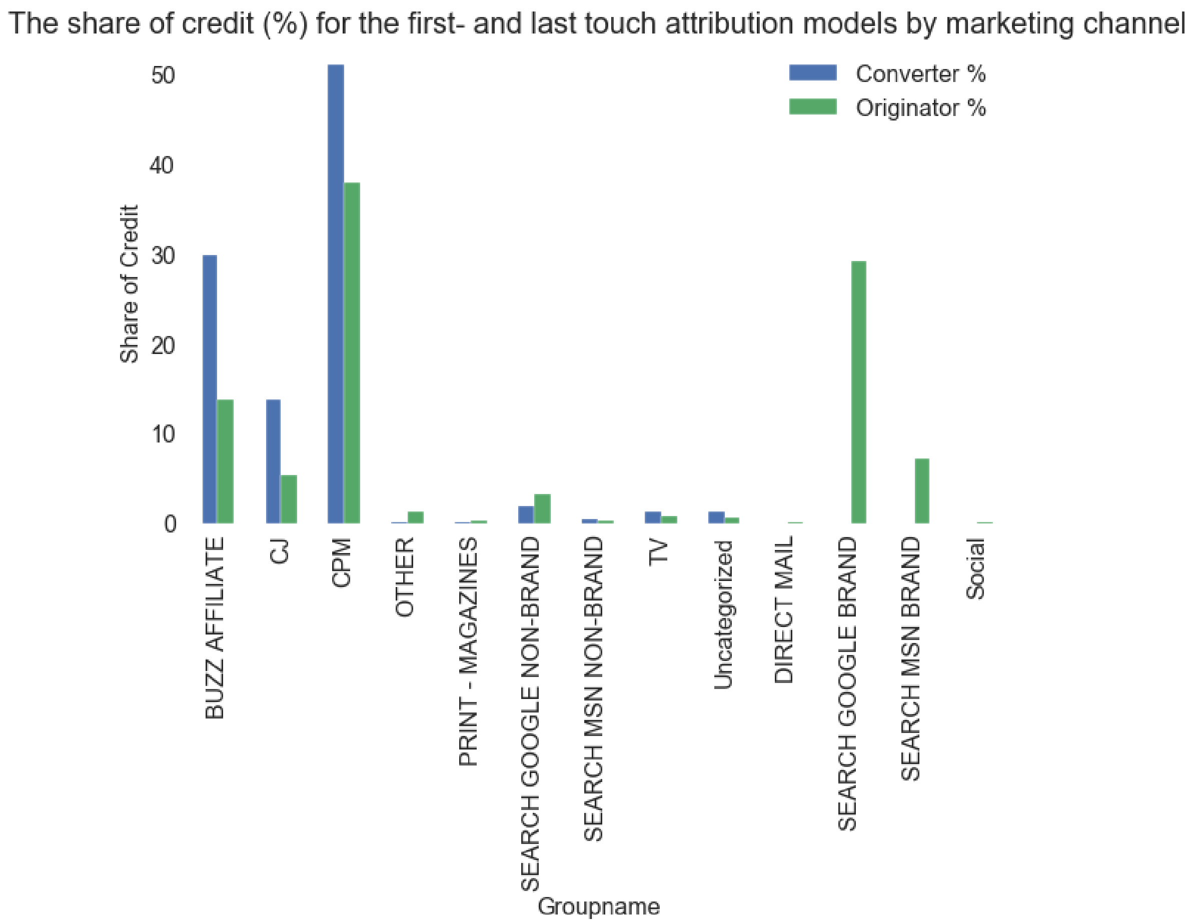
In [37]:
```
first_last
```

Out[37]:

	index	Converter	Originator	Converter %	Originator %
0	BUZZ AFFILIATE	486	225	29.87	13.83
1	CJ	224	87	13.77	5.35
2	CPM	830	618	51.01	37.98
3	OTHER	3	20	0.18	1.23
4	PRINT - MAGAZINES	3	4	0.18	0.25
5	SEARCH GOOGLE NON-BRAND	32	53	1.97	3.26
6	SEARCH MSN NON-BRAND	7	4	0.43	0.25
7	TV	20	14	1.23	0.86
8	Uncategorized	22	9	1.35	0.55
9	DIRECT MAIL	0	1	0.00	0.06
10	SEARCH GOOGLE BRAND	0	474	0.00	29.13
11	SEARCH MSN BRAND	0	117	0.00	7.19
12	Social	0	1	0.00	0.06
13	TOTAL	1627	1627	100.00	100.00

b) (10 pts) In a single bar chart, plot the share of credit (in percentage) for the first- and last touch attribution models by marketing channel.

In [38]:
```
first_last[:13].plot(x='index', y=['Converter %', 'Originator %'], kind='bar',
figsize=(10, 6))
plt.xlabel('Groupname')
plt.ylabel('Share of Credit')
plt.title('The share of credit (%) for the first- and last touch attribution m
odels by marketing channel');
```



c) (10 pts) Compare results from the two attribution model. What would be the consequence to Winters if it allocated its marketing budget entirely based on the lasttouch attribution model?

The CPM channel has the share of credit when using both first and last touch attribution models (51.01% and 37.98% respectively). The Buzz Affiliates channel holds the second highest share of credit when using the last touch attribution model (29.87%), but has a significantly lower proportion of credit share for the first touch attribution model (13.83%). When customers search for google brands, the first touch attribution displays that this accounts to 29.13% of the total share of credit. The CJ channel has the third highest share of credit (13.77%) across the last touch attribution model. We note that all other channels have less than 8% of the total share of credit across both the first and last touch attribution models. This implies that CPM and Buzz Affiliates have the highest share of credits across both models, with an addition of the CJ channel's share of credit only for the last touch attribution model.

If the marketing budget is allocated entirely based on the last touch attribution model, then Winters will not be able to account for the consumer interactions with all other touchpoints. There might be an interaction effect between all these different marketing touchpoints, which a single touch model (either first or last touch model) will fail to take into account.

Q2. (20 pts) Compare new customers and old customers

a) (5 pts) What is the average number of days that it takes for a new customer to convert (from the first touchpoint)? What is the average number of days that it takes for an old customer to convert?

In [39]:
```
num_order_new = len(df[(df['Positionname']=='CONVERTER')&(df['Newcustomer'] == 'Y')])
num_order_old = len(df[(df['Positionname']=='CONVERTER')&(df['Newcustomer'] == 'N')])
```

In [40]:
```
new_firsttouchpoint = df[(df['Newcustomer'] == 'Y') & (df['Positionname'] == 'ORIGINATOR')]
print(np.round(new_firsttouchpoint.DaysToConvert.mean(),2))
```

```
5.5
```

In [41]:
```
old_firsttouchpoint = df[(df['Newcustomer'] == 'N') & (df['Positionname'] == 'ORIGINATOR')]
print(np.round(old_firsttouchpoint.DaysToConvert.mean(),2))
```

```
32.01
```

On average, it takes 5.5 days for a new customer to convert from the first touch point. And it takes 32.01 days for an old customer to convert from the first touch point.

b) (5 pts) What is the average number of touchpoints by new versus old customer's orders? Hint: Use the Touches variable if available. If not, create the 'Touches' variable for the number of touchpoints per order. R users can use the add_count() function.

In [42]:

```
new = df[df['Newcustomer'] == 'Y']
temp = new.groupby('Orderid')['Position'].count()
temp_new = pd.DataFrame(temp)
temp_new['Touches'] = temp_new['Position']
temp_new = temp_new['Touches']
temp_new = pd.DataFrame(temp_new)
temp_new
```

Out[42]:

	Touches
Orderid	
11634052	2
11634059	3
11634191	4
11634217	3
11634218	5
...	...
11777393	2
11777407	3
11777419	2
11777467	3
11777469	4

982 rows × 1 columns

In [43]:
```
old = df[df['Newcustomer'] == 'N']
temp = old.groupby('Orderid')['Position'].count()
temp_old = pd.DataFrame(temp)
temp_old['Touches'] = temp_old['Position']
temp_old = temp_old['Touches']
temp_old = pd.DataFrame(temp_old)
temp_old
```

Out[43]:

	Touches
Orderid	
11634060	8
11634119	2
11635494	4
11636452	6
11637581	4
...	...
11776990	4
11777034	5
11777068	7
11777397	7
11777500	5

645 rows × 1 columns

In [44]:
```
print(np.round(temp_new['Touches'].mean(),2))
print(np.round(temp_old['Touches'].mean(),2))
```

```
4.32
5.24
```

New customers on average have 4.32 touchpoints while old customers on average have 5.24 touchpoints.

c) (5 pts) What is the average order sales amount by new versus old customer's orders?

In [45]:
```
temp2 = new.groupby('Orderid')['Saleamount'].mean()
temp2_new = pd.DataFrame(temp2)
temp2_new
```

Out[45]:

Orderid	Saleamount
11634052	341.50
11634059	339.00
11634191	315.00
11634217	731.60
11634218	256.50
...	...
11777393	253.21
11777407	341.50
11777419	99.00
11777467	175.08
11777469	192.05

982 rows × 1 columns

In [46]:
```
temp2 = old.groupby('Orderid')['Saleamount'].mean()
temp2_old = pd.DataFrame(temp2)
temp2_old
```

Out[46]:

Orderid	Saleamount
11634060	101.79
11634119	174.69
11635494	107.76
11636452	291.48
11637581	184.15
...	...
11776990	177.54
11777034	90.71
11777068	282.69
11777397	171.73
11777500	265.39

645 rows × 1 columns

In [47]:
```
print(np.round(temp2_new['Saleamount'].mean(),2))
print(np.round(temp2_old['Saleamount'].mean(),2))
```

```
267.57
208.22
```

The average order sales for new customers' orders is 267.57 USD while the average order sales for old customers' orders is 208.22 USD.

d) (5 pts) Summarize how new and old customers differ along these three variables.

The three variables used for the summary include the average number of days to convert, average number of touchpoints and average order sales for customers' orders.

Old customers take approximately 27 days more to convert than new customers and they have a marginally higher number of touchpoints on average (old customers have 5.34 touchpoints on average while new customers have 4.32 touchpoints on average). However, the average order sales for new customers' is higher than that of old customers. This indicates that there might be some new customers who might be making bulk purchases, while old customers prefer to visit the site regularly to make smaller purchases. Old customers might prefer browsing on the website longer before making a purchase, which in turn leads to having more touchpoints when browsing longer on the site.

Q3. (20 pts) Consider the revenue per marketing channel using first-touch attribution.

a) (10 pts) Create a table (as in Q1) containing the average sales per order as well as the total revenue by originator channel.

In [48]:
```
df1=pd.DataFrame(df.loc[df['Positionname']=='ORIGINATOR'])
originator1 = pd.DataFrame(df1.groupby('Groupname')['Saleamount'].mean())
originator2 = pd.DataFrame(df1.groupby('Groupname')['Saleamount'].sum())

# merging the 2 tables
merge_1 = np.round(pd.merge(originator1, originator2, how = 'outer', on = 'Gro
upname').fillna(0).rename(
    columns={"Saleamount_x": "avg_sale", "Saleamount_y": "total_revenue"}), 2)
merge_1
```

Out[48]:

Groupname	avg_sale	total_revenue
BUZZ AFFILIATE	253.29	56990.67
CJ	249.26	21685.82
CPM	240.46	148603.61
DIRECT MAIL	170.98	170.98
OTHER	226.38	4527.62
PRINT - MAGAZINES	262.98	1051.91
SEARCH GOOGLE BRAND	243.89	115601.81
SEARCH GOOGLE NON-BRAND	245.82	13028.48
SEARCH MSN BRAND	246.33	28820.56
SEARCH MSN NON-BRAND	242.32	969.27
Social	165.00	165.00
TV	240.81	3371.29
Uncategorized	229.68	2067.08

b) (5 pts) What is the total incremental gross revenue accruing to Winters by originator channel? Express your answer in a table. Assume that Winters has a gross margin of 40%. Also assume 5% of sales from branded search are incremental, and 10% sales are incremental for the remaining channels.

In [49]:
```
merge_2 = merge_1.copy()
merge_2['rate'] = [0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.05, 0.1, 0.05, 0.1, 0.1, 0.1, 0.1]
merge_2['incre_revenue'] = np.round(merge_2['total_revenue'] * merge_2['rate'] * 0.4,2)
merge_2
```

Out[49]:

Groupname	avg_sale	total_revenue	rate	incre_revenue
BUZZ AFFILIATE	253.29	56990.67	0.10	2279.63
CJ	249.26	21685.82	0.10	867.43
CPM	240.46	148603.61	0.10	5944.14
DIRECT MAIL	170.98	170.98	0.10	6.84
OTHER	226.38	4527.62	0.10	181.10
PRINT - MAGAZINES	262.98	1051.91	0.10	42.08
SEARCH GOOGLE BRAND	243.89	115601.81	0.05	2312.04
SEARCH GOOGLE NON-BRAND	245.82	13028.48	0.10	521.14
SEARCH MSN BRAND	246.33	28820.56	0.05	576.41
SEARCH MSN NON-BRAND	242.32	969.27	0.10	38.77
Social	165.00	165.00	0.10	6.60
TV	240.81	3371.29	0.10	134.85
Uncategorized	229.68	2067.08	0.10	82.68

c) (5 pts) You just found out that Winters search ad team spent $4,200 on branded search advertising during the time period in the data. What is your advice to the search team based on the calculation above?

In [50]:
```
#calculating the sum of incremental revenue for the Search Google Brand and Search MSN Brand channels
print(merge_2.iloc[6,3] + merge_2.iloc[8,3])
```

```
2888.45
```

In [51]:
```
# calculating the difference between the amount spent by the ad team and the incremental revenue for the Search Google Brand and Search MSN Brand channels
print(np.round(4200-(merge_2.iloc[6,3] + merge_2.iloc[8,3]),2))
```

```
1311.55
```

The above calculations display that:

- The total amount of incremental revenue for branded search advertising is $2888.45
- The increment revenue for branded search advertising is lesser than the amount spent on branded search advertising by $1311.55, which indicates that the current strategy used (within the time period in the data) is not profitable.

Based on these two points above, we would advice the search ad team to improve their current search ad strategy by:

- Choose and match your keywords with prospective customers and leverage keyword research tools such as Google keyword planner and Moz keyword explorer
- Include ad extensions by specifying all extension available which will improve quality score at no additional costs
- Optimize ad content and landing page

Alternatively, the team can also redirect their advertising spend on other channels that have higher incremental revenue growth.

Q4. (25 pts) Linear/uniform attribution The linear attribution model divides the attribution share between touches equally. For example, an order with one CPM, one CJ, and one TV touchpoint will have place one third attribution share on each touch. This can be accomplished by using the Touches variable (see Q2) to define a new variable: LinearAttributionShare = 1 / Touches

a) (10 pts) For each channel, what is the sum of the linear attribution shares? What is the corresponding share of credit (in percentage) according to the linear attribution model? Express your answer in a table like in Q1.

In [52]:
```
temp = df.groupby('Orderid')['Position'].count()
uniform_df = pd.DataFrame(temp)
uniform_df['Touches'] = uniform_df['Position']
uniform_df = uniform_df['Touches']
uniform = pd.DataFrame(uniform_df)

df_uniform = pd.merge(df, uniform, how = 'outer', on = 'Orderid').fillna(0)
df_uniform['LinearAttributionShare'] = 1/(df_uniform.Touches)
linear = pd.DataFrame(df_uniform.groupby('Groupname')['LinearAttributionShare'
].sum())
linear['Linear_ShareOfCredit %'] = linear['LinearAttributionShare']/sum(linear
['LinearAttributionShare'])*100
linear = np.round(linear, decimals=2)
linear
```

Out[52]:

Groupname	LinearAttributionShare	Linear_ShareOfCredit %
BUZZ AFFILIATE	338.99	20.84
CJ	132.88	8.17
CPM	827.93	50.89
DIRECT MAIL	0.33	0.02
OTHER	8.11	0.50
PRINT - MAGAZINES	3.18	0.20
SEARCH GOOGLE BRAND	200.95	12.35
SEARCH GOOGLE NON-BRAND	31.50	1.94
SEARCH MSN BRAND	46.88	2.88
SEARCH MSN NON-BRAND	4.86	0.30
Social	0.38	0.02
TV	14.03	0.86
Uncategorized	16.99	1.04

b) (10 pts) In a single bar chart, plot the share of credit (in percentage) for all three attribution models: first-touch, last-touch and linear.

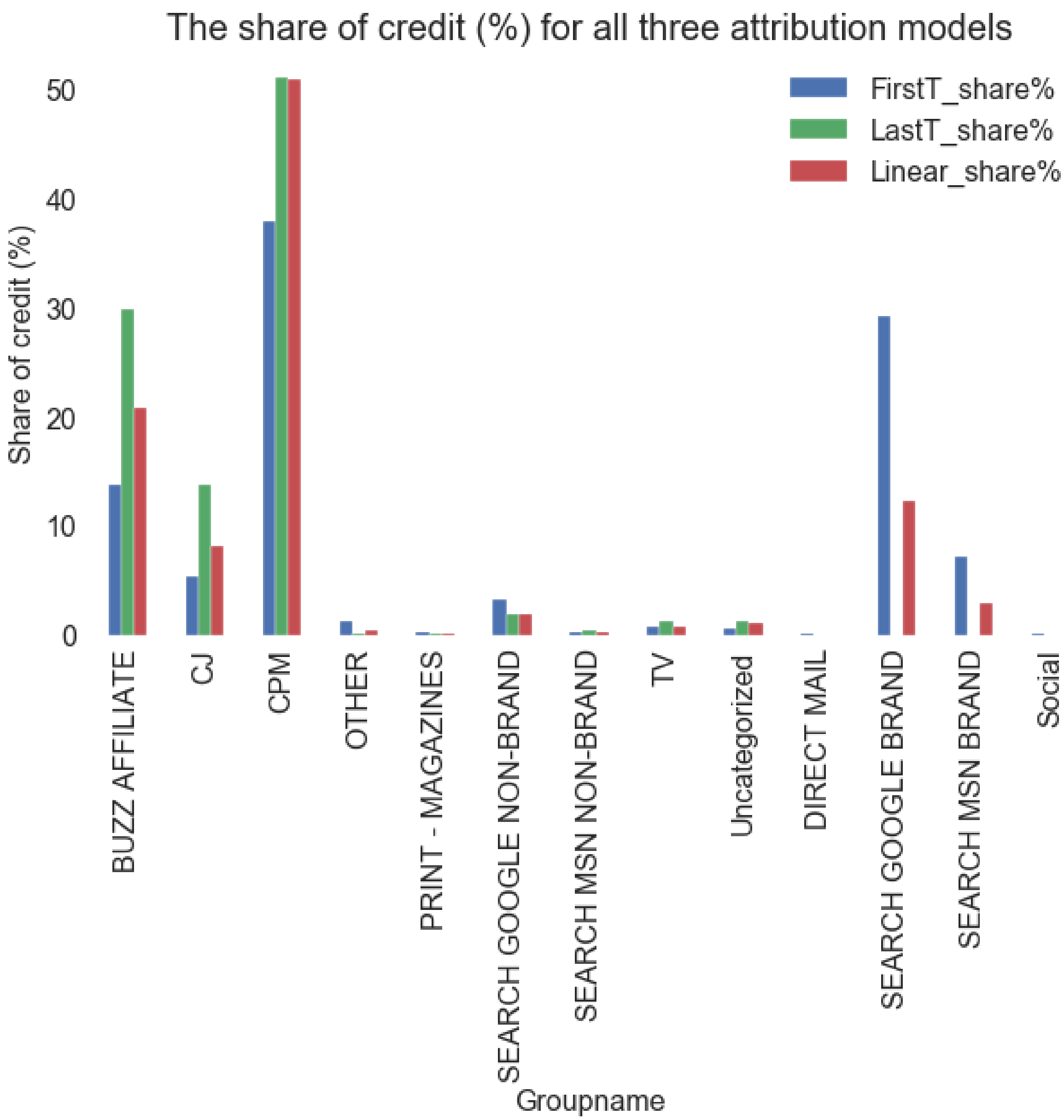
In [53]:
```
first_last['Channels'] = first_last['index']
linear['Channels'] = linear.index
merge_3= np.round(pd.merge(first_last, linear, how = 'outer', on = 'Channels')
.fillna(0), 2)
merge_3['FirstT_share%'] = merge_3['Originator %']
merge_3['LastT_share%'] = merge_3['Converter %']
merge_3['Linear_share%'] = merge_3['Linear_ShareOfCredit %']
merge_3 = merge_3[['index', 'FirstT_share%', 'LastT_share%', 'Linear_share%']]
merge_3 = merge_3[:13]
merge_3
```

Out[53]:

	index	FirstT_share%	LastT_share%	Linear_share%
0	BUZZ AFFILIATE	13.83	29.87	20.84
1	CJ	5.35	13.77	8.17
2	CPM	37.98	51.01	50.89
3	OTHER	1.23	0.18	0.50
4	PRINT - MAGAZINES	0.25	0.18	0.20
5	SEARCH GOOGLE NON-BRAND	3.26	1.97	1.94
6	SEARCH MSN NON-BRAND	0.25	0.43	0.30
7	TV	0.86	1.23	0.86
8	Uncategorized	0.55	1.35	1.04
9	DIRECT MAIL	0.06	0.00	0.02
10	SEARCH GOOGLE BRAND	29.13	0.00	12.35
11	SEARCH MSN BRAND	7.19	0.00	2.88
12	Social	0.06	0.00	0.02

In [54]:
```
merge_3[:13].plot(x='index', y=['FirstT_share%', 'LastT_share%', 'Linear_share%'], kind='bar', figsize=(10, 6))
plt.xlabel('Groupname')
plt.ylabel('Share of credit (%)')
plt.title('The share of credit (%) for all three attribution models')
```

Out[54]:
```
Text(0.5, 1.0, 'The share of credit (%) for all three attribution models')
```



c) (5 pts) Compare the linear model to the first-touch and last-touch models.

CPM holds the highest share of credit across all 3 models (~50% for last touch and linear models and 37.98% for the first touch model). The Buzz Affiliate channel nholds the second highest share of credit across both the linear and last touch models. Noticeably, both search channels (Google and MSN) only display share of credit across linear and first touch models. The linear model is the only attribution model that has share of credit across all 13 channels.

The linear model has some disadvantages as well. While it assigns equal credits to each touchpoint, we lose the ability to examine the true impact of each touchpoint on the sale.

Q5. (30 pts) Examine the role of the intermediate (Roster and Assist) touch points.

a) (10 pts) Focusing on the top channels, what is the proportion of each channel's touchpoints by position name: 1) Originator, 2) Roster, 3) Assist, and 4) Converter. Show your result using a table like the following (with the exact top channels listed)

In [55]:
```
filter_df = df[(df['Groupname'] == 'BUZZ AFFILIATE') | (df['Groupname'] == 'C
J') |  (df['Groupname'] == 'CPM') |  (df['Groupname'] == 'SEARCH GOOGLE BRAND'
) |  (df['Groupname'] == 'SEARCH GOOGLE NON-BRAND') |  (df['Groupname'] == 'SE
ARCH MSN BRAND') |  (df['Groupname'] == 'TV')]
channel = pd.DataFrame(filter_df.groupby(['Groupname', 'Positionname'])['Posit
ion'].count())
channel.reset_index(inplace=True)
channel_pivot = channel.pivot(index='Groupname', columns='Positionname', value
s='Position')
channel_pivot = channel_pivot.fillna(0)
channel_pivot['Total_old'] = channel_pivot.ASSIST + channel_pivot.CONVERTER +
channel_pivot.ORIGINATOR + channel_pivot.ROSTER
channel_pivot['ASSIST'] = channel_pivot['ASSIST']/channel_pivot['Total_old']*1
00
channel_pivot['CONVERTER'] = channel_pivot['CONVERTER']/channel_pivot['Total_o
ld']*100
channel_pivot['ORIGINATOR'] = channel_pivot['ORIGINATOR']/channel_pivot['Total
_old']*100
channel_pivot['ROSTER'] = channel_pivot['ROSTER']/channel_pivot['Total_old']*1
00
channel_pivot['TOTAL'] = channel_pivot.ASSIST + channel_pivot.CONVERTER + chan
nel_pivot.ORIGINATOR + channel_pivot.ROSTER
channel_pivot.drop(columns=['Total_old'], inplace=True)
channel_pivot = np.round(channel_pivot,2)
channel_pivot
```

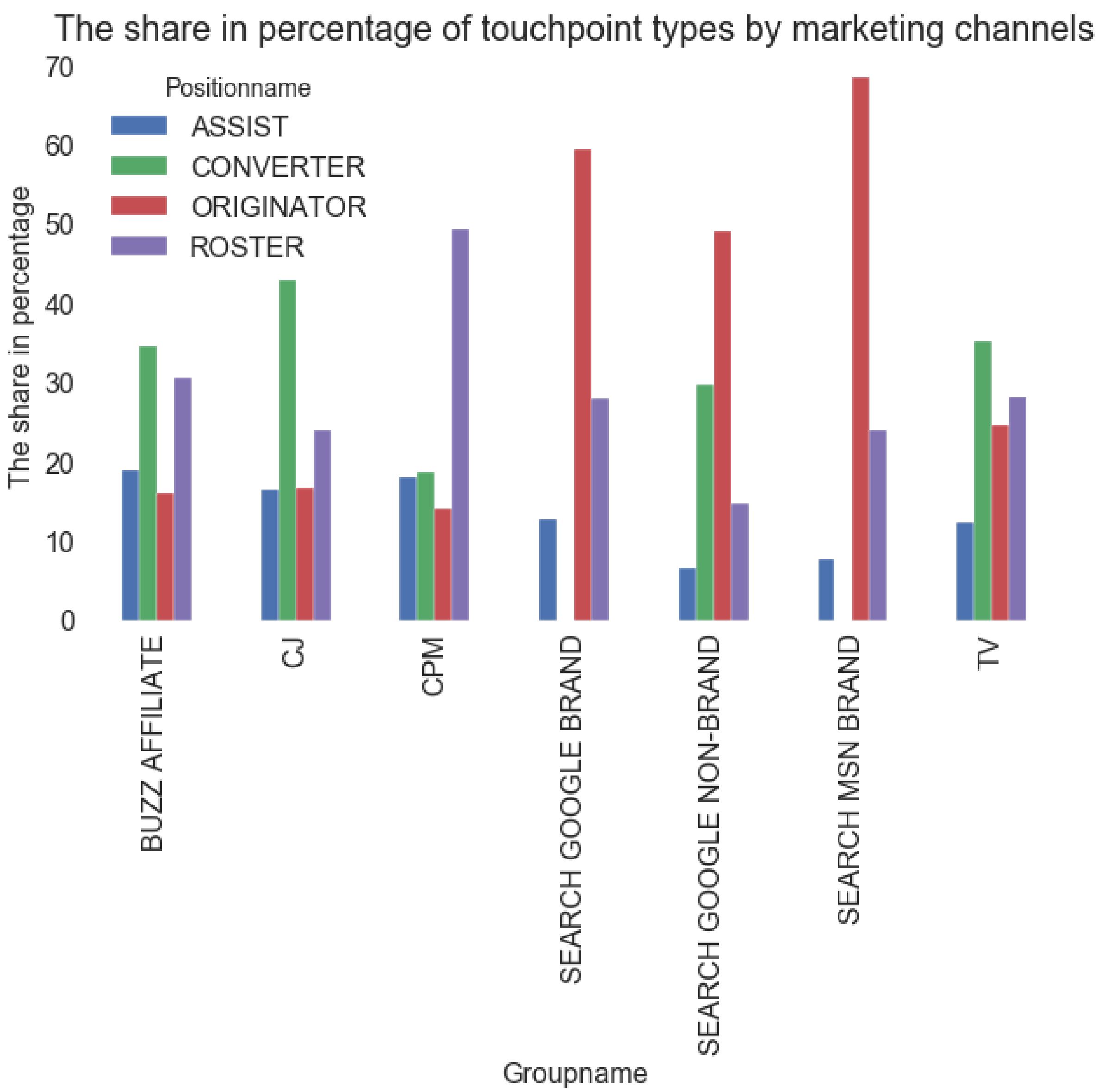
Out[55]:

Positionname	ASSIST	CONVERTER	ORIGINATOR	ROSTER	TOTAL
Groupname					
BUZZ AFFILIATE	18.83	34.54	15.99	30.63	100.0
CJ	16.48	42.91	16.67	23.95	100.0
CPM	18.08	18.76	13.97	49.19	100.0
SEARCH GOOGLE BRAND	12.77	0.00	59.32	27.91	100.0
SEARCH GOOGLE NON-BRAND	6.48	29.63	49.07	14.81	100.0
SEARCH MSN BRAND	7.60	0.00	68.42	23.98	100.0
TV	12.28	35.09	24.56	28.07	100.0

b) (10 pts) In a single bar chart, plot the share in percentage (y-axis) of touchpoint types by marketing channels (x-axis).

In [56]:
```
channel_pivot[['ASSIST', 'CONVERTER', 'ORIGINATOR', 'ROSTER']].plot(kind='bar'
, figsize=(10, 6))
plt.ylabel('The share in percentage')
plt.title('The share in percentage of touchpoint types by marketing channels')
```

Out[56]:
```
Text(0.5, 1.0, 'The share in percentage of touchpoint types by marketing chan
nels')
```



c) (10 pts) Summarize the touch-point type results. Which channels seem to have relatively more or less of its touchpoints as rosters and assist?

All channels include 'rosters' and assist as 'touchpoints', as opposed to the 'converter', where both searches (MSN and Google) don't have any proportion of the 'converter' touchpoint.

Roster

- The CPM, Buzz Affiliate, Search Google Brand and TV channels have a higher proportion of 'Rosters' as their touchpoints (49.18%, 30.63%, 27.91% and 28.07% respectively).
- The CJ, Search Google Non-Brand and Search MSN Brand channels have lower proportion of 'Rosters' as their touchpoints (23.95%, 14.81% and 23.98% respectively).

Assist

- The CPM, Buzz Affiliate and CJ channels have a higher proportion of 'Rosters' as their touchpoints (18.08%, 18.83% and 16.48% respectively).
- The Search Google Non-Brand, Search MSN Brand and TV channels have a lower proportion of 'Rosters' as their touchpoints (6.48%, 7.60% and 12.28% respectively).

Compared with linear attribution, which of these channels would receive too much or too little credit under first- and lasttouch attribution?

- The graph in 4b) displays that the channels with the highest share of credit based on the linear attribution model include CPM, Buzz Affiliates and Search Google Brand (50.88%, 20.84% and 12.35% respectively).
- In the above graph, we notice that the channels with the highest proportion of 'Originator' (first touch attribution) include Search Google Brand, Search Google Non Brand and Search MSN Brand, out of which the only overlap between this and the share of credit in the linear attribution model is with the Search Google Brand channel. The Search Google Brand channel has the second highest proportion of 'Originators' as its touchpoint, and the linear attribution model displays a slightly high share of credit for this channel (12.35%).
- In the above graph, we notice that the channels with the highest proportion of 'Convertor' (last touch attribution) include CJ, Buzz Affiliate, Search Google Non-Brand and TV, out of which the only overlap between this and the share of credit in the linear attribution model is with the Buzz Affiliates. The Buzz Affiliates channel has the third highest proportion of 'Convertors' as its touchpoint, and the linear attribution model displays a high share of credit for this channel (20.84%).
- The CPM channel has relatively low proportions of 'Originator' and 'Convertor' as touchpoints, as compared to the linear attribution model which displays the highest share of credit for this channel (50.88%).