4.2 SUCCESS RATE

Up to now, we have seen that there are different avenues for a digital marketing campaign. Quite a large number of channels are used for digital marketing purposes, from static text messages meant for everyone and none in particular to very personalised and context-based messages and videos.

As opposed to conventional marketing campaigns, a digital marketing one produces a very large amount of data. So, this data can be used to measure the success rate of a campaign or the penetration rate of the campaign itself. The immediate success rate can be measured as well its delayed action.

Let us start with an email marketing campaign for an online shop. Consider a simple scenario where a digital marketing company charges for the number of email sent. Suppose that I receive such an ad email. I can just discard the email or click on the link provided which send me to a website which offers product or services. Similarly I can buy an item or leave the website without doing any transaction.

From here we can derive some simple metrics as listed in **Table 1** below:

Cost to send 1 email:	
No. of emails sent (N):	
Total cost of emails:	
No. of clicks on emails link (n):	
Click Through Rate (CTR = n/N) :	
No of actual customers (k):	
Conversion rate (CR = k/n):	
Profits from sales due to campaign:	
No. of returning (loyal) customers (l):	
Loyal customer retention rate (LCRR = l/k)	
Profits from returning customers:	

Table 1: some simple metrics for email marketing

We can easily get the values to fill the above table and roughly determine whether a campaign is bringing in profits or not. We can get all these metrics from the marketing company, or from the weblog found in our website. Weblogs keep track of who has referred a visitor among others and businesses usually have some webpages dedicated to promotional offers, hence differentiating between normal visitors and those from the marketing campaign. The above is a very simple scenario and the effectiveness of a digital marketing campaign through email can be easily determined.

But in real life we do not buy an item the first time we come across a promotional offer. We may visit the website again and again before finalising our choice. But again websites track visitors making use of the Weblog and there are a number of tools which can combine visits, hence effectively measuring the effectiveness of a campaign.

The other complication comes when a digital marketing campaign is concurrently online on several channels and using conventional means. Also do we stop at a sale or are we going for brand awareness which is going to be converted to a sale in the long run?

So, the scenario gets more complicated with more channels and parameters to keep track of and over a long period of time as well, hence the need of specialised tools for this purpose.

According to the 2015 state of marketing report (available at: https://www.salesforce.com/blog/2015/01/2015-state-of-marketing.html), we can identify some metrics for digital marketing success. We can say that these are the Key Performance Indicators (KPIs) that need to be established to assess the overall digital marketing performance. These KPIs assess performance against the goals and targets set as objectives. Some KPIs that can be used are:

- Revenue growth
- Customer satisfaction
- **Return on Investment**: ROI is maybe the most important KPI especially for businesses.
- Customer retention rates
- Customer acquisition (i.e., audience and/or list growth)

- **Search Engine Rankings:** As will be seen in Unit 6, a higher ranking ensures more traffic to a website. The rank before and after a digital marketing campaigns must be measured.
- **Traffic:** traffic or visits is the source for leads and sales. The visitors can be new ones or returning ones. The devices (mobile, computers etc) used are also tracked. The countries of origin and the pages visited are tracked as well.
- **Conversion Rates**: seen earlier.

These metrics can be applied to any digital marketing channel as we can easily see.

Usually everyone in the business should be directly involved in a campaign effort including top management who is the one to approve the digital marketing objectives. Once we are settled with the list of objectives we must set specific goals for them: brand awareness, sales etc. Depending on our objectives we can have different metrics. If our goal is Email Marketing Success, we can break it down into key targets that can easily be tracked and measured:

- Click-through rate
- Conversion rate
- Click-to-open rate
- Unique open rate
- Lead generation
- Unsubscribe rate
- List growth rate
- Bounce rate
- Inactive user rate

This is in no way an exhaustive list of metrics. As the competition among marketers becomes more intense, more elaborate metrics are devised.

For example if we look at the Click-through rate (CTR) and the Click-to-open rate (CTOR), we may not find much difference.

Click-through rate: the ratio of how many persons clicked on the link provided to the number of emails sent.

Click-to-open rate: the ratio of many persons clicked on the link provided to how many persons opened the email.

With CTOR we are mostly measuring the effect of the message in the email. Is this message powerful enough to entice someone to click on the link? This metric will be helpful to write more messages in the future.

We also have to bear in mind that CTR depend on the digital marketing channel, the type of media used, the target region, the industry, the platform among others. Emarketer (https://www.emarketer.com/performance) provides some data with respect to performance of some digital marketing channels.

As the metrics become more and more complicated, and have to be measured over a long period of time, the assessment of a digital marketing campaign require specialised applications. We have both free to use or paid ones on the market. Two applications are listed below:

- **Google Analytics** – This is a free application provided by Google that allows tracking various information about traffic. It also provides SEO reports with the Google Webmaster Tools.
- **Moz** – This is a comprehensive analytics platform that combine search, social, social listening and inbound marketing analytics.

4.3 CHURN RATE

The churn rate is the percentage of users who unsubscribe over a specific period of time. A high churn rate means that customers are not loyal to the brand. Telecommunications companies are a classic example of high churn rates, sometimes exceeding 25%. The importance of this indicator is the fact that retaining a customer is much cheaper than attracting a new one. In the case of start-ups, a high churn rate might also be a sign that the value offer is not convincing or that user experience is poor, which means they leave.

It is also known as customer attrition, and it is calculated by dividing the number of customers who unsubscribe in the period by the number of customers at the start of the same period. As long as customer acquisition keeps consuming marketing efforts, customer churn rate will continue to rise. When left unchecked, customer churn not only wastes acquisition efforts, but it also reduces revenue and narrows your profit margins. In order to increase customer spending and overall revenue, reducing churn through Retention Marketing is crucial for business success. Measuring churn rate and understanding the ability to retain customers is the first step towards reducing it.

4.4 MEASURING CHURN RATE

Customer churn rate allows the measure of how many of your customers leave within a specific time period. Taken as a percentage, a customer churn rate is often measured on a monthly, quarterly or annual basis. Before measuring churn rate, it is important to first define what constitutes an actual churn event for your business. For a software as a service (SaaS) company it makes sense to measure churn based on the length of a subscription/membership. A churn event is defined as when a customer does not renew or cancels their subscription.

For non SaaS-based companies though it can be a little more unclear. For example, a running shoe retailer who may predict the average customer would repurchase within one and a half to two years when the shoe loses its support; however, for some customers who are athletes, their shoes get worn out and lose support at a faster rate. This is where data science and predictive analytics can drive accuracy: by analysing customer behaviour, a clear rule can be set to define churning customers.

Once churned customers have been clearly understood and identified, churn rate can be calculated as:

The basic formula for churn rate is:

Churn Rate= number of customers lost in a period / number of customers at the beginning

Example:

Let us say you want to measure customer churn over a month period. As a subscription company with 500,000 customers, you have 15,000 customers leave in the month of September.

15,000 customers lost / 500,000 existing customers = 3% monthly churn rate

A 3% monthly churn rate may not seem like anything to worry about initially. However, if this is calculated on an annual basis, that 3% monthly rate equals to 36% of your customer base lost. So in this case, that equates to 180,000 lost customers per year.

Customer churn rate has to be measured both before and after implementing retention campaigns. This allows the business to measure your campaign's effectiveness and make adjustments when needed. In other words if the customer churn rate reduces, campaigns are effective. If it increases then something different needs to be done.

Churn rate can be presented as:

- Number of customers lost
- Value of recurring business lost
- Percent of recurring value lost

In addition to measuring customer churn rate, the business needs to track the win-back rate. This allows the business to measure the number of customers who came back.

4.5 RECOMMENDATION SYSTEMS

A recommendation system, or recommender system or recommendation engine, is a program or information system which will recommend items to users.

The item can be goods to buy, article to read, a person to connect to, a movie to watch or anything in the same line.

The aim is to facilitate the users in their choice which is very vast nowadays, and to ultimately make a purchase.

The analogy is the shop keeper or sales assistant. That person will help us make a choice as they are aware of our preferences as well as the goods in stock. They also update us on new available items.

VIDEOS:

An introductory video is available at: https://www.youtube.com/watch?v=eMlcMAa0IOg

https://www.youtube.com/watch?v=u_V9o2HDCTE

https://www.youtube.com/watch?v=hqFHAnkSP2U

Who are the users of recommendation systems?

Recommendation systems are used in lots of places by big or small companies: LinkedIn, Netflix, and Amazon among the big names. This is true especially for online businesses.

The next question which comes to mind is why businesses use recommendation system. They are already involved in marketing campaigns which have proved effective. So clearly there is an opportunity to make more money or spend less in this case.

From Quora we can see some examples of financial benefits (https://www.quora.com/Which-companies-use-recommender-recommendation-systems):

Netflix: The movie recommendation system saves the company 1Billion USD in terms of marketing cost per year and up to 75% of what consumers watch comes from their recommender system.

Amazon: 35% of their revenue is credited to recommender systems as well as 29% increase in sales.

We can try to imagine how these businesses will work in the absence of recommendation systems. Consider LinkedIn for example: it recommends us to connect to people we might know. This recommendation is based on the data it collects about members. The number of registered user on LinkedIn is about 500 million scattered all over the world. It is very unlikely for us to know any random person out of this number of members. So a random suggestion method will not work. LinkedIn has a recommendation system which looks at a large number of parameters it has collected from us: our interests, our location, our educational track, our previous and current jobs, our contact list which we have shared with it among others. So the connections it suggests are more likely to be accepted than a random one.

In the absence of this recommender, we can search for a connection using LinkedIn search facility if they are members. We can also wait for a post with that contact to appear or send an invite to someone in our contact list. So these options are less interesting.

We can have a look at how a recommendation engine works. The main idea behind it is similarity. So, we need a mechanism to calculate similarity between products or users. We can then use this similarity to recommend items. For this purpose, we need to represent our data which can be persons or products for our recommender to use. We can use a vector, borrowed from maths to simplify. Then using some mathematical techniques we can calculate the similarity between vectors. The more similar the vectors are means the more similar the persons or products they are representing. Some more introductory material is available at http://recommender-systems.org/

But in real life recommendation systems are much more complex to be able to cater for a very competitive market. We can easily see this with the materials available at http://www.recommenderbook.net/

There are several categories of recommendation systems depending on the way they work. We are going to have a brief look at the two main types here.
Collaborative filtering recommendation systems predict of what may interest a person. This prediction is based on the taste of other users or on the purchase/rating pattern of the user.
Amazon can be used as illustration: https://www.youtube.com/watch?v=S4RL6prqtGQ

Consider the following table (or database) showing the ratings preferences of some buyers about some articles. The aim is to predict how Alice will rate Item 5 (chocolate) and consequently whether she will buy it or nor.

	1: Ice cream	2: Lollypop	3: Yoghurt	4: Candy	5: Chocolate
1. Alice	5	3	4	4	?
2: Bob	3	1	2	3	3
3: Cyril	4	3	4	3	5
4: Danny	3	3	1	5	4
5: Eric	1	5	5	2	1

Table 2: Preferences of buyers

As mentioned previously we can have User-based collaborative filtering or Item-based collaborative filtering.

We treat each row or column of the table above as a vector depending on the type of filtering we are using.

To measure similarity we can use Pearson correlation, the dot product or cosine similarity among others. Any metric will give a measure of similarity and we are concerned with the most similar rows or columns with respect to Alice or Chocolate.

Then we generate a prediction from the neighbours' ratings. We usually use several neighbours and assign them a weight depending on their similarity with Alice/Chocolate and the more the similarity, the higher their weight.

The rows or columns can be represented as vectors:

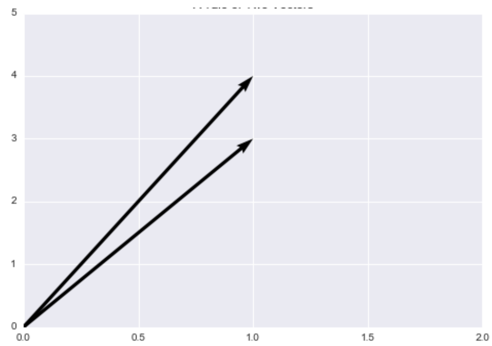

Figure 1: Vectors

To illustrate the use of cosine similarity between Alice and Bob:

Let the angle between the two vectors be θ:

Cos θ = (Alice . Bob)/ |Alice| |Bob| = $\begin{pmatrix}5\\3\\4\\4\end{pmatrix} . \begin{pmatrix}3\\1\\2\\3\end{pmatrix} / \begin{vmatrix}5\\3\\4\\1\end{vmatrix} . \begin{vmatrix}3\\1\\2\\3\end{vmatrix}$

$$= = \frac{5*3+3*1+4*2+4*3}{sqrt(\,25+9+16+16)*sqrt(9+1+4+9)}$$

= 0.975

We do the same calculation between Alice and the other users and keep the one(s) having the highest similarity. Alice’s rating for chocolate should be similar as the other persons most similar to her.

Another category of recommendation system is content-based filtering where the recommendation system focuses on the products themselves: their properties are listed. The system then recommends other products that have similar attributes.

Search engines are a good example of content-based filtering. Similarly, Netflix uses content based filtering.

Both these categories have limitations. A collaborative filtering cannot recommend a new product as none has bought or rated it. Content-based filtering on the other hand relies on the characteristics of the products and hence does not need other users to interact with them before making a recommendation.

Hybrid Recommendation Systems use both techniques together to make the best of both categories.