

# *User Activity Logs*

Capstone project of Machine Learning Track

**Presented by:**  
Desert Ninjas

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**Date Presented:**  
Nov 20th, 2022

# Outline

Team members

Introduction

Dataset Overview

Data Preprocessing

EDA

Dashboards

Machine Learning Models

Future Work and Conclusion

# *Team Members*

## *Desert Ninjas*

Team under big data and  
artificial intelligence bootcamp.

Reema Alaswad  
Raghad Aleisa  
Eman Aldosari  
Maha Alhazzani  
Aljohara Alkanhal

# *Introduction*

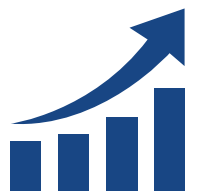
# Company Overview



Established since 2020



Listed under FinTech lab initiative sandbox, supervised by the Capital Market Authority



Highest growing FinTech startup in 2 years



Contributes to the whole Saudi economic growth and 2030 vision (i.e., GDP, job opportunities)



Highest consumers retention rates, amongst other Saudi FinTech's

# *Problem Statement*

A startup FinTech company named X is interested in knowing its customers' behaviors and **whether they're going to invest** based on their users activity logs

## Challenges

- The number of users is unknown to us
- No users demographics
- No useful features
- Huge preprocessing time

# *Dataset Overview*



Sep 8th → Sep 15th  
2022



User Activity Logs



95K Rows



3K Visitors

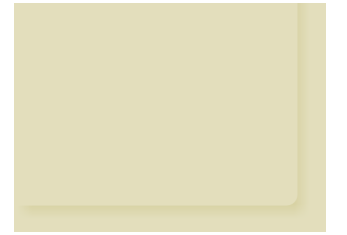


5th Path is Longest Path

# *Objective*



## Main Objectives



1

**Predict customer behavior and activity logs to see whether the customer would invest in the company.**

2

**Predicting the potential investors to target them with marketing strategies.**



# Questions

1. **What kind of data does their website collect from users?**
2. **What is the path that gets visited by users usually? And how much time do users spend on this path?**
3. **Does the average time spent on a page differ based on the user type?**
4. **Which path has the maximum time? Is this the path that leads to a successful transaction (investment)?**



فنتك السعودية  
FintechSaudi

# *Data Preprocessing*

# Data preprocessing



*Before data preprocessing process:*

```
{"$os":"Windows","$browser":"Chrome","$device_type":"Desktop","$current_url":"https://company.sa/investor/dashboard","$host":"company.sa","$pathname":"/investor/dashboard","$browser_version":105,"$screen_height":864,"$screen_width":1536,"$viewport_height":714,"$viewport_width":1536,"$lib":"web","$lib_version":"1.26.0","$insert_id":"ryqkpj2yyv4ob7iq","$time":1662659942.785,"distinct_id":"1831e41502a288-0aadb2e8522fed-26021c51-144000-1831e41502b504","$device_id":"1831e41502a288-0aadb2e8522fed-26021c51-144000-1831e41502b504","$referrer":"$direct","$referring_domain":"$direct","$active_feature_flags":[],"$event_type":"click","$ce_version":1,"token":"phc_TfMQhNNAvw1adnHEWilG1LMpLeszOjUV5y1X6EXAqwR","$session_id":"1831e4150303a0-04a83b401e337e-26021c51-144000-1831e4150316d8","$window_id":"1831e4150327d1-0f02fd620ee793-26021c51-144000-1831e4150338f5","$set_once":{"$initial_os":"Windows","$initial_browser":"Chrome","$initial_device_type":"Desktop","$initial_current_url":"https://company.sa/investor/dashboard","$initial_pathname":"/investor/dashboard","$initial_browser_version":105,"$initial_referrer":"$direct","$initial_referring_domain":"$direct"},"$
```



*After data preprocessing process:*

session_id	Type	window_id	browser	device_type	os	host	current_url
1831e4150303a0-04a83b401e337e-26021c51-144000-1831e4150316d8	pageview	1831e4150303a0-04a83b401e337e-26021c51-144000-1831e4150316d8	Chrome	Desktop	Windows	company.sa	https://company.sa/investor/dashboard
1831fa67f29b-0f02fd620ee793-26021c51-144000-1831fa67f29b	pageview	1831fa67f29b-0f02fd620ee793-26021c51-144000-1831fa67f29b	Chrome	Desktop	Windows	company.sa	https://company.sa/investor/dashboard
18327baf015d-0f02fd620ee793-26021c51-144000-18327baf015d	pageview	18327e69801e-0f02fd620ee793-26021c51-144000-18327e69801e	Chrome	Desktop	Windows	company.sa	https://company.sa/investor/dashboard
1832bff50503-0f02fd620ee793-26021c51-144000-1832bff50503	pageview	1832bff50503-0f02fd620ee793-26021c51-144000-1832bff50503	Chrome	Desktop	Windows	company.sa	https://company.sa/investor/dashboard
1832ce79918b-0f02fd620ee793-26021c51-144000-1832ce79918b	pageview	1832ce79918b-0f02fd620ee793-26021c51-144000-1832ce79918b	Chrome	Desktop	Mac OS X	company.sa	https://company.sa/investor/dashboard
18330ae0043d-0f02fd620ee793-26021c51-144000-18330ae0043d	pageview	18330ae0043d-0f02fd620ee793-26021c51-144000-18330ae0043d	Mobile Safari	Mobile	iOS	company.sa	https://company.sa/investor/dashboard
18330ae082c3-0f02fd620ee793-26021c51-144000-18330ae082c3	pageview	18330ae082c3-0f02fd620ee793-26021c51-144000-18330ae082c3	Mobile Safari	Mobile	iOS	company.sa	https://company.sa/investor/dashboard
18330ae40b1e-0f02fd620ee793-26021c51-144000-18330ae40b1e	pageview	18330ae40b1e-0f02fd620ee793-26021c51-144000-18330ae40b1e	Microsoft Edge	Desktop	Windows	company.sa	https://company.sa/investor/dashboard
18330aeb0c5d-0f02fd620ee793-26021c51-144000-18330aeb0c5d	pageview	18330aeb0c5d-0f02fd620ee793-26021c51-144000-18330aeb0c5d	Microsoft Edge	Desktop	Windows	company.sa	https://company.sa/investor/dashboard
18330b065d1e-0f02fd620ee793-26021c51-144000-18330b065d1e	pageview	18330b065d1e-0f02fd620ee793-26021c51-144000-18330b065d1e	Mobile Safari	Mobile	iOS	company.sa	https://company.sa/investor/dashboard

# *Data preprocessing*



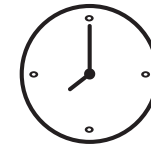
**Extract the most important columns.**



**Removing all unwanted symbols/signs.**



**Columns type conversion**



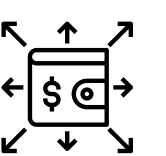
**Handling Time column**



**Generate new columns**



**Handling missing values**



**Labeling the dataset**

# 1. *Extract the Most Important Columns.*

```
def Extract_column(data , column):  
    if(column in data):  
        data = str(data)  
        data = data.split(column)[1]  
        data = data.split(',')[0]  
        data = data.replace('$', '')  
        data = data.replace(':', '')  
        data = data.replace('"', '')  
        return data  
  
for column in columns:  
    df2[column] = df2['Raw data'].apply(lambda data : Extract_column(data, column))
```

# 1. *Extract the Most Important Columns.*

*Before*

**Raw data**

'os ":" <i>Windows</i> ', "browser":"Chrome","\$device_...
'os ":" <i>Windows</i> ', "browser":"Chrome","\$device_...
'os ":" <i>Windows</i> ', "browser":"Chrome","\$device_...
'os ":" <i>Windows</i> ', "browser":"Chrome","\$device_...
'os ":" <i>Windows</i> ', "browser":"Chrome","\$device_...

*After*

**os                      browser**

{"\$os":"Windows"    \$browser:"Chrome"    \$current_url:"https://compa
{"\$os":"Windows"    \$browser:"Chrome"    \$current_url:"https://comp
{"\$os":"Windows"    \$browser:"Chrome"    \$current_url:"https://comp
{"\$os":"Windows"    \$browser:"Chrome"    \$current_url:"https://comp

## 2. *Removing All Unwanted Symbols/Signs.*



```
def Remove_signs(x):  
    x = str(x)  
    name = x.split(':')[0]  
    x = x.replace(name, '')  
    x = x.replace('$', '') #Remove $ symbol  
    x = x.replace(':', '') #Remove : symbol  
    x = x.replace('"', '') #Remove " symbol  
    return x
```



## 2. Removing All Unwanted Symbols/Signs.

*Before*

os	browser	current_url
{"\$os":"Windows"	\$browser:"Chrome"	\$current_url:"https://company.sa/investor/dash..."
{"\$os":"Windows"	\$browser:"Chrome"	\$current_url:"https://company.sa/investor/inve..."
{"\$os":"Windows"	\$browser:"Chrome"	\$current_url:"https://company.sa/investor/inve..."
{"\$os":"Windows"	\$browser:"Chrome"	\$current_url:"https://company.sa/investor/inve..."
{"\$os":"Windows"	\$browser:"Chrome"	\$current_url:"https://company.sa/investor/inve..."

*After*

os	browser	current_url	host
Windows	Chrome	https://company.sa/investor/dashboard	company.sa
Windows	Chrome	https://company.sa/investor/investment-portfolio	company.sa
Windows	Chrome	https://company.sa/investor/investment-portfolio	company.sa
Windows	Chrome	https://company.sa/investor/investment-portfolio	company.sa
Windows	Chrome	https://company.sa/investor/investment-portfolio	company.sa



### *3. Columns Type Conversion*



```
df[column]= pd.to_numeric(df.column, errors='coerce')  
df[column].fillna(df[column].mean(), inplace=True)
```

# 3. Columns Type Conversion

*Before*

6	browser_version	95818	non-null	object
7	screen_height	95818	non-null	object
8	screen_width	95818	non-null	object
9	viewport_height	95818	non-null	object
10	viewport_width	95818	non-null	object

*After*

27	browser_version	2949	non-null	float64
28	screen_height	2949	non-null	int64
29	screen_width	2949	non-null	int64
30	viewport_height	2949	non-null	float64
31	viewport_width	2949	non-null	float64

## *4. Handling Time column*

### 4.1 Timestamp conversion:

- Currently, The time format in "Time" column is in the float representing a Unix epoch in units of seconds.



```
def convert_to_timestamp(x):  
    x = float(x)  
    x = pd.Timestamp(x, unit='s')  
    return x
```

## 4. *Handling Time column*

*Before*

0	1662659942.785
1	1662660028.357
2	1662660365.581
3	1662660346.708
4	1662660067.629

*After*

0	2022-09-08	17:59:02.785000086
1	2022-09-08	18:00:28.357000113
2	2022-09-08	18:06:05.581000090
3	2022-09-08	18:05:46.707999945
4	2022-09-08	18:01:07.628999949

## *4. Handling Time column*

**4.2 Remove the sub-seconds "parts of a second" from "Time" column:**

17:59:02.785000

```
def remove_micro_seconds(time):  
    time=str(time).split('.')[0]  
    return time
```



## *4. Handling Time column*



*Before*

0	17:59:02.785000
1	18:00:28.357000
2	18:06:05.581000

*After*

0	17:59:02
1	18:00:28
2	18:06:05

[illegible]



# 5. *Generate New Columns*



The Result:

pathname	path1	path2	path3	path4	path5
/investor/opportunity/WX0	investor	opportunity	WX0	blank	blank



## 5. *Generate New Columns*

### 5.2 Generate "Number of Pages" column

- Calculate the pages based on the number of backslashes "/" in each pathname.



```
#This function will calculate how many pages have the user entered using the "/" symbol.  
def count_pages (path):  
    number_of_pages = path.count('/')  
    return number_of_pages
```



# 5. *Generate New Columns*



The Result:

path1	path2	path3	path4	path5	number_of_pages
investor	dashboard	blank	blank	blank	2
investor	investment-portfolio	blank	blank	blank	2

## 5. *Generate New Columns*

### 5.3 Separate the date and time into two new and different columns.



```
#Separate the date and time into two new and different columns.  
df['new_date'] = [d.date() for d in df['time']]  
df['new_time'] = [d.time() for d in df['time']]
```

## 5. *Generate New Columns*

The Result:

time
2022-09-08 17:59:02.785000086
2022-09-08 18:00:28.357000113



date	time
2022-09-08	17:59:02.785000
2022-09-08	18:00:28.357000

## 5. *Generate New Columns*

### 5.4 Extract the year, month, and day from "date" column.



```
#Extract the year, month and day from "date" column.  
df['year'] = pd.DatetimeIndex(df['date']).year  
df['month'] = pd.DatetimeIndex(df['date']).month  
df['day'] = pd.DatetimeIndex(df['date']).day
```



# 5. *Generate New Columns*



The Result:

date	time	year	month	day
2022-09-08	17:59:02.785000	2022	9	8
2022-09-08	18:00:28.357000	2022	9	8

## 5. *Generate New Columns*

### 5.4 Extract month name and day name from "date" column.



```
#This function will extract the name of the month "not the number". e.g. September.
def get_month_name(date):
    d = pd.Timestamp(date)
    return d.month_name()
#This function will extract the name of the day "not the number". e.g. Thursday.
def get_day_name(date):
    d = pd.Timestamp(date)
    return d.day_name()
```



# 5. *Generate New Columns*



The Result:

year	month	day	month_name	day_name
2022	9	8	September	Thursday
2022	9	8	September	Thursday





## *5. Generate New Columns*



### **5.5 Classify the days as weekend or as weekday.**

- Sunday, Monday, Tuesday, Wednesday, Thursday → Weekday
- Friday, Saturday → Weekend



# 5. *Generate New Columns*



The Result:

year	month	day	month_name	day_name	week_label
2022	9	8	September	Thursday	Weekday
2022	9	8	September	Thursday	Weekday



## *5. Generate New Columns*



### **5.6 Categorize time into different categorical classes based on the week label.**

**In weekdays:**

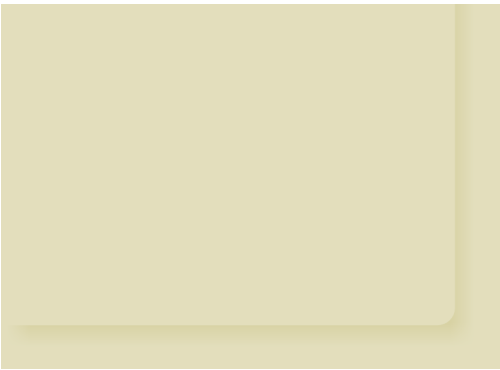
1. From 0:00 to 7:59 → Morning.
2. From 8:00 to 11:59 and from 13:00 to 16:59 → During work.
3. From 12:00 till 12:59 → Launch hour.
4. Otherwise → Night.

**In weekend:**

1. From 4:00 to 11:59 → Morning.
2. From 12:00 to 18:59 → Evening.
3. Otherwise → Night.



# 5. *Generate New Columns*



## The Result:

time	year	month	day	month_name	day_name	week_label	day_parts
17:59:02	2022	9	8	September	Thursday	Weekday	Night
18:00:28	2022	9	8	September	Thursday	Weekday	Night
18:06:05	2022	9	8	September	Thursday	Weekday	Night
18:05:46	2022	9	8	September	Thursday	Weekday	Night

## 5. *Generate New Columns*

### 5.7 Calculate the time duration of each session in hours, minutes and seconds.

- In Python, timedelta denotes a span of time. It's the difference between two date, time, or datetime objects.

```
def time_duration_hours(end_time, start_time):  
    from datetime import datetime  
    # the string is changed to the DateTime object  
    end_time = datetime.strptime(end_time, "%H:%M:%S")  
    start_time = datetime.strptime(start_time, "%H:%M:%S")  
    delta = end_time - start_time  
    # get difference in seconds  
    sec = delta.total_seconds()  
    # get difference in min  
    min = sec / 60  
    # get difference in hours  
    hours = sec / (60 * 60)  
    # round the hours time  
    return round(hours, 2)
```

# 5. Generate New Columns

## The Result:

	min_time	max_time	duration_hours	duration_minutes	duration_seconds
session_id					
1831e4150303a0-04a83b401e337e-26021c51-144000-1831e4150316d8	17:59:00	18:21:10	0.37	22.17	1330.0
1831fa67f29acf-03acc8ab0c94e8-26021c51-144000-1831fa67f2a10ea	00:29:08	00:39:01	0.16	9.88	593.0
18327baf015d6c-01519b84418c49-26021c51-144000-18327baf016e38	14:08:26	14:56:09	0.80	47.72	2863.0
1832bff5050393-0f084138f6836c-26021c51-1fa400-1832bff50529e	10:01:36	10:43:55	0.71	42.32	2539.0
1832ce7991833a-0fd268fb672d8b-1b525635-fa000-1832ce7991993a	14:15:19	14:15:56	0.01	0.62	37.0



## *6. Handling Missing Values*



### 4.1 Handling Missing Values in Event Type column;

- There are 35K missing values out of 95K.
- Possibilities were: Click, Change and Submit
- Technically, If the user was just visiting the website without doing anything → they did not do any action.



Filling the NaN's with "**No Action**"



## *6. Handling Missing Values*



**The Result:**

click	49033
no action	35414
change	10990
submit	381



## 6. *Handling Missing Values*

### 4.2 Handling Missing Values in the paths;

- There are some missing values in path 3, 4 and 5.



Filling the NaN's with "**Blank**"



```
df["path3"].fillna('blank', inplace=True)
df["path4"].fillna('blank', inplace=True)
df["path5"].fillna('blank', inplace=True)
```

# 6. *Handling Missing Values*

The Result:

path1	path2	path3	path4	path5
investor	dashboard	blank	blank	blank
investor	investment-portfolio	blank	blank	blank
investor	investment-portfolio	blank	blank	blank

## 7. Labeling the Dataset

```
#Based on our research on the website and on the information given to us by the development  
#team who developed the website, this is the path that leads to investment.  
df_investor=df_concat.loc[(df_concat.path1 == "investor")&(df_concat.path2 == "transactions")  
                          & (df_concat.path3 == "detail")]
```

```
#Here we found out that those who entered the transactions of investment page are diveded  
#into two parts:  
#788 of them "clicked" --> investors  
#1550 did not do any action --> may invest "potential investors"  
df_investor['event_type'].value_counts()
```

```
no action    1550  
click        788  
Name: event_type, dtype: int64
```

- **Investor condition:**

Users who entered the `/investor/transactions/detail` and they clicked.

`path1 == "investor" AND path2 == "transactions" AND`

`path3 == "detail" AND event_type == 'click'`



## *7. Labeling the Dataset*



- **Potential Investor condition:**

1. Users who entered the `/investor/transactions/detail` and they did not do any action.

`path1 == "investor" AND path2 == "transactions" AND`

`path3 == "detail" AND event_type == 'no action'`

2. Users who entered `/investor/investment/.../form-step1` and they filled and submitted the investment form.

`path1 == "investor" AND path2 == "investment" AND`

`path4 == "form-step1" AND event_type == 'submit'`

# 7. Labeling the Dataset

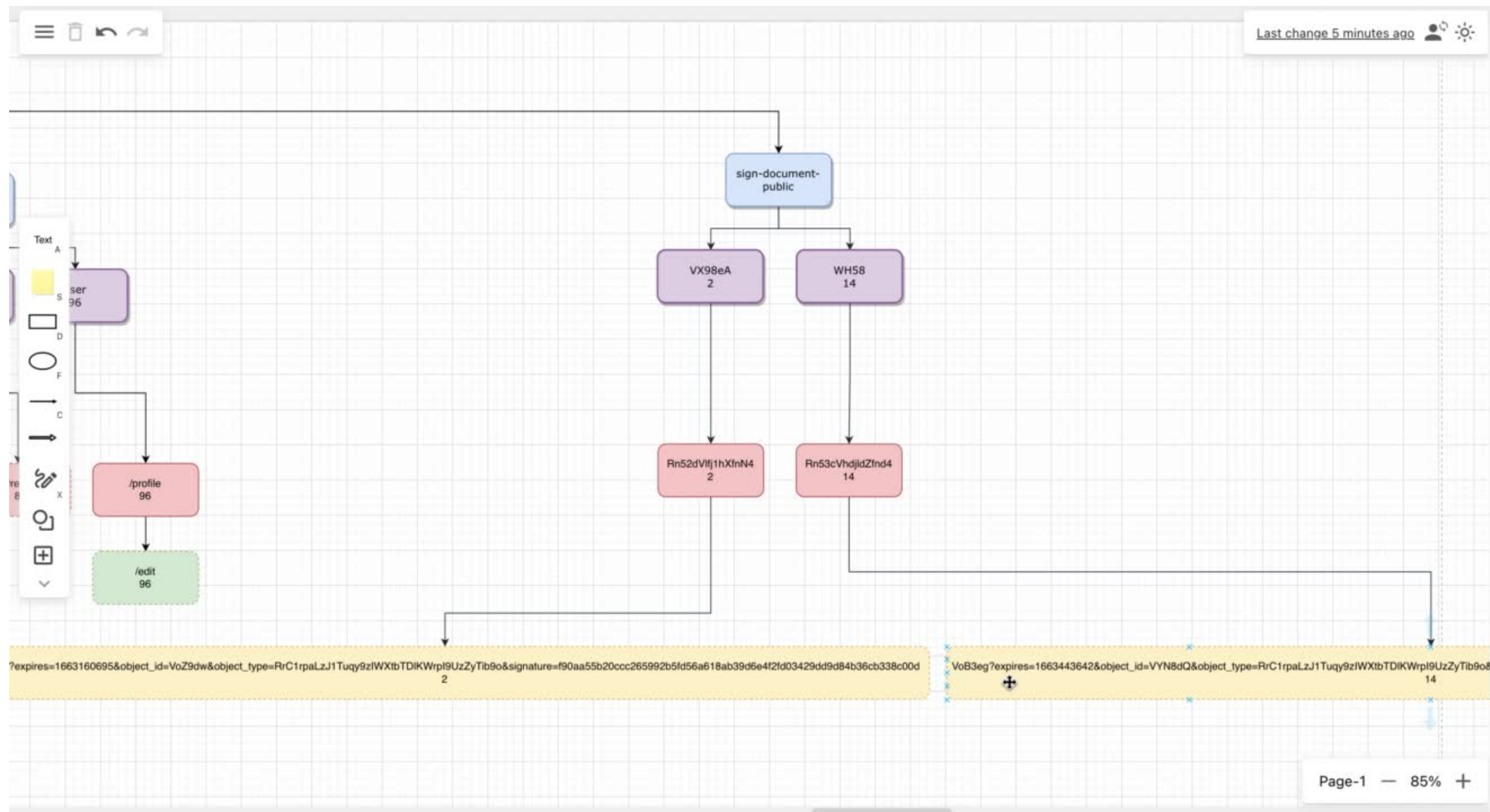
## The Result:

duration_hours	duration_minutes	duration_seconds	invest
0.37	22.17	1330.0	No
0.16	9.88	593.0	No
0.80	47.72	2863.0	No

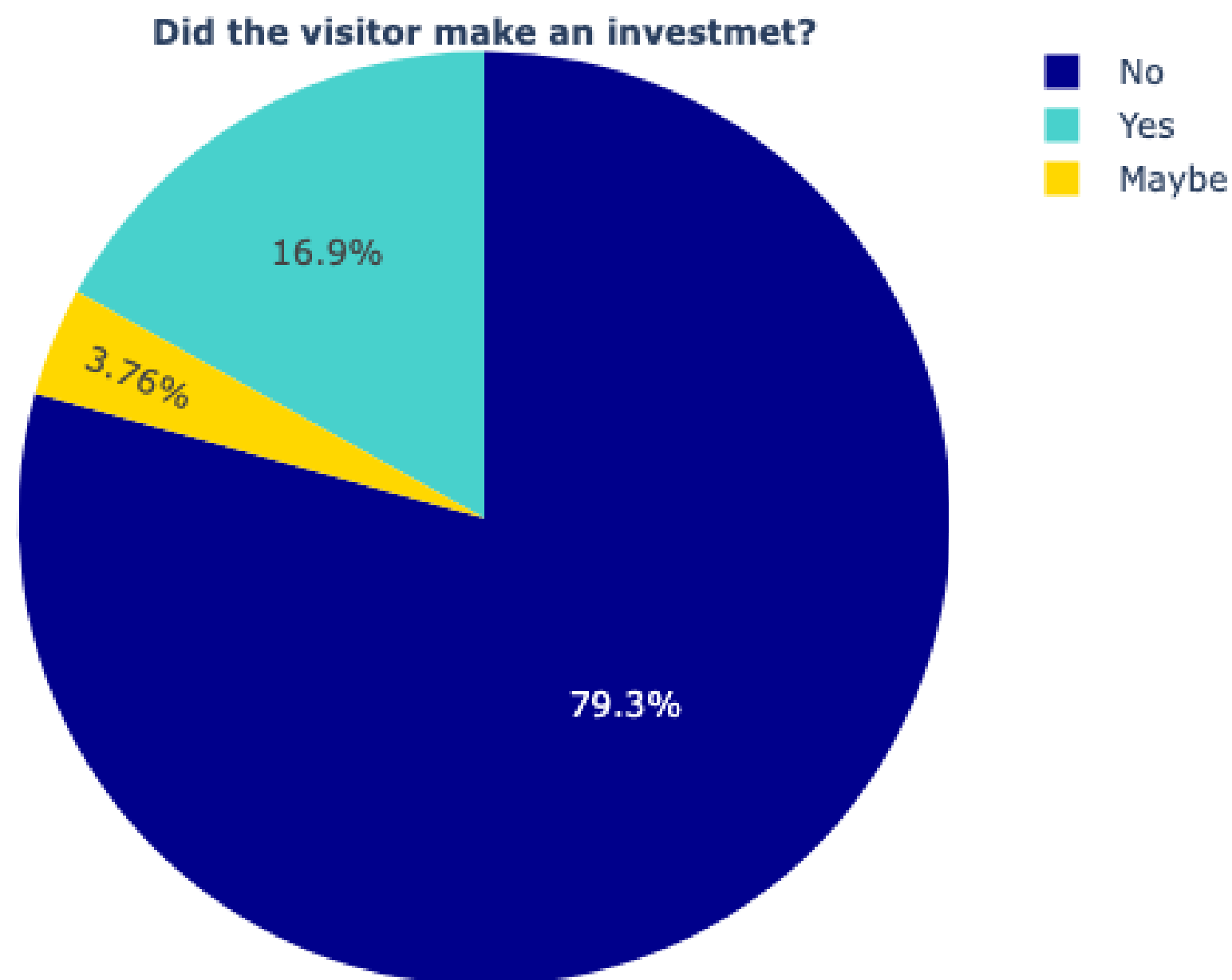
No	2339
Yes	499
Maybe	111

# *Exploratory Data Analysis*

# Paths visual tree



# What is the type of website visitation?



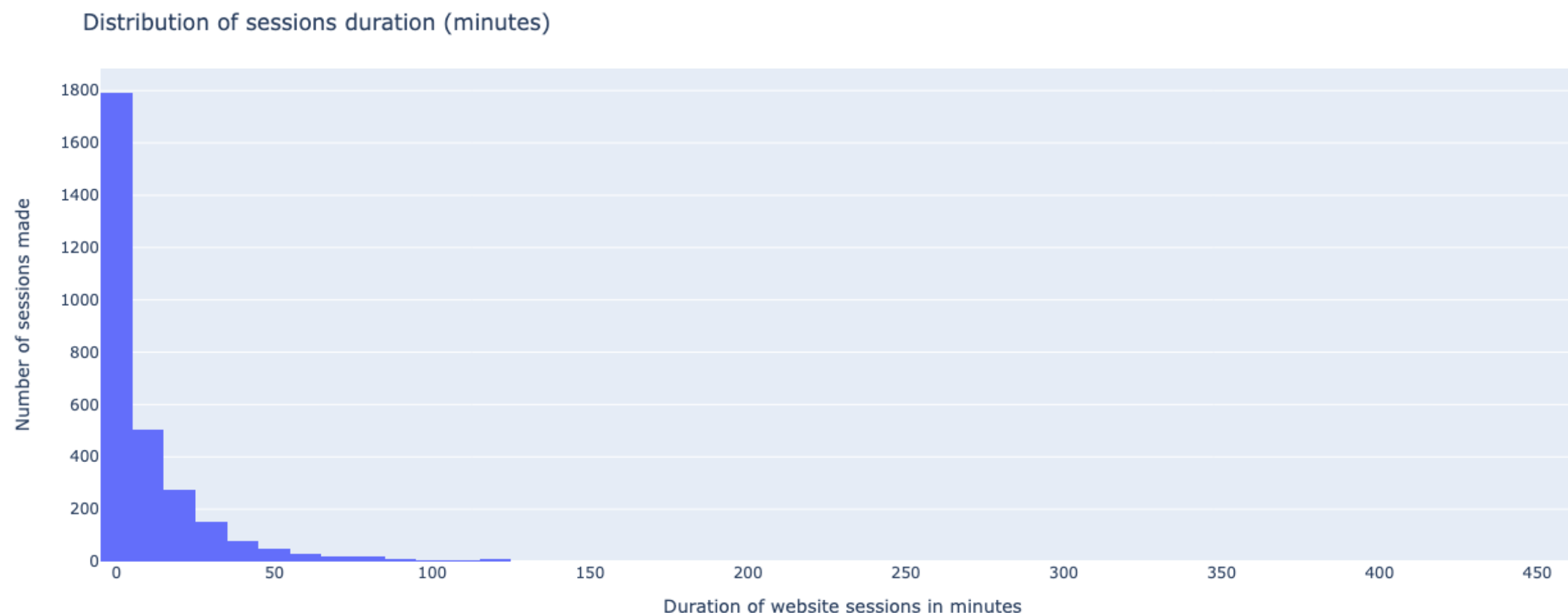
## Key insights:

- **Majority of visitations** on the period on the analysis **did not make an investment**, where they represent **79%**
- **17% represents visitors who made a successful investment**
- While **4% represents visitors who tying to initiate an investment**, however they dropped out where we will call them the (Potential investors)





# What was the duration of the visits?

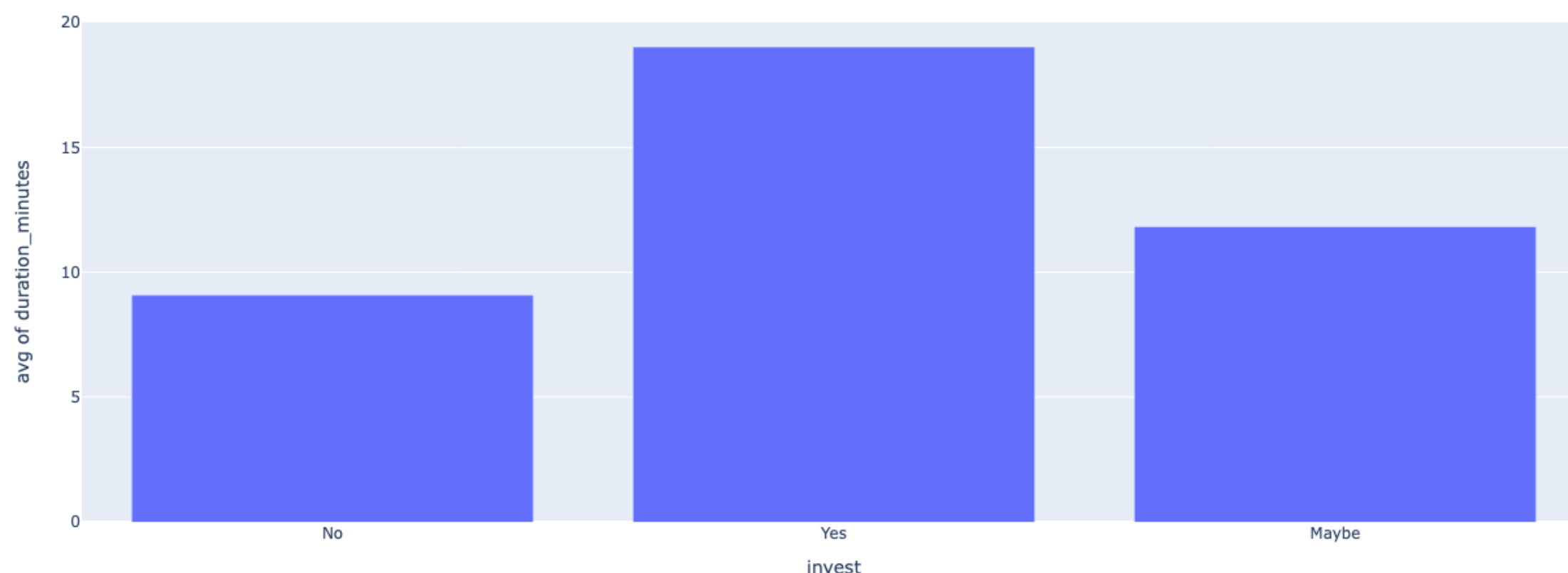


## Key insights:

- Majority of website visits remained for less than 5 minutes



# In-depth view: Does investors stay less or more duration wise?



## Key insights:

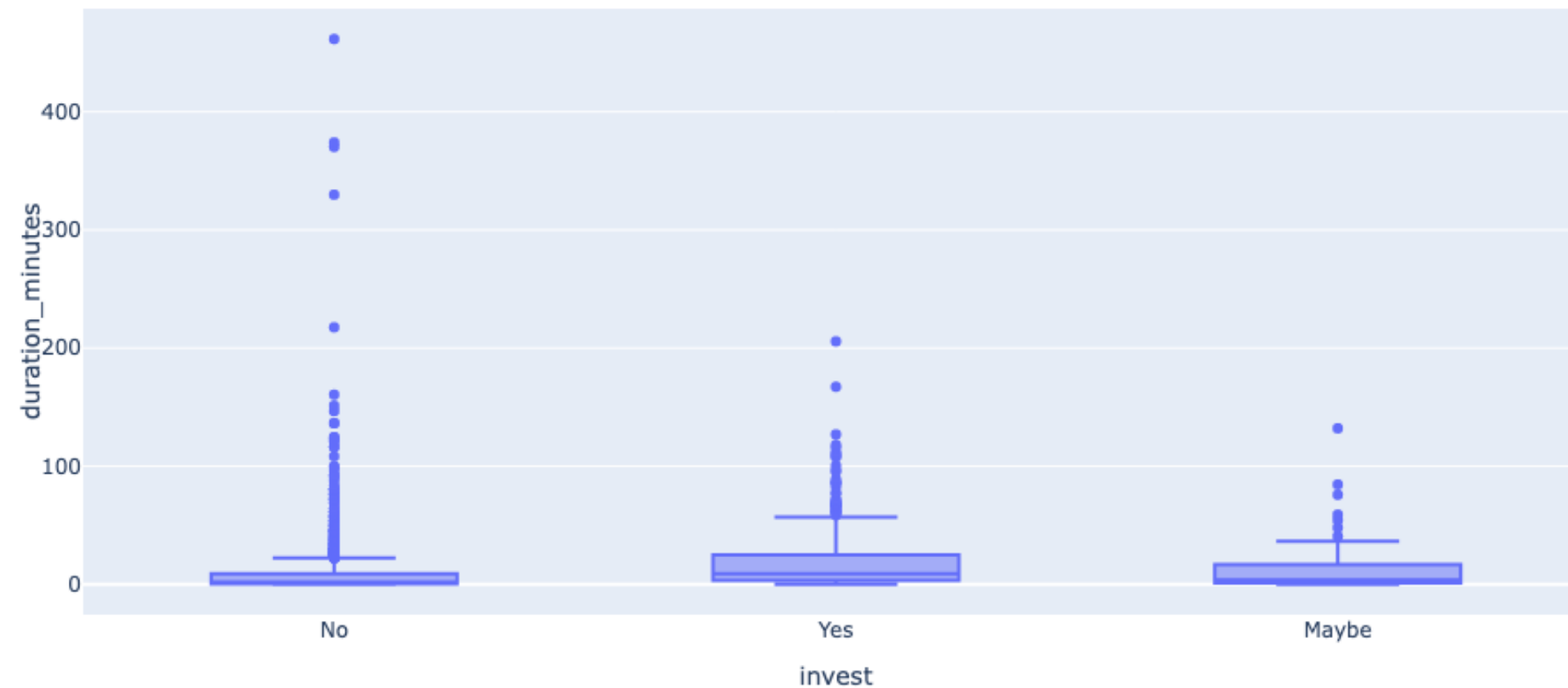
- **Investors have the highest average of sessions duration staying on average 19 minutes**
- **Followed by the Potential investors visitors with ~ 11 minutes.**
- **The non-investors visitors staying on the website for around 9 minutes on average.**



# In-depth view: Does investors stay less or more duration wise (excluding outliers)



Distribution based on sessions duration and investment



**Investors**

**9  
mins**

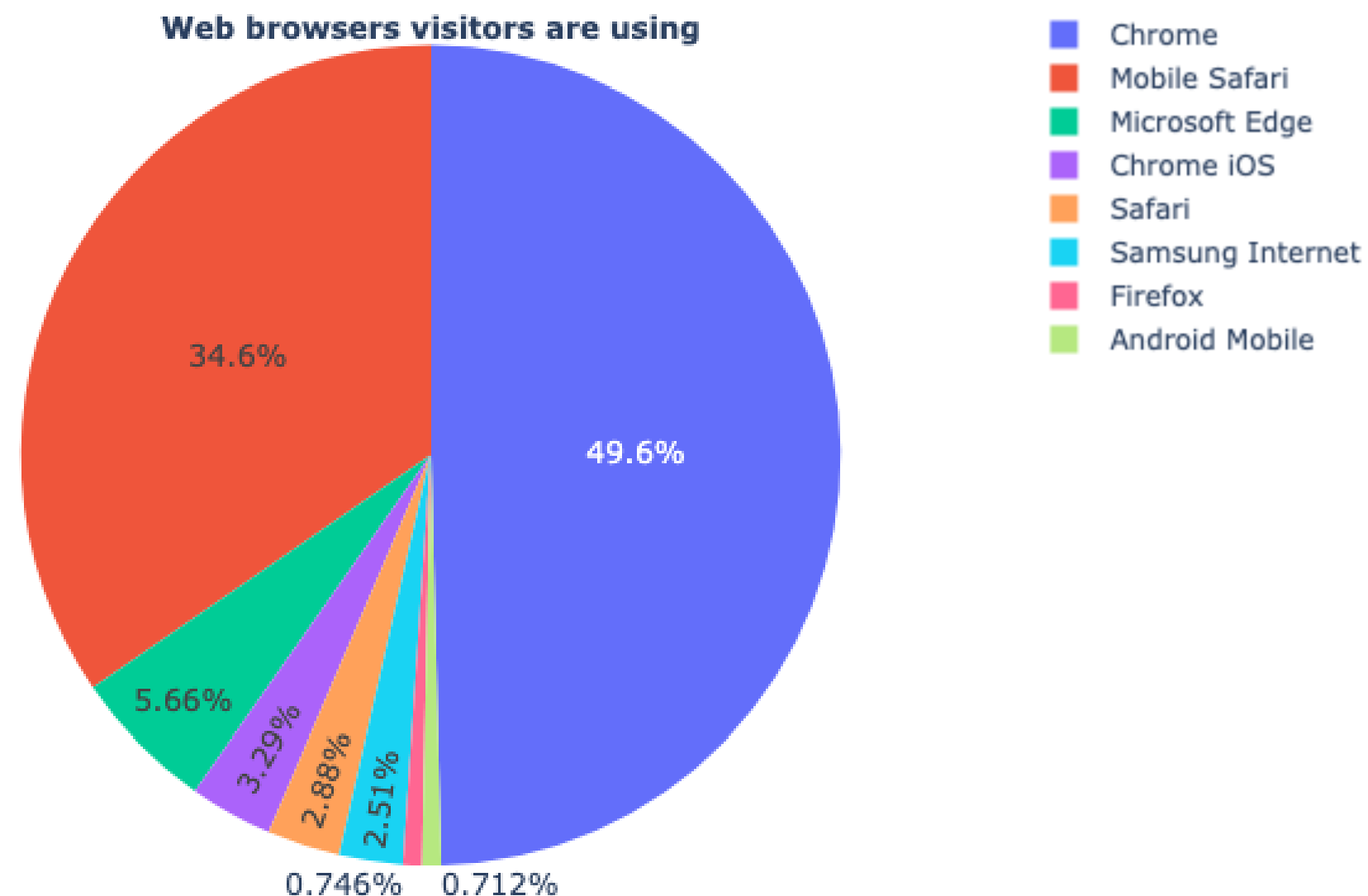
**Potential investors**

**4  
mins**

**Non-Investors**

**2  
mins**

# Browsers visitors are using through their website visitation?



## Key insights:

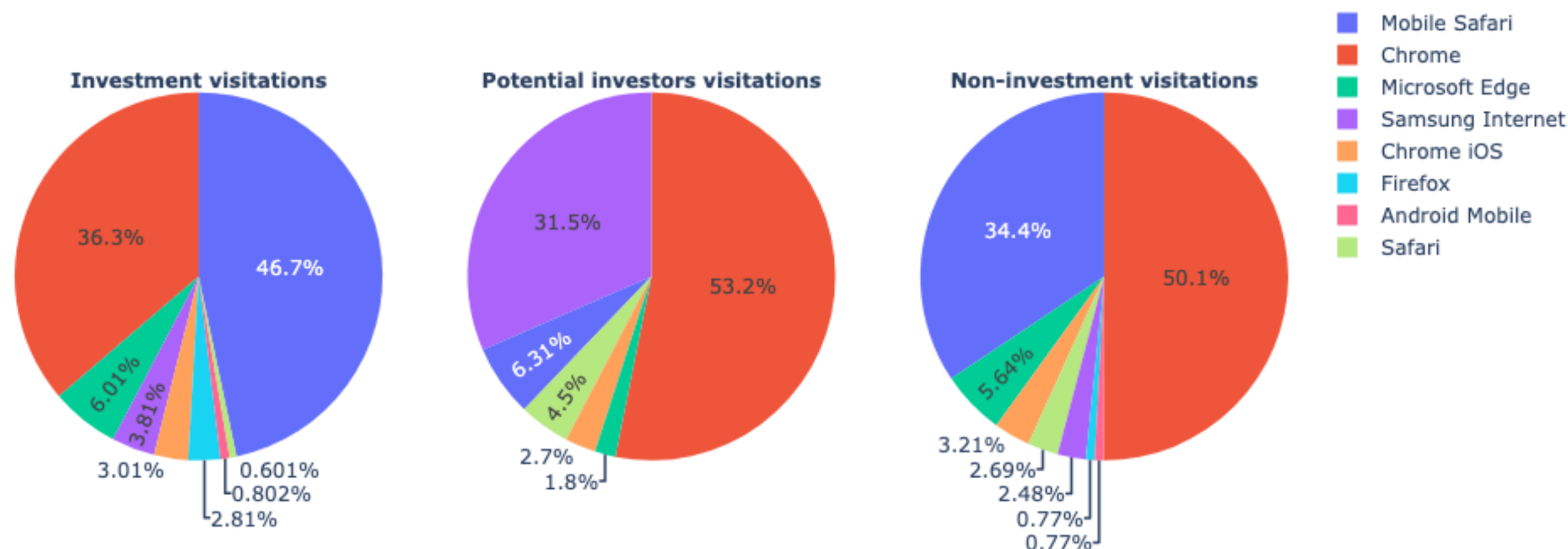
- **Half of the website visitations were using Chrome** as their web browser when browsing the website
- Followed by **Safari users counting for 34%** of the visitations



# In-depth view: Browsers visitors are using through their website visitation?



Web browsers visitors are using?

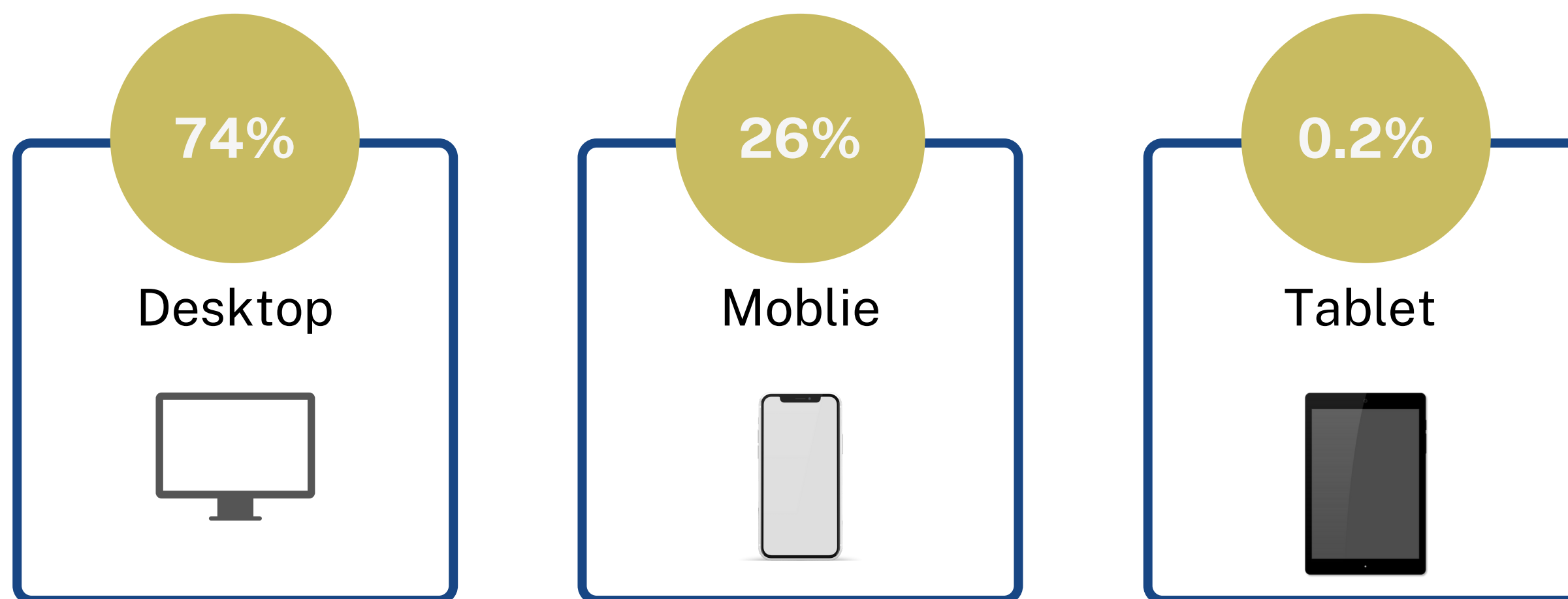


## Key insights:

- ~47% from the investment visitations where using **Mobile Safari**, followed by 36% using Chrome browser
- **More than half of the potential investors** visitations where using **Chrome** as their browser, followed by 32% Samsung internet browser users
- **Half of the non-investment visitations** where using **Chrome** as their browser, followed by Mobile Safari users counting for 35% of users



# Devices users are using when visiting the website?

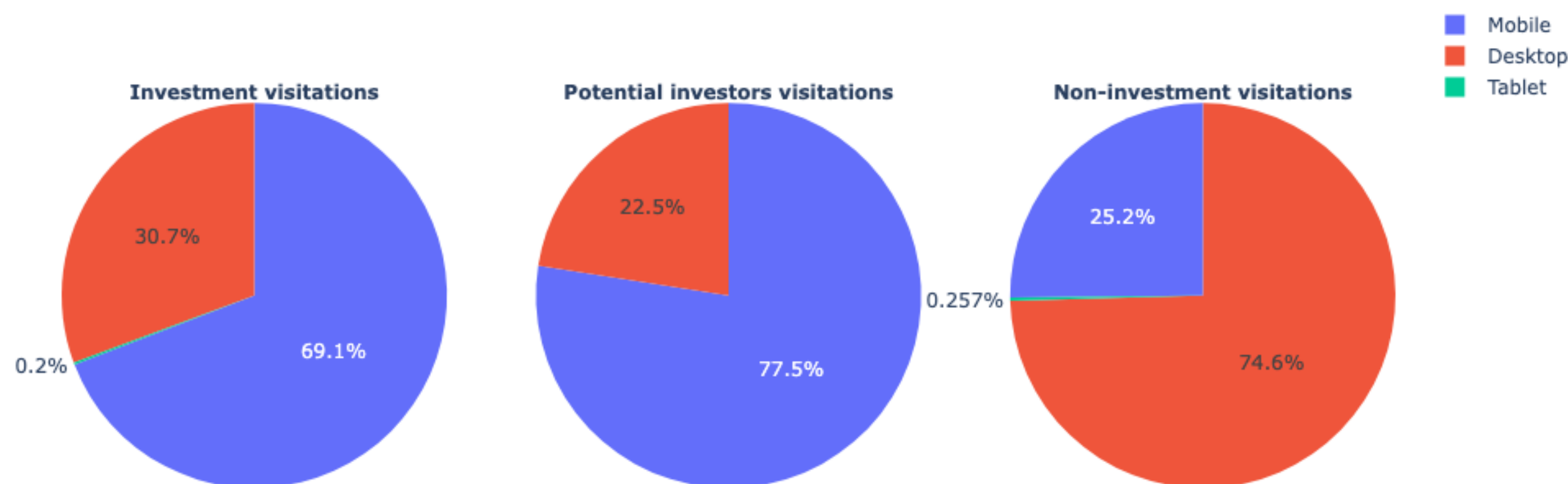




# In-depth view: Devices users are using when visiting the website?



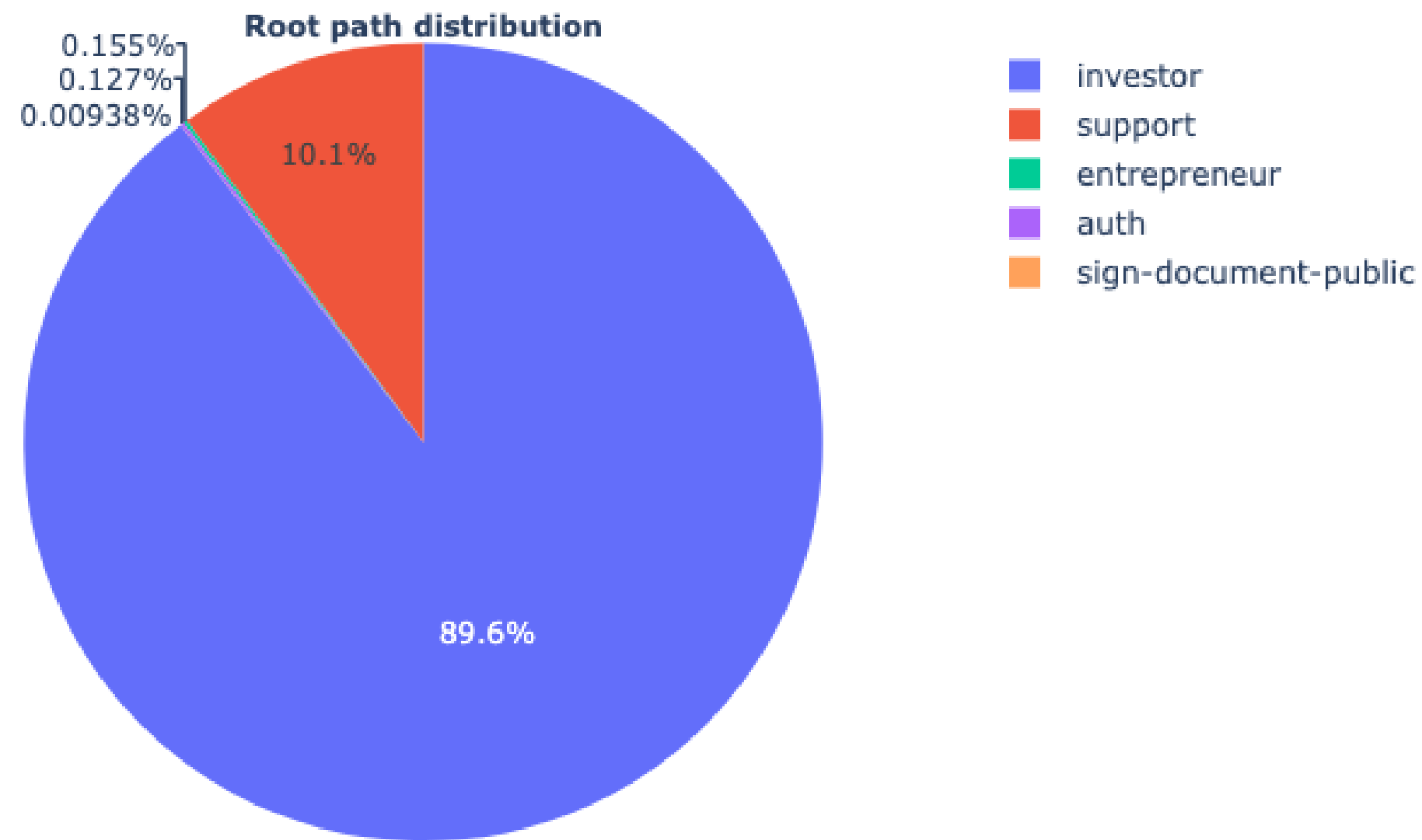
Devices visitors are using?



**Key insights:**

- The majority of Investors & potential investors visitations where using their Mobiles
- 75% of the Non-investment visitations they where using their Desktops

# Root path distribution



## Key insights:

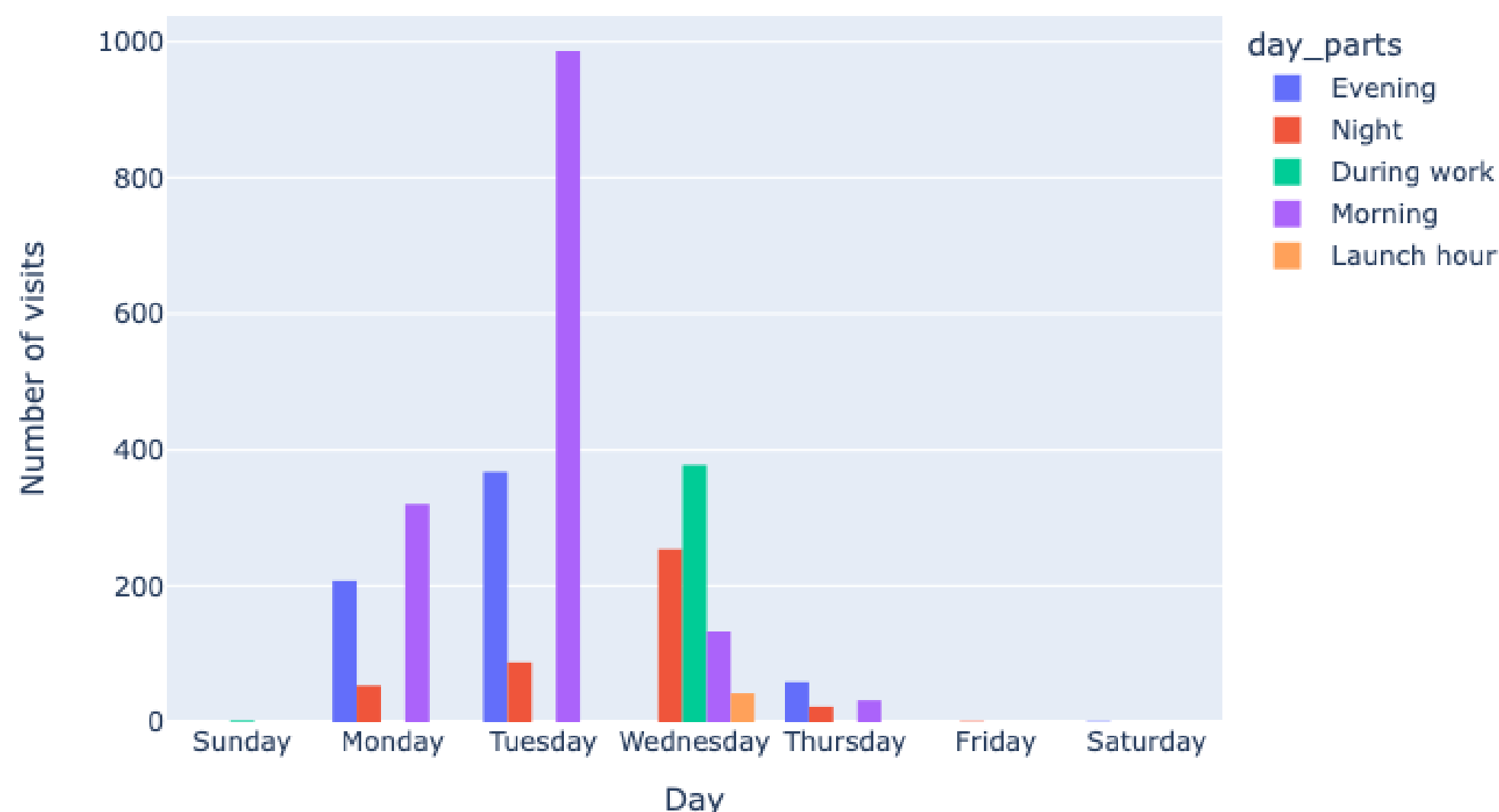
- **Majority of visits where at the investor web path 90%** (i.e., users looking at their investment profiles, wallets and investment opportunities)
- **Followed by the support web path at 10%** (i.e., where issues are raised, following up with previous issues raised)





# Visitations around the week and by the part of the day

User visitation throughout the week

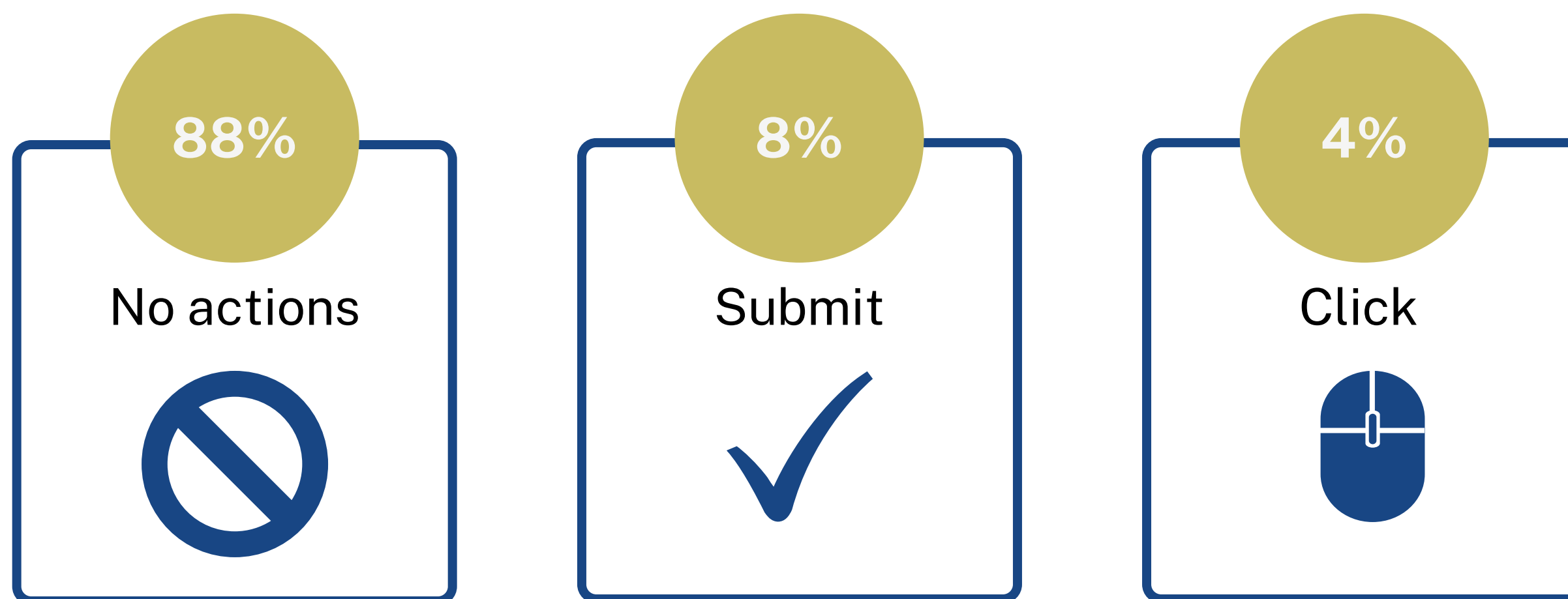


## Key insights:

- Thursday morning had the highest visitation counting for around 1000 visits
- Weekends had the lowest visitation, nearly no visitations were counted



# Type of window action

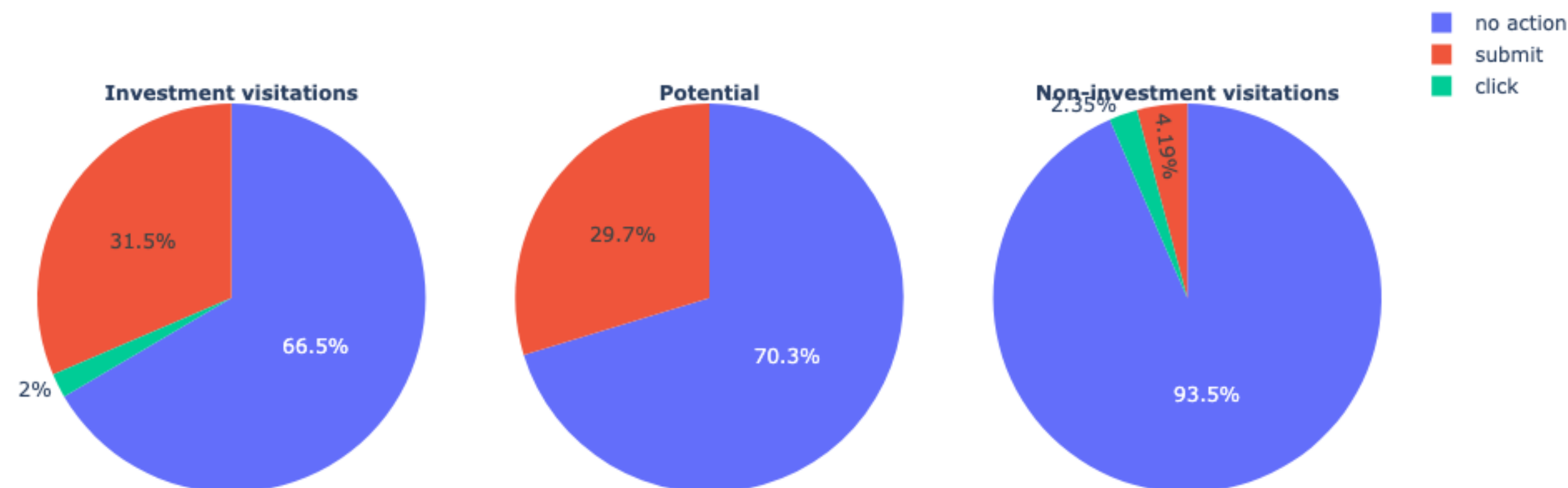




# In-depth view: Type of window action?



Type of window action



## Key insights:

- Nearly all of the non-investment visitations had no window action.
- Investment and potential investors visitations had submit window action as the majority.

# Average number of clicks by type of visit



**Investors**  
**80 clicks on average**



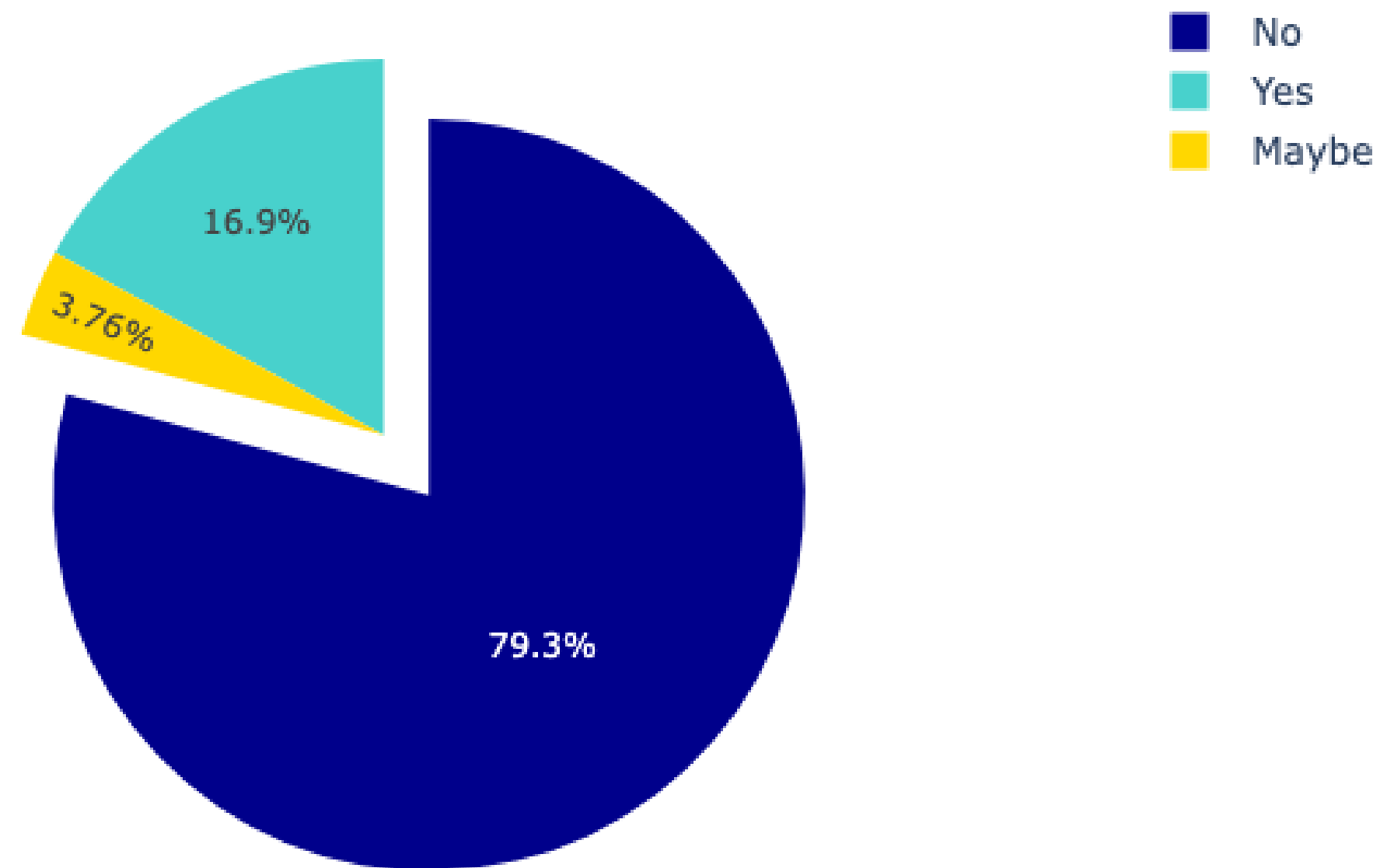
**Potential investors**  
**47 clicks on average**



**Non-Investors**  
**21 clicks on average**

# Who are the investors & potential investors and how can we predict them?

Who are they and how can we predict them?





فنتك السعودية  
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# *Dashboards*

# *Machine Learning Models*

# Feature Engineering

## Label Encoding

- week\_label
- type
- browser
- device\_type
- os
- day\_parts
- event\_type
- day\_name
- path1
- path2
- path3

## Mapping

### Invest

**No** → **0**

**Yes** → **1**

**Maybe** → **2**

## Scaling

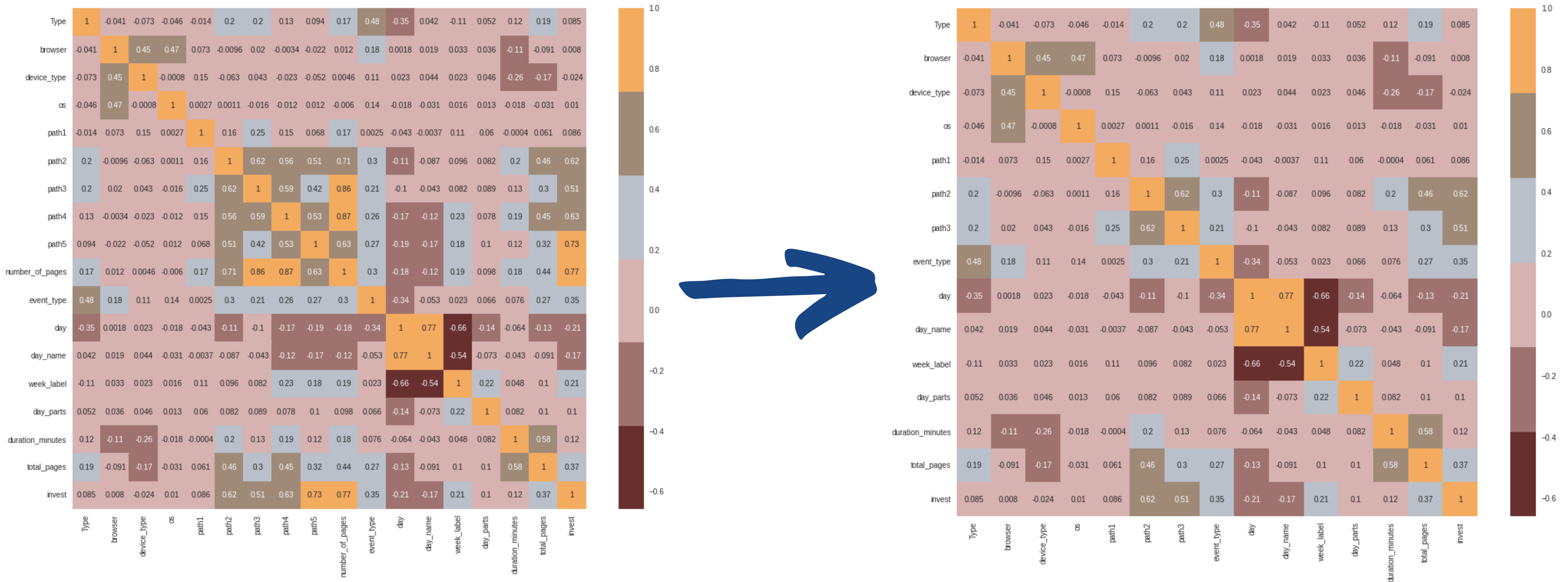
- duration\_minutes
- total\_pages
- day
- path2
- path3

## Over-Sampling

	Before		After
0	1892	→	1892
1	384	→	1892
2	83	→	1892



# Feature Selection



# ML Models

85%

**Decision Trees**

86%

**k-Nearest  
Neighbors**

90%

**Support Vector**

92%

**Gradient Boosting**

93%

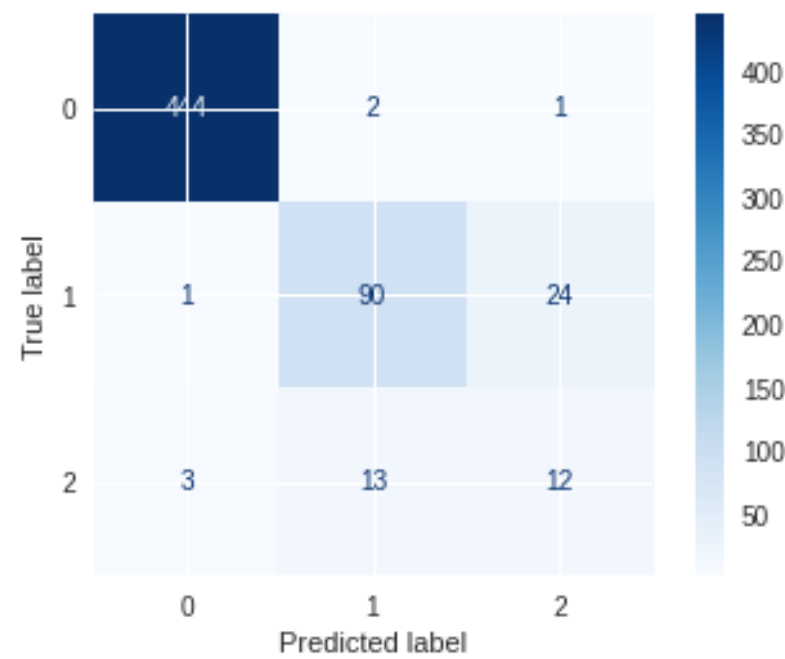
**Random Forest**

93%

**XGBoost**

# Models Evaluation

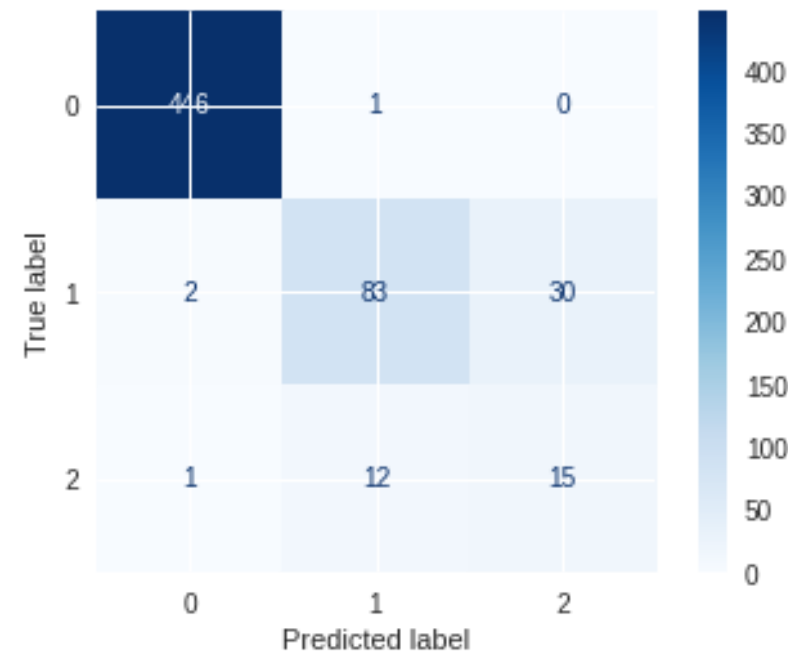
## Random Forest



Classification Report for Random Forest Classification model:

	precision	recall	f1-score	support
0	0.99	0.99	0.99	447
1	0.86	0.78	0.82	115
2	0.32	0.43	0.37	28
accuracy			0.93	590
macro avg	0.72	0.73	0.73	590
weighted avg	0.93	0.93	0.93	590

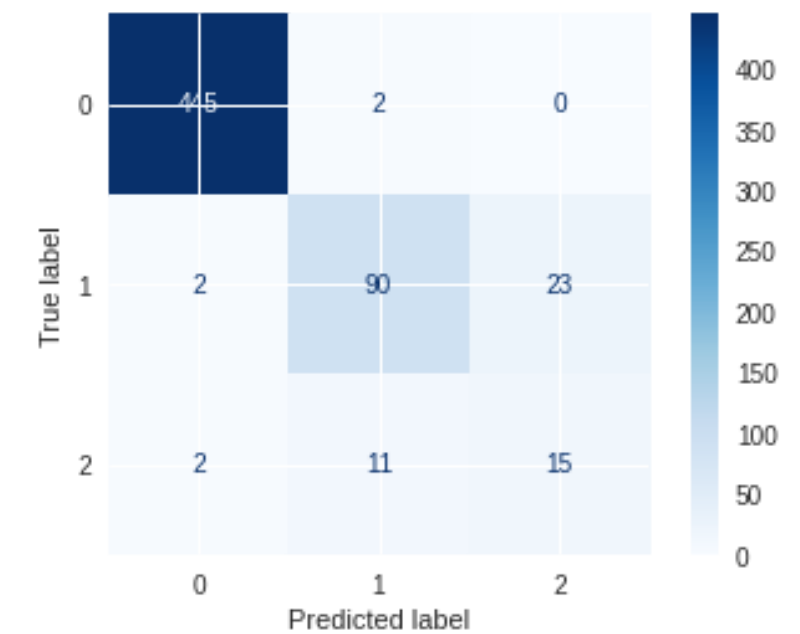
## Gradient Boosting



Classification Report for Gradient Boosting Classification model:

	precision	recall	f1-score	support
0	0.99	1.00	1.00	447
1	0.86	0.72	0.79	115
2	0.33	0.54	0.41	28
accuracy			0.92	590
macro avg	0.73	0.75	0.73	590
weighted avg	0.94	0.92	0.93	590

## XGBoost



Classification Report for XGBoost Classification model:

	precision	recall	f1-score	support
0	0.99	1.00	0.99	447
1	0.87	0.78	0.83	115
2	0.39	0.54	0.45	28
accuracy			0.93	590
macro avg	0.75	0.77	0.76	590
weighted avg	0.94	0.93	0.94	590

# Model Selection

- **XGBoost**

Classification Report for XGBoost Classification model:

	precision	recall	f1-score	support
0	0.99	1.00	0.99	447
1	0.87	0.78	0.83	115
2	0.39	0.54	0.45	28
accuracy			0.93	590
macro avg	0.75	0.77	0.76	590
weighted avg	0.94	0.93	0.94	590

- **Baseline Model**

No	0.79315
Yes	0.16921
Maybe	0.03764

# Recommendations



## **Potential investors' recommendation system**

Create an automated dashboard based on behavioral parameters, where potential investors are flagged, for marketing purposes to target the potential investors (e.g., Advertising via email, SMS, pop-up windows related to the undecided investment opportunities, with the investment important KPIs)



## **User unique id**

Collect the user's unique id, as part of the user logs collected (i.e., user's frequency of visitation, user frequency of visitation for a specific investment opportunity)



## **User's demographics**

Tie dataset with Google Analytics collected data and utilize its benefits to provide better understanding of website users



## **Attract new customers (Investors),**

Increase incoming new traffic, leaning from current investors characteristics to attract similar new investor

# *Future Work and Conclusion*

**1**

**Creating a package to handle the preprocessing of user activity logs datasets.**

**2**

**Create a more customizable model using the users ID and user demographics.**

*Thank you*

———— For your attention

*Desert Ninjas*