Cross Channel Marketing and Budgeting Optimization:

Criteo has published an online advertising dataset which has details of campaigns and budget allocated for each of them. The aim is to check the cross-channel optimization using various parameters to assess which channel should be getting the maximum budget for advertisement.

Data

The dataset contains the following fields:

- Timestamp: timestamp of the impression
- UID: unique user identifier
- Campaign: unique campaign identifier
- Conversion: 1 if there was a conversion in the 30 days after the impression; 0 otherwise
- Conversion ID: a unique identifier for each conversion
- Click: 1 if the impression was clicked; 0 otherwise
- Cost: the price paid for this ad
- Cat1-Cat9: categorical features associated with the ad. These features' semantic meaning is not disclosed

What is an Attribution Model ?

Attribution modeling is a framework for analyzing which touchpoints/marketing channels receive credit for a conversion.
Each attribution model distributes the credit across each touchpoint differently.
By analyzing each attribution model one can derive the ROI for each marketing channel.

The models that are being used are:

- Last Touch Attribution
- First Touch Attribution
- Time Decay Attribution
- Linear Attribution
- U- Shaped Attribution
- Logistic Attribution

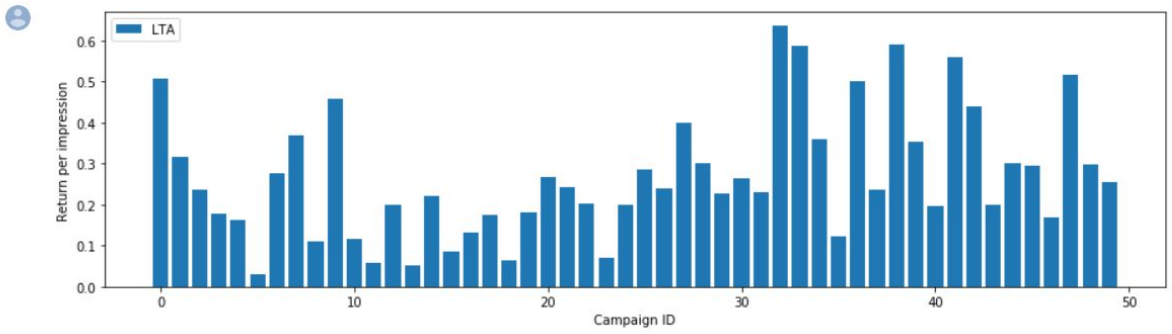
Last Touch Attribution

The Last Touch Attribution model gives all credits to the last touchpoint in the journey which essentially means that the campaign which is very close to the time a customer converted the ad into revenue.
Last touch helps marketers to prioritize productive channels.

The data is preprocessed to filter them

```
def last_touch_attribution(df):

    def count_by_campaign(df):
        counters = np.zeros(n_campaigns)
        for campaign_one_hot in df['campaigns'].values:
            campaign_id = np.argmax(campaign_one_hot)
            counters[campaign_id] = counters[campaign_id] + 1
        return counters

    campaign_impressions = count_by_campaign(df)

    df_converted = df[df['conversion'] == 1]
    idx = df_converted.groupby(['jid'])['timestamp_norm'].transform(max) == df_converted['timestamp_norm']
    campaign_conversions = count_by_campaign(df_converted[idx])

    return campaign_conversions / campaign_impressions

lta = last_touch_attribution(df6)
```

Visualisation

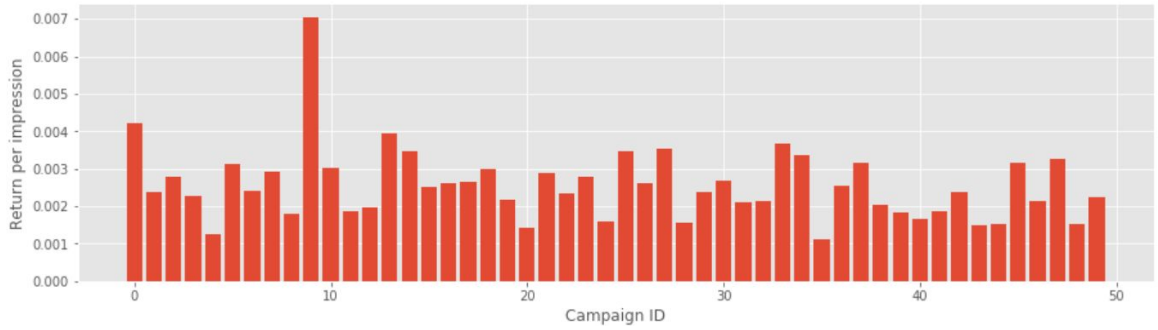


Logistic Regression Attribution

To identify the real contribution of each touchpoint, logistic regression is used. Here, each journey is represented as a vector in which each campaign is represented by a binary feature, a regression model is fit to predict conversions, and the resulting regression coefficients are interpreted as attribution weights.

```
# Quick sanity check
from sklearn.linear_model import LogisticRegression

logisticRegr = LogisticRegression()
logisticRegr.fit(x_train, y_train)
score = logisticRegr.score(x_test, y_test)
print(score)
```

```
from keras.models import Sequential
from keras.layers import Dense, Dropout
from keras.constraints import NonNeg

m = np.shape(x)[1]

model = Sequential()
model.add(Dense(1, input_dim=m, activation='sigmoid', name = 'contributions'))

model.compile(optimizer='rmsprop', loss='binary_crossentropy', metrics=['accuracy'])
history = model.fit(x_train, y_train, batch_size=128, epochs=10, verbose=1, validation_data=(x_val, y_val))
score = model.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])
```

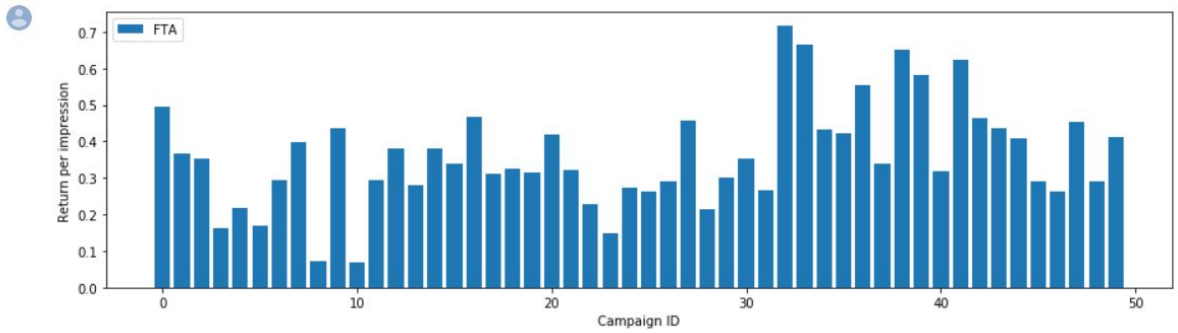


First Touch Attribution

The First Touch Attribution Model gives all credits to the first touch point in the marketing journey . 100 % of the credit goes to that particular channel/ activity that acquired or discovered the customer.
First touch attribution emphasizes discovery.

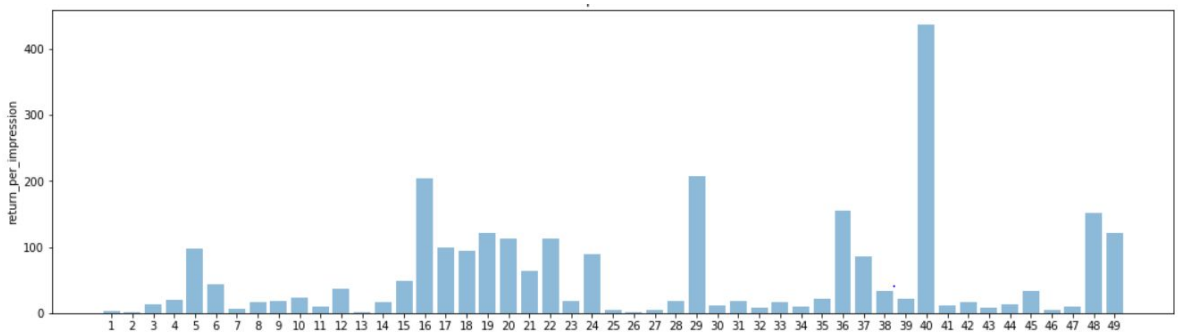
```
def first_touch_attribution(df):

    def count_by_campaign(df):
        counters = np.zeros(n_campaigns)
        for campaign_one_hot in df['campaigns'].values:
            campaign_id = np.argmax(campaign_one_hot)
            counters[campaign_id] = counters[campaign_id] + 1
        return counters

    campaign_impressions = count_by_campaign(df)

    df_converted = df.copy()
    idx = df_converted.groupby(['jid'])['timestamp_norm'].transform(min) == df_converted['timestamp_norm']
    campaign_conversions = count_by_campaign(df_converted[idx])

    return campaign_conversions / campaign_impressions

fta = first_touch_attribution(df6)
```

Visualisation



Linear Attribution Model

The credit for a conversion is equally split between all the campaigns/ touchpoints that a user had in his journey.
Linear attribution gives a more balanced look but fails to highlight the most effective strategies that actually helped in the conversion.
In the given model, the linear score is assumed to be one for a normalized effect.



```
def Linear_attribution(df):
    # Assuming the linear score to be 1 for normalized effect
    linear_score = 1
    def count_by_campaign(df):
        counters = np.zeros(n_campaigns)
        for campaign_one_hot in df['campaigns'].values:
            campaign_id = np.argmax(campaign_one_hot)
            counters[campaign_id] = counters[campaign_id] + 1
        return counters

    def linear_campaign(df):
        counters = np.zeros(n_campaigns)
        for campaign_one_hot in df['campaigns'].values:
            campaign_id = np.argmax(campaign_one_hot)
            for i in range(campaign_id+1):
                counters[i] = (linear_score/campaign_id) # Adding 1 to all campaigns leading up to conversion.
        return counters

    campaign_impressions = count_by_campaign(df)

    dfc = df[df['conversion'] == 1]

    idx = dfc.groupby(['jid'])['timestamp_norm'].transform(max) == dfc['timestamp_norm']
    campaign_conversions = linear_campaign(dfc[idx])

    return campaign_conversions / campaign_impressions

la = Linear_attribution(df6)
```

Time Decay Attribution

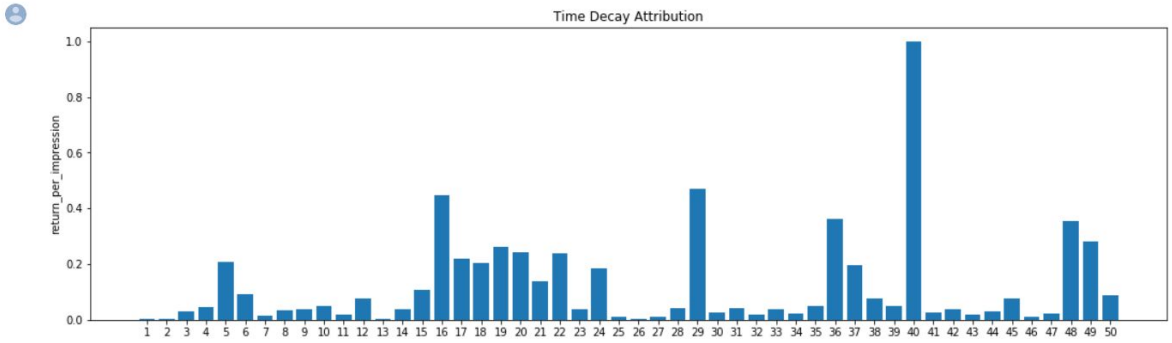
Formula - y= 2^(-x/7)

Time Decay Attribution is similar to linear attribution model and gives importance to all the touchpoints, but it also takes into consideration when the touchpoint occurred.
The interactions that occur closer to the time of conversion get more credit.

In our model, since the timestamp is not definitive and the data or time cannot be deduced from the dataset so we are going with the approach - 2*((campaign_id-counter)/campaign_id))

```
[ ]  def time_decay_attribution(df):


        def count_by_campaign(df):
            counters = np.zeros(n_campaigns)
            for campaign_one_hot in df['campaigns'].values:
                campaign_id = np.argmax(campaign_one_hot)
                counters[campaign_id] = counters[campaign_id] + 1
            return counters

        def discount_by_campaign(df):
            counters = np.zeros(n_campaigns)
            for campaign_one_hot in df['campaigns'].values:
                campaign_id = np.argmax(campaign_one_hot)
                for i in range(campaign_id + 1):

                    counters[i] =  2*((campaign_id-i)/campaign_id)
            return counters


        campaign_impressions = count_by_campaign(df)

        dfc = df[df['conversion'] == 1]

        idx = dfc.groupby(['jid'])['timestamp_norm'].transform(max) == dfc['timestamp_norm']
        campaign_conversions = discount_by_campaign(dfc[idx])

        return campaign_conversions / campaign_impressions

    tda = time_decay_attribution(df6)
```

Visualisation

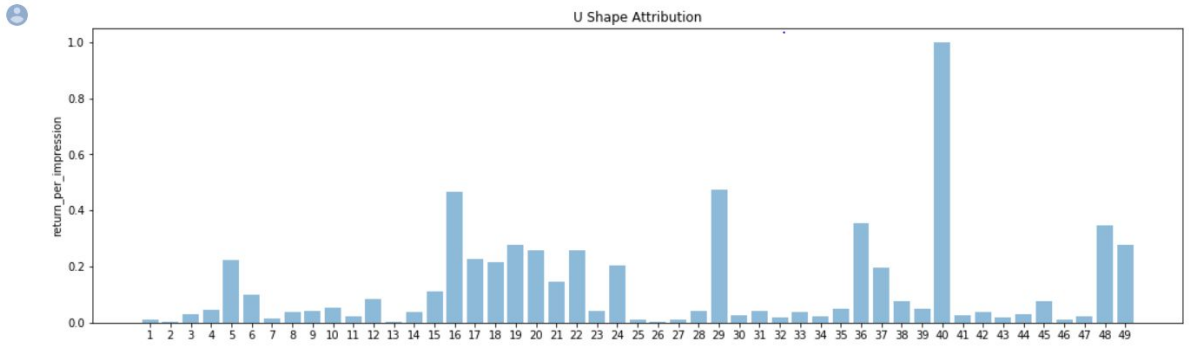


U Shaped Attribution

The U shaped attribution model is a multi touch model which counts all the touchpoints with emphasis on the first and the last touchpoints. In the model created, the first and the last touch points have been given a score of 1 and the other points have been given a score 0.5

```
[ ]  def U_shape_attribution(df):
         #Assuming u score to be 1 as max and 0.5 as min
         u_score_max = 1
         u_score_min = 0.5
         def count_by_campaign(df):
             counters = np.zeros(n_campaigns)
             for campaign_one_hot in df['campaigns'].values:
                 campaign_id = np.argmax(campaign_one_hot)
                 counters[campaign_id] = counters[campaign_id] + 1
             return counters

         def ushape_campaign(df):
             counters = np.zeros(n_campaigns)
             for campaign_one_hot in df['campaigns'].values:
                 campaign_id = np.argmax(campaign_one_hot)
                 for i in range(campaign_id):
                     if i == 0:
                         counters[i] += u_score_max
                     elif i == campaign_id:
                         counters[i] += u_score_max
                     else:
                         counters[i] += u_score_min
             return counters

         campaign_impressions = count_by_campaign(df)

         dfc = df[df['conversion'] == 1]

         idx = dfc.groupby(['jid'])['timestamp_norm'].transform(max) == dfc['timestamp_norm']
         campaign_conversions = ushape_campaign(dfc[idx])

         return campaign_conversions / campaign_impressions

     usa = U_shape_attribution(df6)
```

Visualisation



Budget Optimization

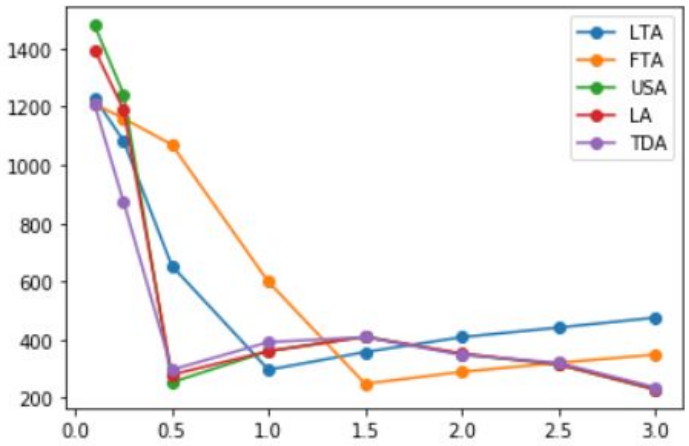
To identify which model gives the best ROI, we go for the campaign simulation idea which goes by two assumptions:

1) Define the budget just as the number of events (impressions) that we can pay for, ignoring actual dollar costs.
2) Assume that once a campaign runs out of money, all journeys that have more events associated with this campaign will never convert

The highest pitch here is assumed to be 3.

```
[ ]  # Key assumption: If one of the campaigns in a journey runs out of budget,
     # then the conversion reward is fully lost for the entire journey
     # including both past and future campaigns

     def simulate_budget_roi(df, budget_total, attribution, verbose=False):
         budgets = np.ceil(attribution * (budget_total / np.sum(attribution)))

         if(verbose):
             print(budgets)

         blacklist = set()
         conversions = set()
         for i in range(df.shape[0]):
             campaign_id = get_campaign_id(df.loc[i]['campaigns'])
             jid = df.loc[i]['jid']
             if jid not in blacklist:
                 if budgets[campaign_id] >= 1:
                     budgets[campaign_id] = budgets[campaign_id] - 1
                     if(df.loc[i]['conversion'] == 1):
                         conversions.add(jid)
                 else:
                     blacklist.add(jid)

             if(verbose):
                 if(i % 10000 == 0):
                     print('{:.2%} : {:.2%} budget spent'.format(i/df.shape[0], 1.0 - np.sum(budgets)/budget_total ))

             if(np.sum(budgets) < budget_total * 0.02):
                 break

         return len(conversions.difference(blacklist))
```

```
[ ]  a=[lta_list,fta_list,usa_list,la_list,tda_list]
     b=['LTA','FTA','USA','LA','TDA']

     for i, j in zip(a, b):
       plt.plot(pitch_list, i,marker='o',label=j)
     #plt.plot(pitch_list, fta_list,marker='o',label='FTA')
     #plt.plot(pitch_list, usa_list,marker='o',label='USA')
     plt.legend()
     plt.show()
```



At the raw attribution weight p=0.1, the U-Shaped Attribution model provides the best Budget allocation. FTA performs well with better pitch value. TDA has poor performance across different pitches.