Unleashing the Power of Machine Learning for Email Lead Scoring

A Case Study & Guided Project Using the Business Science Problem Framework

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1.0 Introduction

Businesses face challenges in identifying and prioritizing potential customers and/or identifying future purchase potential of current customers based on their email interactions, leading to suboptimal allocation of resourcesa nd missed opportunities.

Email lead scoring plays a crucial role in determining the quality and conversion potential of leads generated through email marketing campaigns. Email lead scoring is a method used by marketers and sales teams to evaluate and prioritize leads based on their potential to become customers. It involves assigning scores or ratings to individual leads based on their behaviour, interations, and other characteristics. However, the traditional manual lead scoring methods are time-consuming, subjective, and often produce inconsistent results. Additionally, these methods do not fully leverage the available data, such as email content, sender information, and historical customer interactions.

Machine learning-based solution that can effectively evaluate the probability of leads converting into customers based on various data points extracted from email interactions. This solution should take into account factors like email open rates, click-through rates, response times, engagement patterns, and historical customer data to provide a comprehensive lead score.

By leveraging machine learning algorithms, such as classification models or predictive analytics techniques, businesses can create a reliable and automated system that can accurately score and rank email leads according to their conversion potential. The solution will empower email marketers to prioritize their efforts and resources more effectively, enabling them to focus on the most promising leads and improve overall sales and marketing efficiency.

This analysis works through and end-to-end email lead scoring solution for a business, from analysis to deployment. Skills demonstrated in this project include -

- Project management.
- Stakeholder management.
- Business understanding.
- Business return on investment and sensitivity analysis.
- Exploratory data analysis.
- Machine learning (using tools like python, pycaret, mlflow).
- Model deploying (using tools like fastapi and streamlit).

Above all, the project demonstrates how to solve key business problems in the real world.

2.0 Problem Statement & Objective

2.1 Problem Statement

As mentioned earlier, this analysis provides a lead scoring solution for a company (Business Science University). The company offers training cources (the **product**) in data science and has a large email list of **100,000** subscribers, with a monthly growth rate of **6,000** new subscribers. The marketing team also sends out **5** emails per month and the business's scales cycle generates approximately **$550,000** in revenue per month.

However, the email list also experiences a significant number of unsubscribes, about **500** per email, resulting in a total of **2,500** unsubscribers per month.

This High unsubscribe rate indicates potential inefficiencies in the email marketing strategy. In addition, high unsubscribe rates can result in reduced revenue especially if the business relies heavily on email marketing as a primary channel for generating leads and driving conversions. To sustain and increase revenue, it is crucial to optimize the email marketing approach and maximize customer conversion rates. The business also believes that nurturing lost customers has the potential to convert approximately 5% of them back into active customers.

2.2 Objective

Given these key insights, the problem at hand is to develop an effective email list scoring and segmentation strategy. The goal is to identify and prioritize the most valuable customers while reducing unsubscribe rates and increasing overall customer conversions. By segmenting the email list based on various factors and implementing tailored communication and nurturing strategies, the business aims to optimize the use of marketing resources and enhance revenue generation.

In summary, the primary objective is to leverage email list scoring and segmentation techniques to improve customer engagement, reduce unsubscribes, increase customer conversion rates, and ultimately maximize revenue and customer lifetime value.

Now that we have a general understanding of the problem statement and the objective, the next sections will focus on a business solution process using the BSPF.

3.0 Business Understanding

BSPF Phase: Business Understanding | View Business as a Machine.

We know that tackling business problems such as this requrires alot of resources including time and money. Therefore a key question to ask is **is this problem worth solving?.**

In this phase, the key is to analyze if solving this problem should be a business prority. One way to achive this is by calculating the cost of the business problem by understand how high unsubscribe rates lead to lower revenue. Our goals in this phase include:

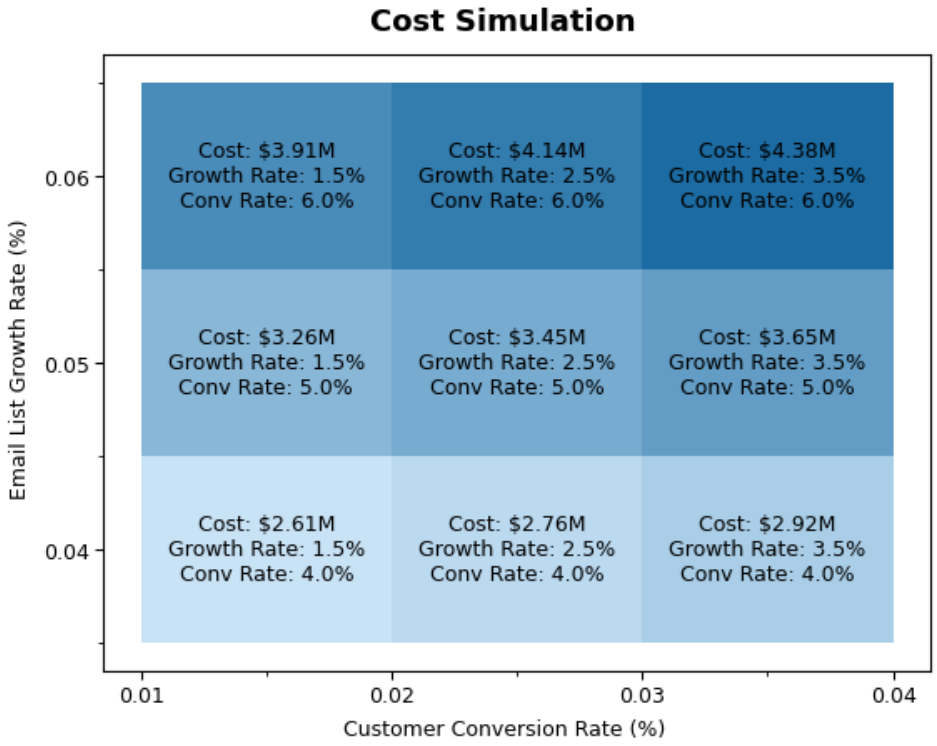
- Cost Assessment - Assign a cost to high unsubscribe rates, thus giving the business a point estimate of annual costs of unsubscribe rates. This step does NOT account of growth rate of email lists.
- Improve Cost Analysis - Improve on cost assesment by account for email list growth uncertainty.
- Business Cost Simulation - This is also necessary when accounting for uncertainty and helps model cost when key inputs change.

3.1 Cost Assessment

Given the values highlighted in the problem statement section, we can estimate the monthly lost revenue (we'll refer to this as **cost** going forward) due to unsubscribers to be around $250K per month (or $3M annually), not factoring in email list growth rate. After factoring in a 3.5% monthly email list growth rate, we can expect the annual lost revenue due to unsubscribers to rise to around $364K per month (or $4.3M per year), an increase of 46% in lost revenue. The table below shows this scenario.

Metrics / Drivers	0% Growth Scenario (Month 12)	3.5% Growth Rate Scenario (Month 12)
Email List Size	1,000,000	1,459,970
Unsubscribe Count Per Sales Email	500	500
Unsubscribe Rate	0.05%	0.05%
Count of Sales Emails Per Month	5	5
Conversion Rate	5%	5%
Lost Customers	2,500	3,650
Average CLV Per Customer	$2,000	$2,000
Lost Revenue Per Month	**$250,000**	**$364,992**

We can see the high cost of this problem which is the lost revenue to the business. However, the values shown in the table above do not factor in uncertainty. We can thus improve on our cost assessment by factoring in uncertainty in some of the drivers. Let assume some monthly variablity in email list growth rate and conversion rate. The heatmap below shows a cost simulation with variablity. The *y* axis represents various levels of customer converstion rate while the *x* axis represents various levels of email list growth rate.



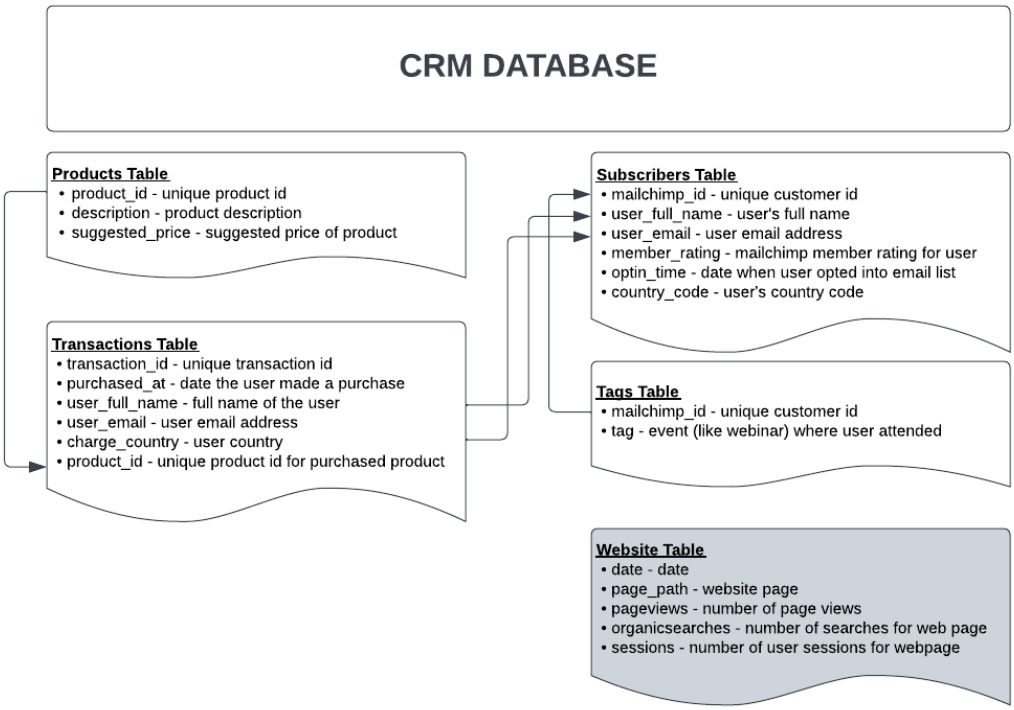
We can see that regardless of how the drivers vary, we can still expect to see annual costs ranging from $2.61M to $4.38M. Thus this is definitely a problem worth solving.

At this point, a key question is can we reduce the unsubscribe rate. Recall that the business is loosing 500 customers for every email sent out. What if we can reduce that number by 50% or 250, while maintaning 90% of revenue. What impact will that have on the business?

The only problem is that we still do not know a lot about what causes a subscriber to make a purchase. If we do we can focus on targeting the ones that are more likely to purchase with sales emails and nurture the ones who are unlikely to covert. This will help with our goal of reducing the unsubsbribe rate while maintaning 90% of revenue.

4.0 Data Understanding

This phase requires understanding the data available at our disposal to tackle this problem. The visual below gives an overview of the companies crm database including table and field descriptions. Connecting arrows show how each table can be connecting to other tables based on common fields.



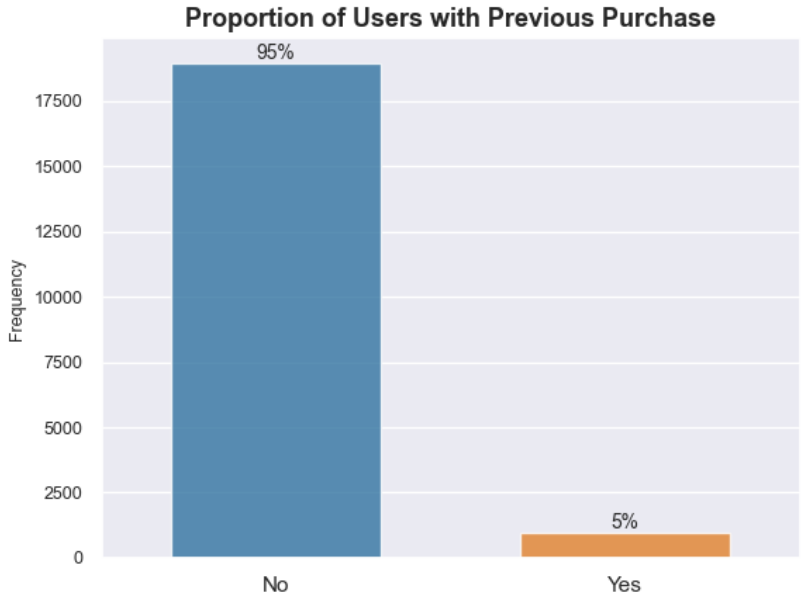
Note that we will not be using the website table for this analysis.

4.1 Exploratory Data Analysis

After some initial data manipulation to get the data in the right format we need for analysis, including adding a **target** feature which is a binary flag of if a user has made a previous purchase or not (we'll call this target feature **made_purchase**), we can then begin to do some initial exploratory analysis to get a sense what features in our dataset could be predictive of users making a purchase.

First lets analyze our target feature *made_purchase*:

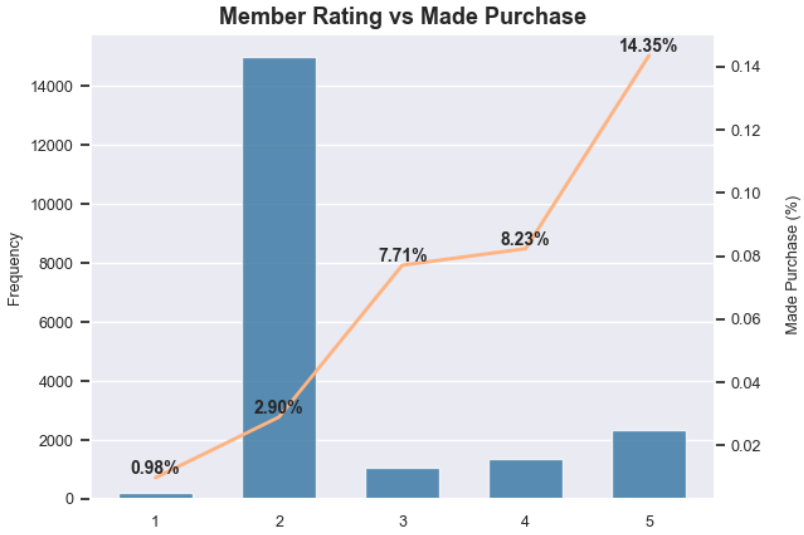
4.1.1 Proportion of Users with a Previous Purchase



Observation: Only 5% of users have made a previous purchase, meaning we are dealing with a highly imbalanced dataset.

4.1.2 Member Rating vs Made Purchase

The plot below shows the different values of *member_rating* vs the proportion of *made_purchase* for users with each value of *member_rating*:



Observation: Member rating appears to be quite predictive of *made_purchase*. We can see that the likelihood of a user making a purchase increases 3x when the *member_rating* goes from 1 to 2. Additionally the likelihood of making a purchase increases 5x when the *member_rating* goes from 2 to 5.

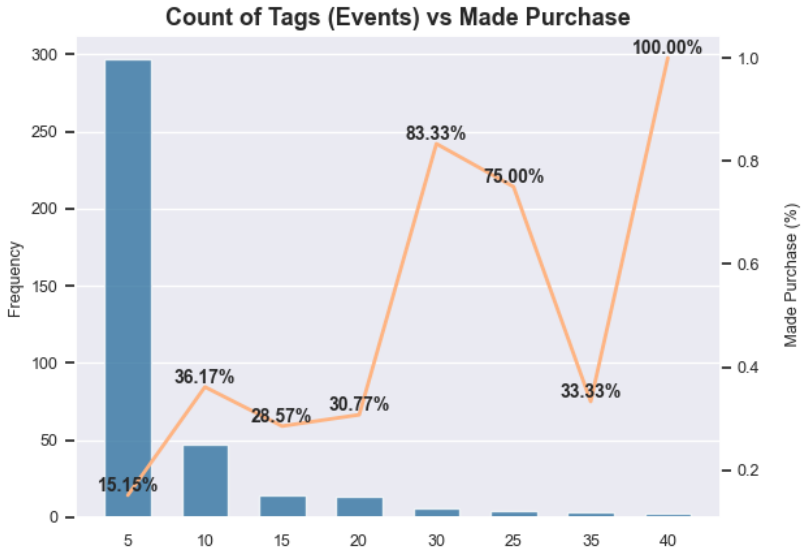
4.1.3 Country Code vs Made Purchase

The plot below shows *country_code* along with the within group *made_purchase* proportion, for the top 10 countries in terms of count of users.

Observation: Country code appears to be quite predictive of *made_purchase* as well.For example we can see that while the US has the most users (over 3,500), the proportion of US users who have made a purchase is ~10%. However a country like AU which has less than 500 users has a higher proprtion of users who have made a purchase (~12%).

4.1.4 Tag Count vs Made Purchase

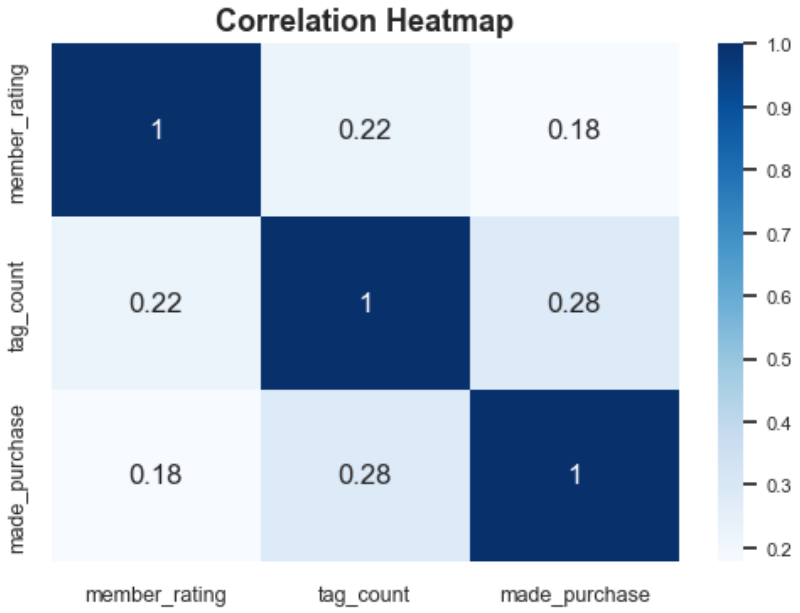
The plot below shows *tag_count* along with the within group *made_purchase* proportion, for a selected number of *tag_count*. Recall that tags here refer to various events like trainings and webinars. Therefore *tag_count* refers to the number of such events a user has attended:



Observation: We can see that if a subscriber has 40 or more tags (events), they are 100% likely to make a purchase. That likelihood drops as *tag_count* decreases. Note that a subscriber with 0 tags only have a 2% likelihood of making a purchase. For those with 0 tags (meaning they have not attended any events yet) we may not want to send them emails just yet. We may want to try and nurture them to attend more events before trying to get them to make a purchase. Overall if the business can get subscribers to attend more events, it drastically increases their likelihood of making a purchase.

1.4.5 Correlation

The plot below is a correlation heatmap of numberic features only. These correlation values further validatates some of the data we saw earlier. We can see that *tag_count* and *member_rating* do show a fairly high correlation with *made_purchase*.



5.0 Formulating KPIs

Now that we have a bit more understanding of some of the potential drivers of *made_purchase*, we may want to develop some hypothesis about how to improve the likelihood of a user making a purchase by applying some of the insights we just learned. For example:

- Can we reduce the number of sales emails sent to subscribers by 30% and still maintain 99% of sales revenue.
- Can we segment our email list into **hot** and **cold** leads. Hot leads meaning those who are more likely to purchase (subscribers with high *member_rating* for example), and cold leads meaning those less likely to purchase (subscribers with low *member_rating*). This way we could come up with a strategy to only send sales emails to hot leads, while nuturing cold leads to increase their likelihood of purchase.

One of such KPIs could be to increase the median *tag_count*. Looking at the table below, we can see that the median *tag_count* for those who have not made a purchase is 0 while for those who have made a purchase, the median *tag_count* is 2. Thus we could establsh a KPI for cold leads to get their median tag count to 2 or more (attend 2 or more webinars/events) and increase their likelihood of making a purchase.

	Made Purchase	Mean Tag Count	Median Tag Count	Count Subscribers
0	No	1.138313	0	18957
1	Yes	4.715177	2	962

6.0 Feature Engineering

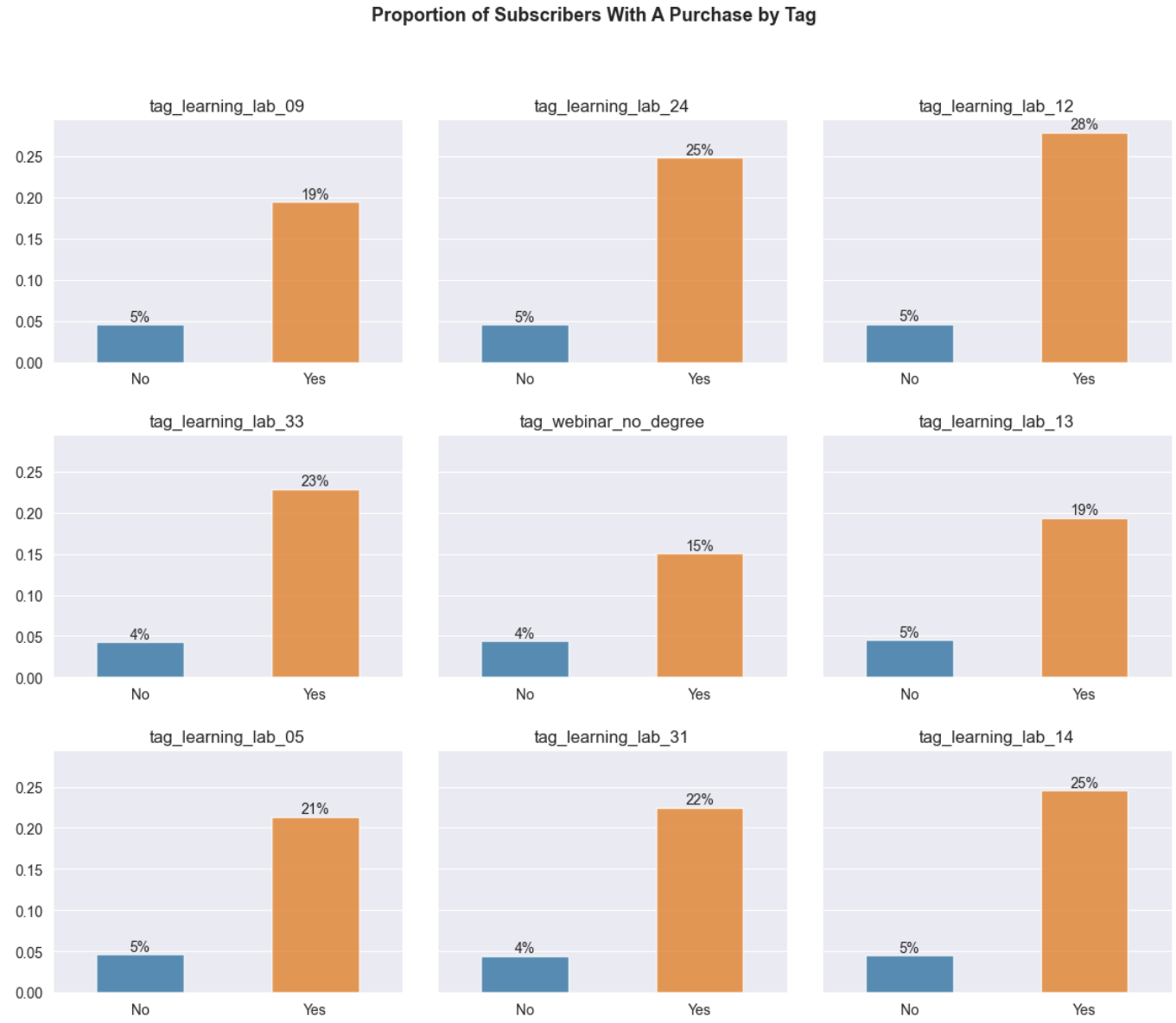
Now that we have a better understand of our data and what features might be predictive of a subscriber making a purchase, the next phase in our workflow is creating preprocessing pipelines to get our data in the right form for machine learning algorithms. Feature Engineering is the process of selecting, manipulation and transforming raw data into features that can be used in supervised learning.

Understanding the business context and having domain expertise can greatly influence the choice and creation of features. Different businesses and domains may have unique characteristics, specifc factors that impac the target variable, and relevant attributes that need to be considered during feature engineering.

For this analysis, the following addition features were created from existing data;

1. Optin Days - Generated from *optin_time*. This is the number of days the subscriber has been on the companies email list.
2. Email Provider - Generated from *user_email*. Multiple email providers (such as gmail, hotmail) etc are being used by subscribers, and could be helpful in predicting *made_purchase*.
3. Activity Per Time - Generated by dividing *tag_count* (count of events a subscriber has attended) by the newly created *optin_days*.
4. One-To-Many Features (Tags) - These are binary features (0s or 1s) for each tag (event) to indicate if a user attend the event or not.
5. Reducing High Cardinality - Applied to *country_code*. Using a threshold of 6, this process lumps countries that have less than 6 subscribers in the dataset into an ***other*** *category in*country_code*.

To demonstrate the importance of feature engineering in this analysis, we'll show an example of some of the new features created and their relationship with our target *made_purchase*. The plot below shows the proportion of subscribers who made a purchase for 9 randomly selected tags (events). Looking at one example (Learning Lab 09) we can see that if a subsriber attended that event, they have a 19% likelihood of making a purchase vs only 5% if they did not attend the event. For learning lab 12, the likelihood of making a purchase if they attended the event is 28% vs 5% if they did not. We can also see similar trends for the other tags.



This indicates that having these additional features could be very indicative of *made_purchase*.