Certification CDSD

April 1st, 2025 – Louis Le Pogam

Agenda

- Block 1 - Build & Manage a Data Infrastructure – Kayak Project
- Block 2 – Exploratory Data Analysis – Steam Project
- Block 3 – Supervised Machine Learning – Conversion Project
- Block 3 – Unsupervised Machine Learning – Uber Pickups Project
- Block 4 – Deep Learning – AT&T Spam Detection Project
- Block 5 – Deployment – Getaround Project
- Block 6 – Lead a Data Project – Offensive Speech Recognition

Project Reminder

Project

- Kayak Marketing Team would like to create a holiday recommendation application based on :
  - Weather
  - Hotels in the area
  - Based on real-time data

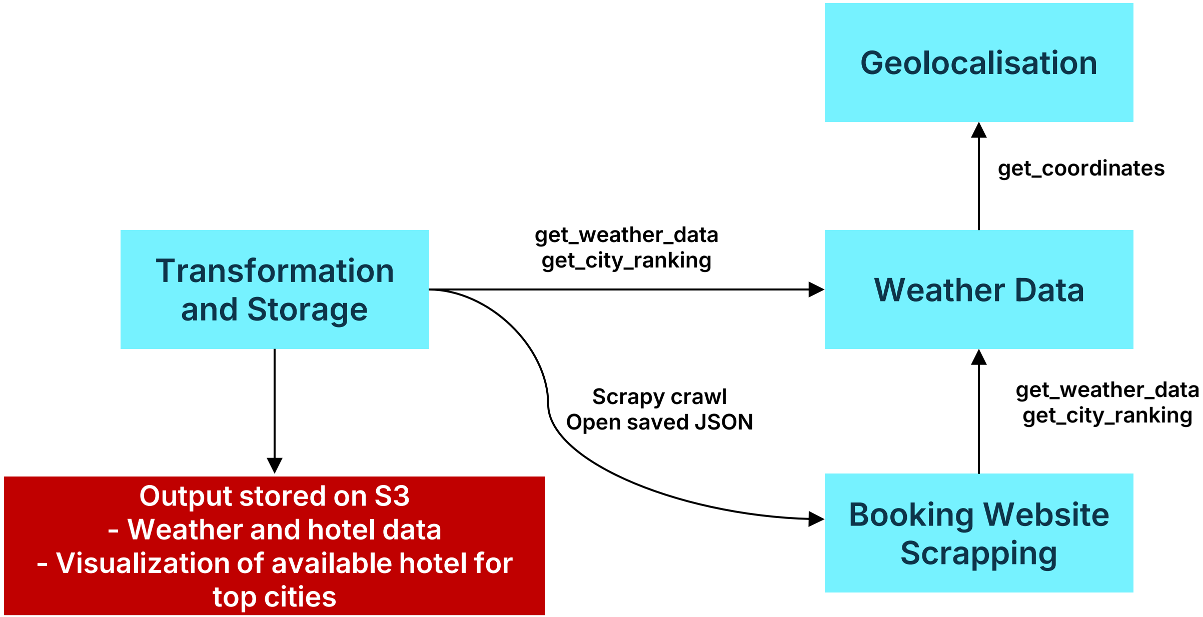
Goal

- The data are not available and the goal is to get the needed data as following:
  - Scrape data from destinations.
  - Get weather data from each destination.
  - Get hotels' info about each destination.
  - Store all the information above in a data lake.
  - Extract, transform and load cleaned data from your datalake to a data warehouse.

4 building blocks for the data scrapping model

	Description
1 Geolocalisation	• Processing of list of cities by obtaining GPS coordinates and INSEE codes with API • Saving all data to CSV for weather queries
2 Weather Data	• Retrieving 7-day weather forecasts for cities based on INSEE codes • Ranking cities based on customizable criteria and creates aggregated rankings • Saving ranked list based on number of favorable days to CSV
3 Booking Website Scrapping	• Taking the top 5 cities based on previous analysis • Searching for hotels in each city available on booking.com • Saving in into a JSON file
4 Transformation and Storage	• Processing previous data by removing low-quality hotels and identifying consecutive night availability • Creating interactive visualizations and uploads all results to AWS S3 storage.

All 4 blocks are used to get the final output



The weather module scraps the weather by city and ranks them based on defined ideal conditions

get_weather_data

- Reads a list of French cities from a file based on the INSEE code
- Connects to a weather service (Meteo Concept API) for each city
- Gathers 7-day forecasts including:
  - Daily rainfall predictions
  - Temperature highs and lows
  - Wind speed information
- Organizes everything in a DataFrame where each row represents one day's weather forecast for a specific city

Output : DataFrame with weather prediction for eachs targeted cities

get_city_ranking

- Flags Less-Than-Ideal Weather Days when:
  - Too hot / Too cold / Too rainy / Too windy
  - Default value: 35°C / 20°C/ 10mm / 50 km/h
  - Can be changed depending on the season
- Calculates Problem Days for each city over the forecast period
- Ranks Cities by:
  - Fewest problematic weather days
  - Lowest average rainfall as tiebreaker

Output : DataFrame with a prioritized list of cities with optimal weather conditions for travelers

700 pages scrapped to get the available hotels of the next 7 days

Get Weather Data

- Open file of ranked cities and select top 5

Get URL for each city and date

- Loop on each cities and for the next 7 days
- Get the URL of the search for each city x date

Get the Details from the Search Results

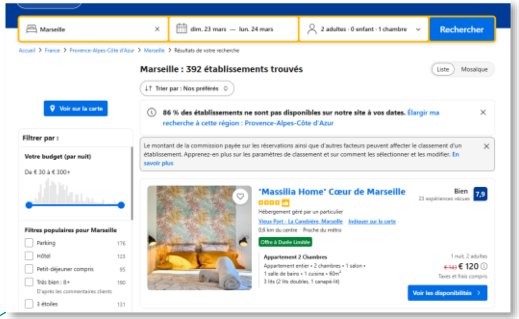
- For each results on the search page, get the main info : Name, ranking, price, distance...
- Keep only 20 first results to limit output size

Open each page and get detailed data

- For each hotel, open the hotel page to get detailed info : Adress, latitude, longitude, description, URL...

Store Data in a JSON file

- Gather all data in one JSON
- 700 pages scrapped (5 cities x 20 hotels x dates x 7 dates) in 6 minutes



Marseille | dim. 23 mars — lun. 24 mars | 2 adultes · 0 enfant · 1 chambre | Rechercher

Accueil > France > Provence-Alpes-Côte d'Azur > Marseille > Résultats de votre recherche

Marseille : 392 établissements trouvés

Liste | Mosaïque

Trier par : Nos préférés

Voir sur la carte

86 % des établissements ne sont pas disponibles sur notre site à vos dates. Élargir ma recherche à cette région : Provence-Alpes-Côte d'Azur

Le montant de la commission payée sur les réservations ainsi que d'autres facteurs peuvent affecter le classement d'un établissement. Apprenez-en plus sur les paramètres de classement et sur comment les sélectionner et les modifier. En savoir plus

Filtrer par :

Votre budget (par nuit)

De € 30 à € 300+

Filtres populaires pour Marseille

□ Parking	176
□ Hôtel	123
□ Petit-déjeuner compris	95
□ Très bien : 8+ D'après les commentaires clients	190
□ 3 étoiles	131

"Massilia Home" Cœur de Marseille

Bien 7,9 23 expériences vécues

Hébergement géré par un particulier

Vieux Port - La Canebière, Marseille · Indiquer sur la carte

0,6 km du centre · Proche du métro

Offre à Durée Limitée

Appartement 2 Chambres

Appartement entier • 2 chambres • 1 salon • 1 salle de bains • 1 cuisine • 60m²

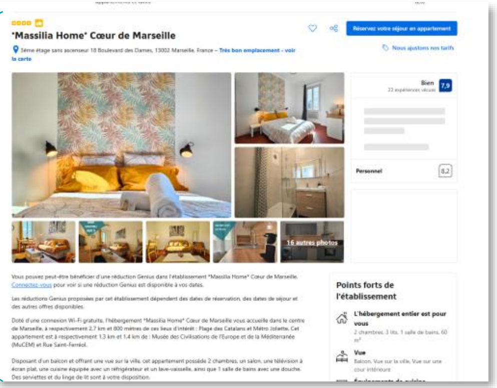
3 lits (2 lits doubles, 1 canapé-lit)

1 nuit, 2 adultes

€ 143 € 120

Taxes et frais compris

Voir les disponibilités



"Massilia Home" Cœur de Marseille

Réservez votre séjour en appartement

3ème étage sans ascenseur 18 Boulevard des Dames, 13002 Marseille, France – Très bon emplacement - voir la carte

Nous ajustons nos tarifs

Bien 7,9 23 expériences vécues

Personnel 8,2

16 autres photos

Vous pouvez peut-être bénéficier d'une réduction Genius dans l'établissement "Massilia Home" Cœur de Marseille. Connectez-vous pour voir si une réduction Genius est disponible à vos dates.

Les réductions Genius proposées par cet établissement dépendent des dates de réservation, des dates de séjour et des autres offres disponibles.

Doté d'une connexion Wi-Fi gratuite, l'hébergement "Massilia Home" Cœur de Marseille vous accueille dans le centre de Marseille, à respectivement 2,7 km et 800 mètres de ces lieux d'intérêt : Plage des Catalans et Métro Joliette. Cet appartement est à respectivement 1,3 km et 1,4 km de : Musée des Civilisations de l'Europe et de la Méditerranée (MuCEM) et Rue Saint-Ferréol.

Disposant d'un balcon et offrant une vue sur la ville, cet appartement possède 2 chambres, un salon, une télévision à écran plat, une cuisine équipée avec un réfrigérateur et un lave-vaisselle, ainsi que 1 salle de bains avec une douche. Des serviettes et du linge de lit sont à votre disposition.

Points forts de l'établissement

L'hébergement entier est pour vous

2 chambres, 3 lits, 1 salle de bains, 60 m²

Vue

Balcon, Vue sur la ville, Vue sur une cour intérieure

All outputs are stored on a AWS S3 and ready to be used

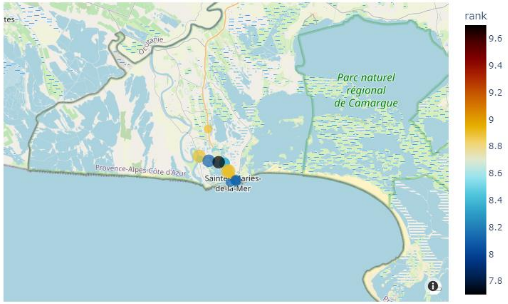
Output 1 : All database

Output 2 : Visualization of available hotels for each top 5 cities

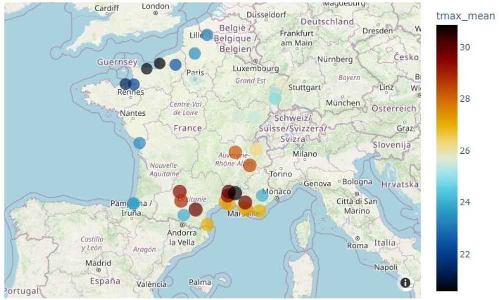
Output 3 : Overview of average temperature for the next 7 days of all targeted cities

- Dataframe with weather forecast
- Dataframe with City Ranking
- JSON with all booking.com data scrapped

Hotels available in Saintes Maries de la mer



Average max temperature for the next 7 days per city



All outputs are stored in a S3 and ready to be extracted and used

Q&A

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Project Reminder

UBISOFT

Project

- Ubisoft is requesting an analysis on the games available on Steam to create the perfect game

Goal

- The target is to identify and analyze the key factors influencing video game popularity and sales through a multi-dimensional market analysis examining:
    - Video games market trends
    - Market segmentation
    - Business model analysis
    - Ubisoft positioning

Key Insights

Steam sales macro-overview

There are around 55k games available on Steam with strong growth between 2012 and 2020 but limited ever since, especially following covid

- The CAGR of the number of games was 77.2% p.a. between 2012 and 2017 and +4.4% p.a. between 2017 and 2022
- The growth were stopped in 2022 where there were a huge dropped in number of games released this year
- We can assume that this was following the decrease in development in the covid period in 2020-2021 that delayed games supposed to be launched in 2022

Steam has strongly contributed to market access of small developers

- The #1 genre is Indie game
- Large majority of developer and published have created between 1 and 3 games
- The growth in number of games has been driven by games with below 20k owners

There is a high risk of over-supply and bankruptcy among small developers

- Most of the games have less than 20k owners
- All this small games have a very low number of rating, which would limit the reach to new customers
- In 2022, Indie Genre games have known one of the highest decrease in number of games released

After a massive increase between 2012 of 2017, the number of new release is getting slower with a reduction post covid

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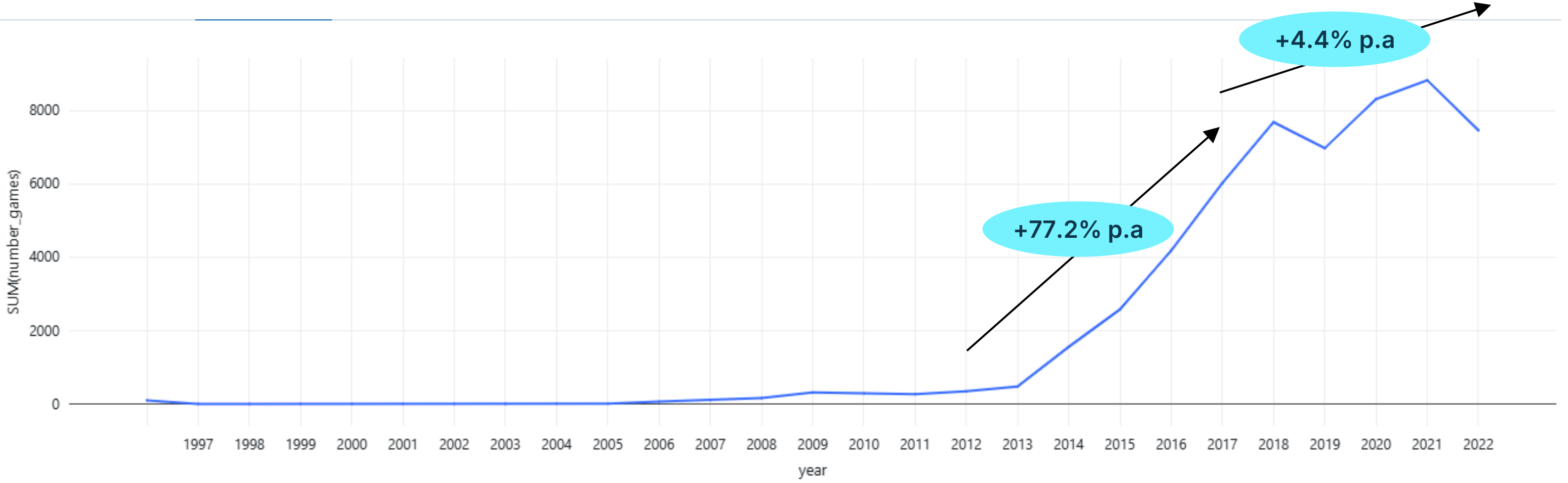
Number of new games in Steam |

in number of games, 1997-2023



Steam has allowed all developer to release then game leading to a strong growth of small games and a majority of existing games owned by less than 100k players

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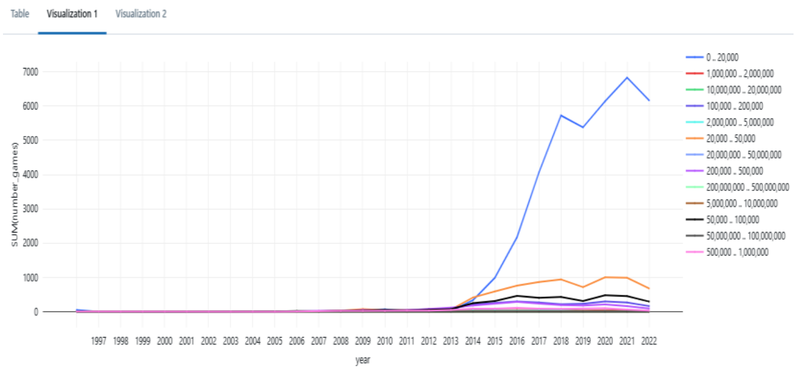
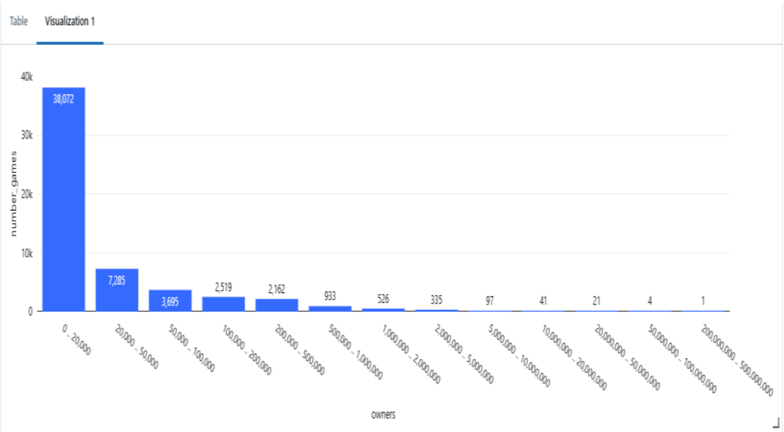
Number of new game in Steam per nbr of owners | in number of games, 1997-2023



Main growth of number of games coming from games owned by less than 20k users

Number of new game in Steam per nbr of owners | in number of games

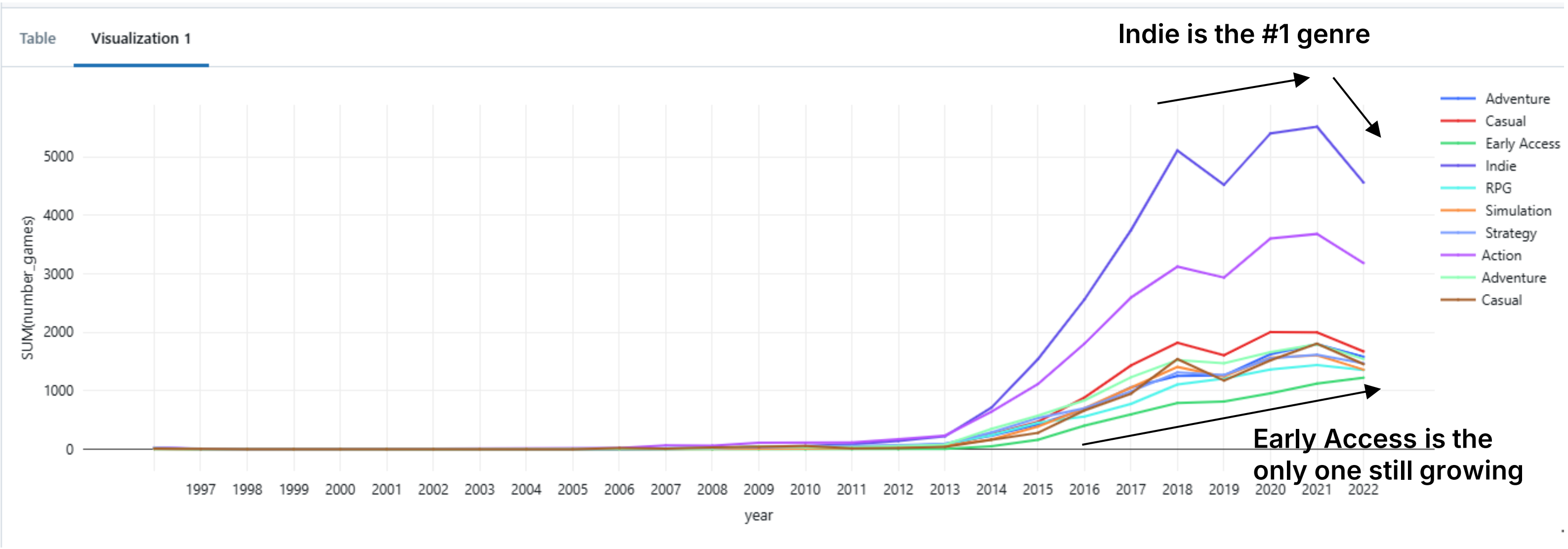


Majorities of game are owned by less than 100k users

Indies is the top 1 genre which has driven the growth but also shown a strong decrease is 2022; Early access still growing to insure game development

Number of genre tagged on each games in Steam |

in number of tags, 1997-2023, one game can have several tag



Indie is the #1 genre

Early Access is the only one still growing

Large majority of developers have released just a couple of games in Steam with a low number of ratings

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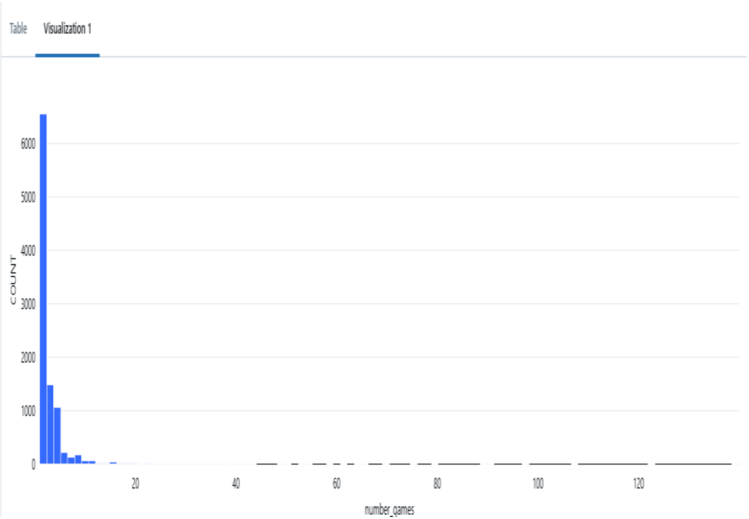
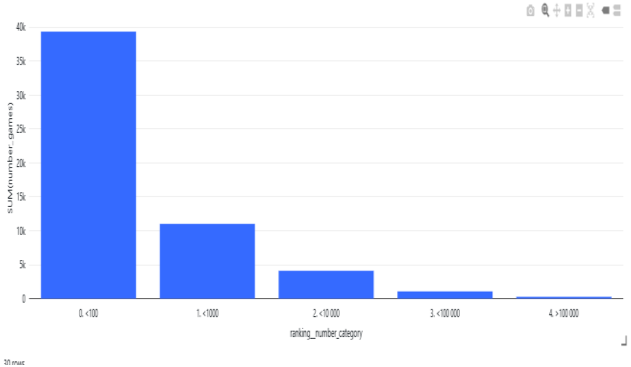
Histogram of number of games per developer | 1997-2023



Main category between 1 and 3 games

Histogram of number of games per number of rating| 1997-2023



70% of games have less than 100 ratings

Key Insights

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Business Model

Overall, the market seems to be split into two main distribution modes with their own business models:

- Free-to-play games rely on the number of concurrent users to generate revenue from in-game sales
- Paid games are driven by game price tags, discounts, and number of owners
- The free-to-play market is highly competitive with a large number of games that do not seem profitable

The F2P market is highly concentrated, with 2 games gathering half of the users and 10 games covering 84% of the total users:

- More than 7.4k free-to-play games have fewer than 100 concurrent users, making it difficult to be profitable
- Only 100 games out of the 7.7k F2P games available have more than 1,000 concurrent users
- Free-to-play game releases strongly decreased between 2020 and 2022

For paid games, there are sub-segments depending on the price tag, which are also very competitive:

- Prices can vary from a few dollars to more than $70 and reflect the production value: the more it costs, the better value for money the player expects
- Based on a hypothesis to be confirmed, there is a direct correlation between price tag and development costs: the higher the production value, the higher the cost
- For each segment, only 15% to 30% of the games appear to be profitable, showing how competitive the market is

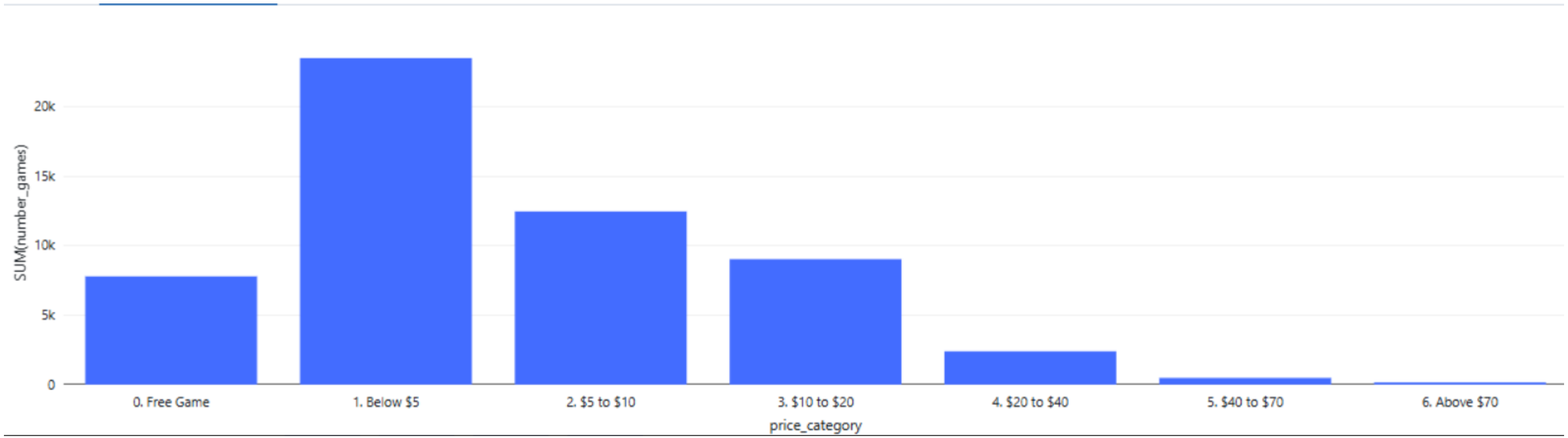
2 different business models : Free to play games and paid games

Number games per price category|

in number of games, 1997-2023,

Free to Play

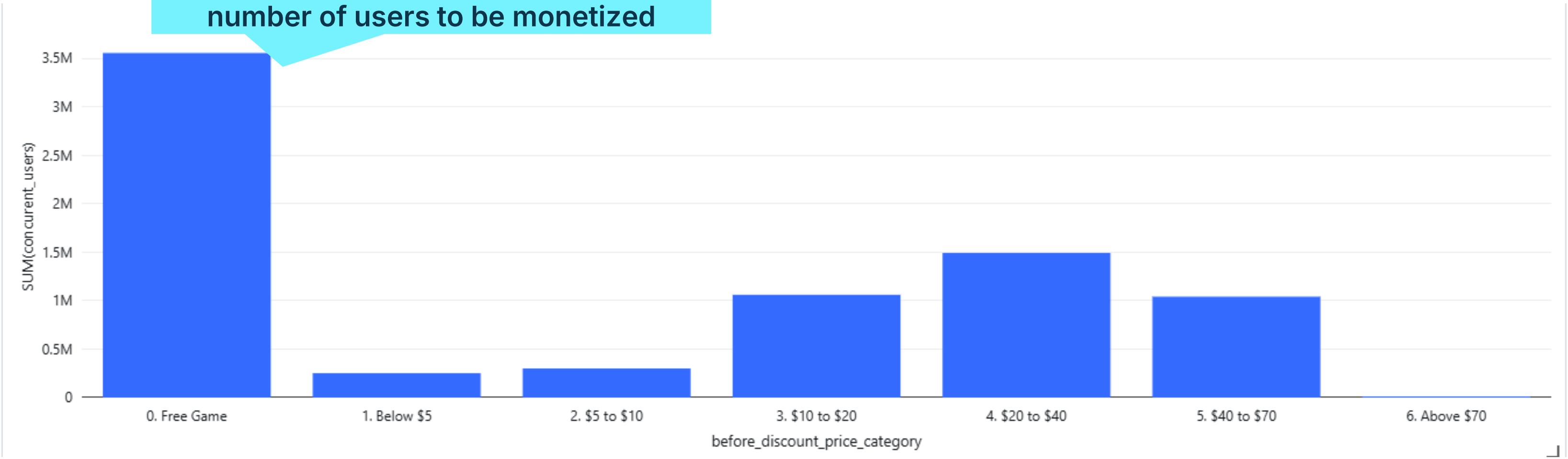
Paid Games



Largest number of concurrent users are on Free to Play games, used for monetization

Number of concurrent users per price category |
in number of games, 1997-2023,

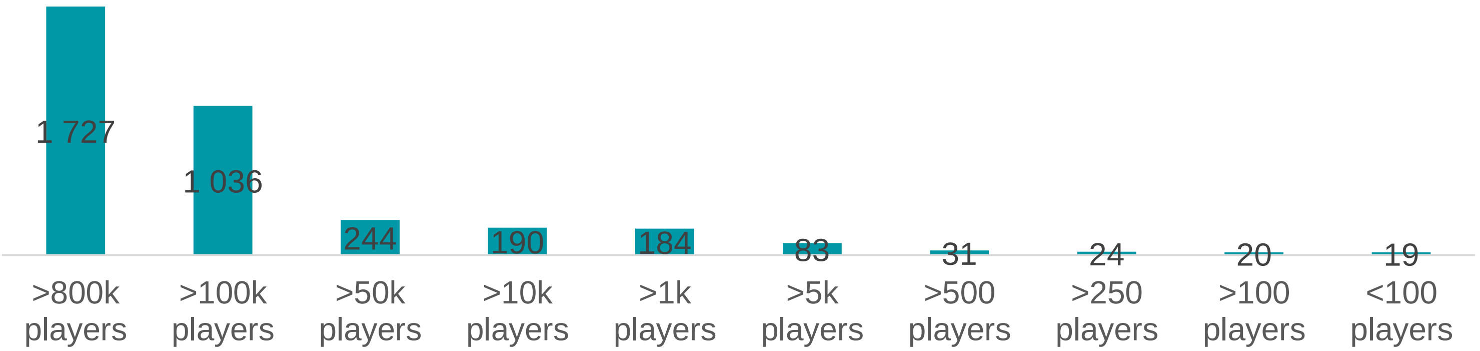
Free to play games driven by the number of users to be monetized



Free to play games is very concentrated as 2 games have 50 % of all users and 6 have 80% of the total

UBISOFT

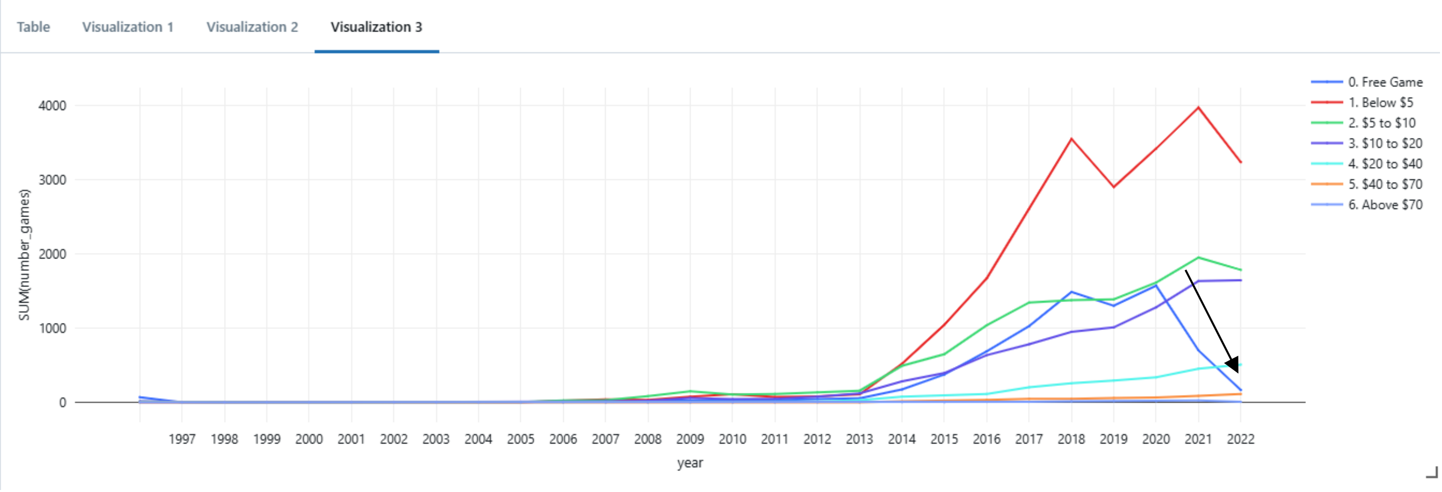
Number of concurrent users per category of games |



# games	2	4	4	8	80	12	46	69	123	7,432
% total users	49%	29%	7%	5%	5%	2%	1%	1%	1%	1%

Free to Play release have strongly decrease showing the difficulty to handle this type of games

Number of game release per year per price category |

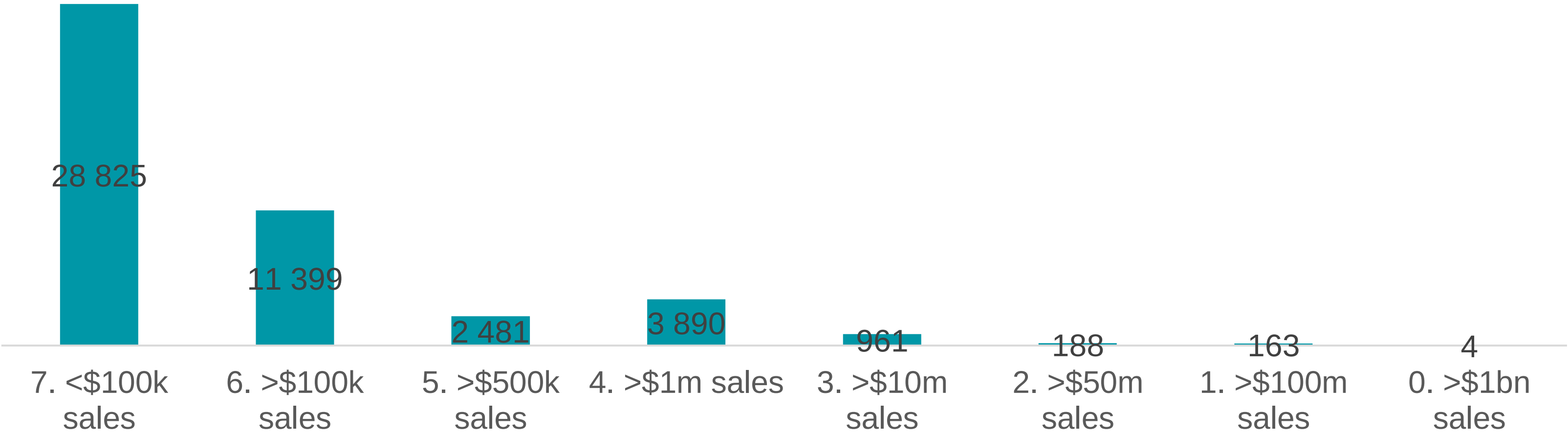


Strongest decrease on the F2P segment

Majority of the games are creating less than $100k revenues

Number of games users per category of games |

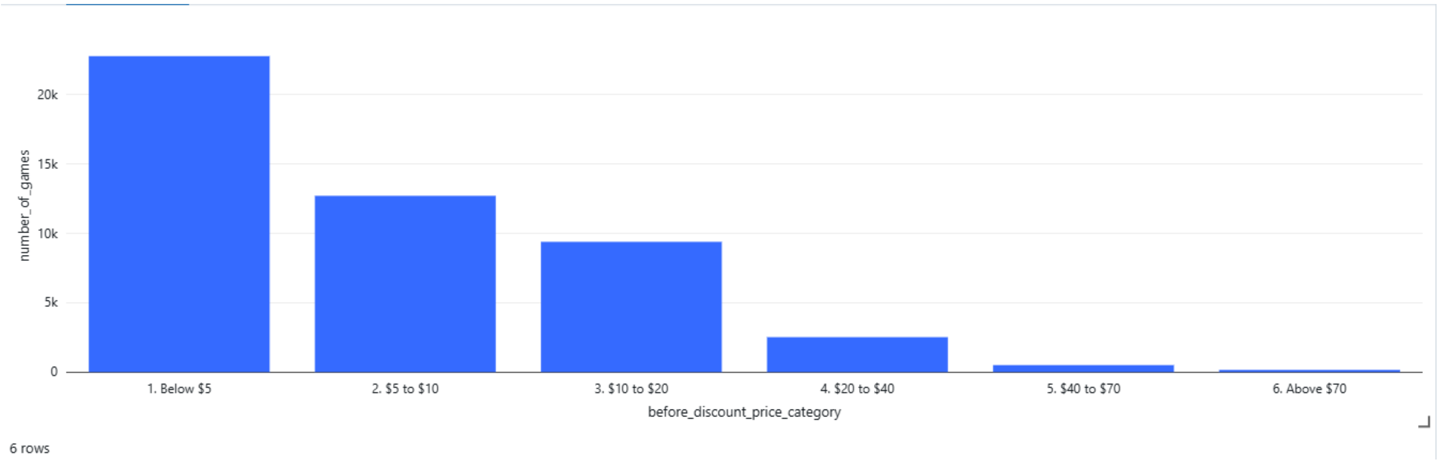
Sales estimation based on number of owner and price after discount



Majority of games are below $5 with an average revenues below $100k. High average turnover per game is between $40 and $70

UBISOFT

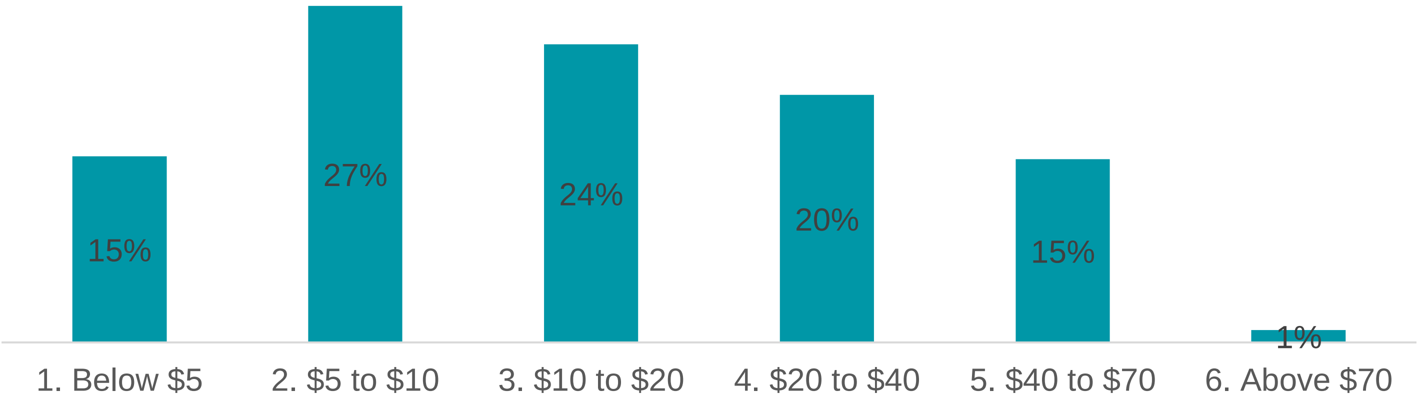
Number of games users per price after discount |
Sales estimation based on number of owner and price after discount



Average Revenues per game in $m	0.1	0.7	3.0	12.1	39.5	10.9

In average, less than 30% of games of each category are profitable

Percentage of profitable project based on estimated cost | Preliminary profitability threshold



Profitability Threshold in $m	**0.1**	**0.1**	**1**	**10**	**50**	**70**

Key Insights

Ubisoft Review

Given Ubisoft's partnership with Epic, the Steam sales dataset seems not relevant to analyze gaming market and Ubisoft's position

- Ubisoft had not game released on Steam since its partnership with Epic in 2020
- The market share of Ubisoft cannot be analyzed as there are almost 3 years' worth of release missing in the dataset
- Given Ubisoft decision, we can assume there are other case like this one and therefore, the dataset is not representative of the market

Based on the data before 2020, we can see that Ubisoft is the #1 published in revenues with $3.6bn in total, with a strong focus on paid games related to big franchise

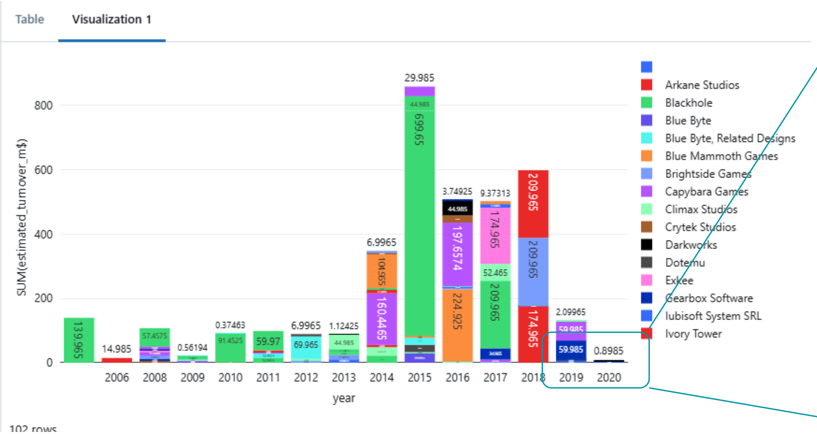
- Ubisoft's games have made above $3.6bn between 2006 and 2020 with a peak in 2015, with the release of "Tom Clancy's Rainbow Six Siege"
- On the free to play games, Ubisoft has only one significant game with around 10k users, in 18th position of the F2P games
- 61% of sales are concentrated into 3 franchises: Tom Clancy's, Assassin's Creed and Far Cry
- However, there are no information of Ubisoft release since 2020

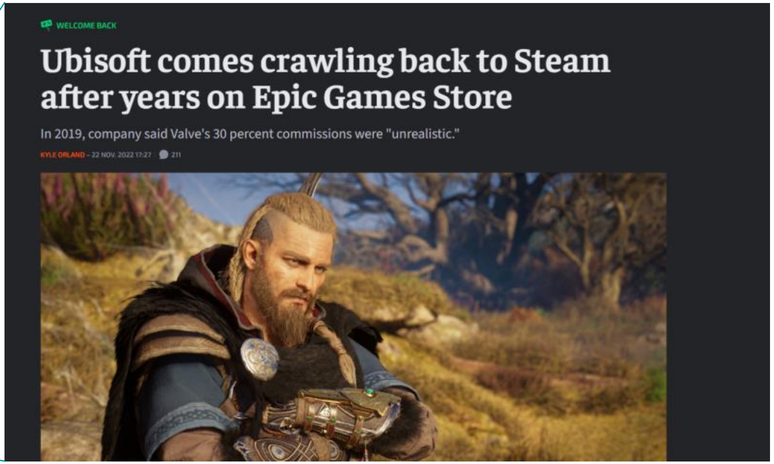
No data from Ubisoft after 2020 as the publisher left Steam in 2019

UBISOFT

Ubisoft estimated turnover by development company |

in $bn, based on price before discount and number of games owners, list of dev company not exhaustive





WELCOME BACK

Ubisoft comes crawling back to Steam after years on Epic Games Store

In 2019, company said Valve's 30 percent commissions were "unrealistic."

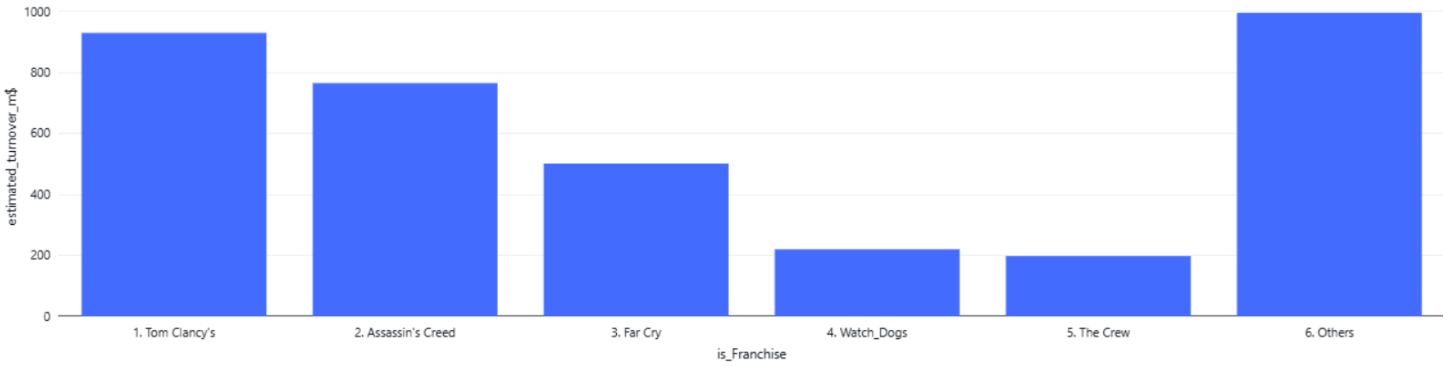
KYLE ORLAND – 22 NOV. 2022 17:27 211

Ubisoft paid games are focused on main franchise with 60% of revenues in 3 of them

UBISOFT

Ubisoft estimated turnover by franchise |

in $m, based on price before discount and number of games owners



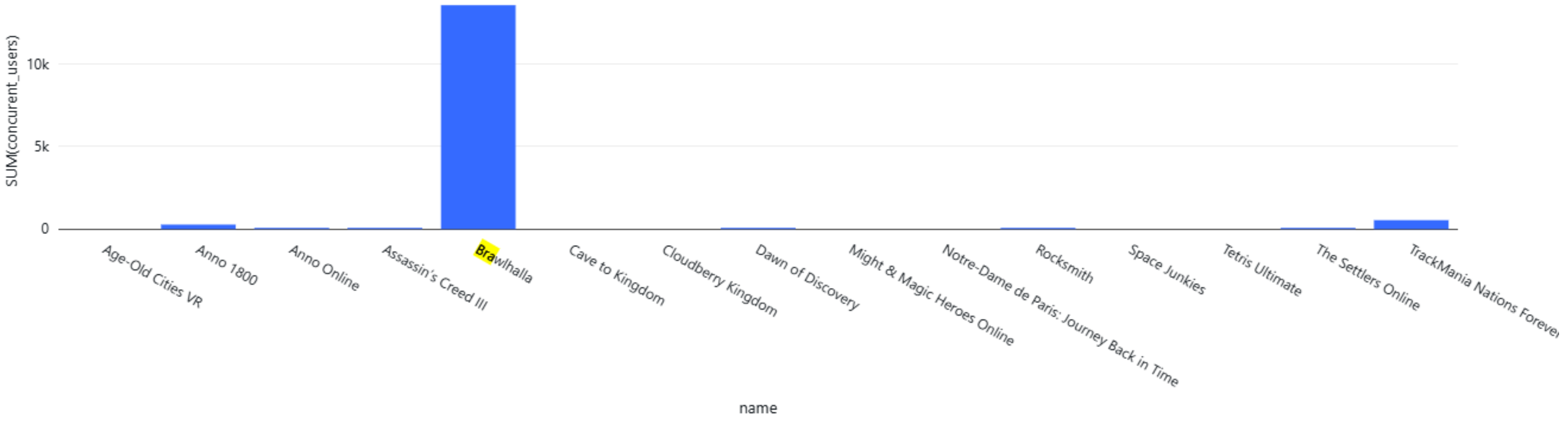
% of total revenus	26%	21%	14%	6%	5%	28%

Ubisoft has only 1 important F2P game, which is in 18th position in the market

UBISOFT

Number of concurrent users on Ubisoft free to play games

Top 18 game on the F2P segment



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Project Reminder

Project

The newsletter team wants to

- understand user behavior on their website
- build a predictive model for subscription conversions using minimal user information

Their goals are to:

- Identify key features that explain subscription
- Discover potential new levers to improve conversion rates

Goal

This project builds a machine learning model to predict customer conversion rates based on user behavior and demographic data. Here are the main steps

- Exploratory Data Analysis
- Data Preprocessing
- Model development and comparison
- Final model and predictions

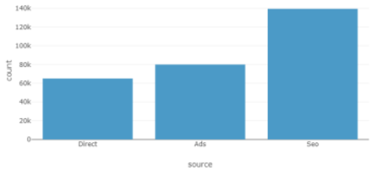
First analysis of the dataset is showing non missing data and a low conversion rate

Dataset description

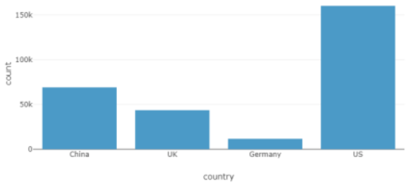
- There are 6 columns with 284k lines and no missing data :
  - Country : User origin among China, Germany, UK and US
  - Age : Age of the user
  - New_User : If it is a new user or not
  - Source : How the user were obtained
  - Total_pages_visited : Nbr of pages visited
  - Converted : Target
- First insights
  - US and China are the main countries is term of visitors
  - SEO is the main source
  - The visitors are visiting just a few page in average

Distribution of main columns of the dataset

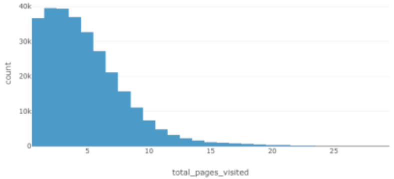
Source



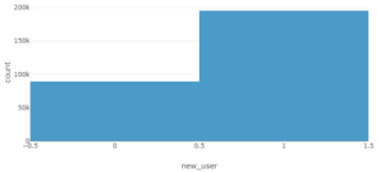
Country



Page Visited



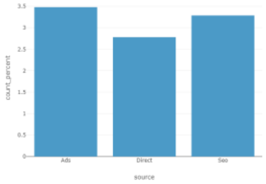
New User



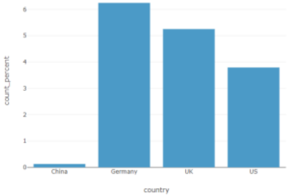
The conversion rate is the higher for GE and the UK, for historic customer and user visiting a large number of pages

Conversion rate in % depending on the colum

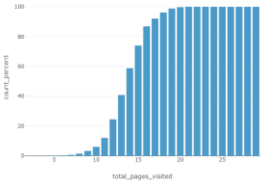
Source



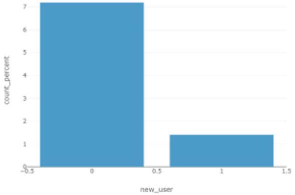
Country



Page Visited



New_user



Key Insights

- The highest converting rate is coming from Germany and the UK. There are almost no conversion in China
- Each source seems to have the same conversion rate
- High conversion for historic customer
- The highest the number of page, the higher the conversion rate. After 20 page visiting, there is a 100% conversion rate

After testing different model, the best performance were achieved with Logistic Regression with a f1 of 0.76

Mode selection

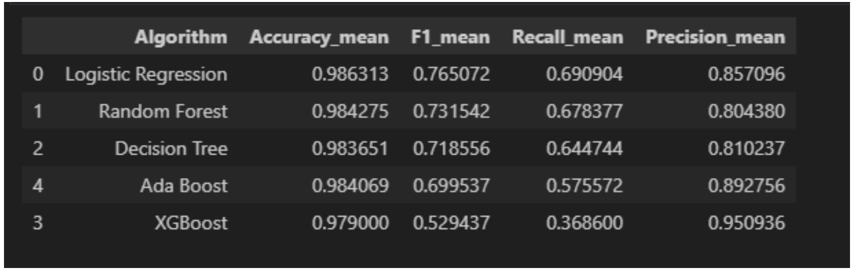
Preprocessing

- Standard preprocessing :
  - Standard Scaler for numerical data
  - One Hot Encoder for categorical data
- Train and Test split

Experiments

- Several model testes
  - Logistic Regression
  - Random Forest
  - Decision Tree
  - Ada Boost
  - XGBoost
- Use cross-validation to get model performance
- Model selected based on f1 score

Results

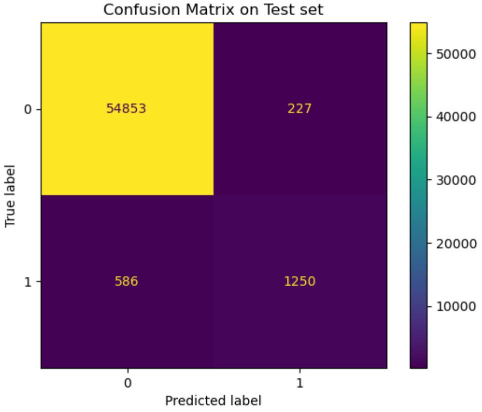


	Algorithm	Accuracy_mean	F1_mean	Recall_mean	Precision_mean
0	Logistic Regression	0.986313	0.765072	0.690904	0.857096
1	Random Forest	0.984275	0.731542	0.678377	0.804380
2	Decision Tree	0.983651	0.718556	0.644744	0.810237
4	Ada Boost	0.984069	0.699537	0.575572	0.892756
3	XGBoost	0.979000	0.529437	0.368600	0.950936

Best performance with the Logistic Regression with a f1 of 0.76

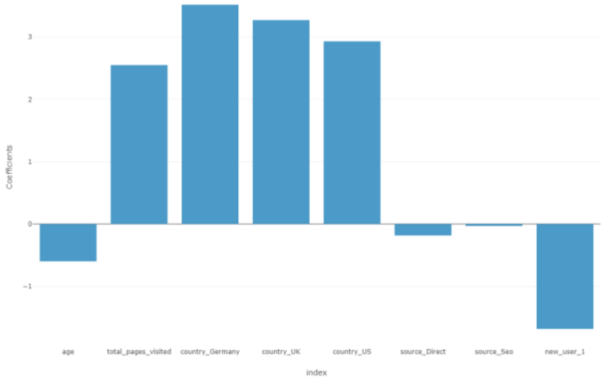
Model confirmed EDA first conclusions

Confusion Matrix



Lots of converted customers not correctly created leading to a recall of only 0.69

Coefficient per column comparison



Model confirmed the importance of the country, the number of page and the type of user
Age is slightly less important

Business recommendation

Improve Chinese Market Experience
- Investigate localization needs or technical improvements
- Address product-market fit issues

Focus on User Retention
- Implement strategies to encourage repeat visits
- Develop loyalty programs or incentives

Age-Targeted Marketing
- Consider campaigns specifically targeting younger demographics
- Adapt content style and offerings for different age groups

Channel Optimization
- Since all traffic sources convert similarly, optimize based on acquisition costs
- Redistribute marketing budget toward most cost-effective channels

Q&A

Agenda

- Block 1 - Build & Manage a Data Infrastructure – Kayak Project
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Project Reminder

Uber

Project

- One of the main pain point that Uber's team found is that sometimes drivers are not around when users need them.
- Therefore, Uber's data team would like to work on a project where their app would recommend hot-zones in major cities to be in at any given time of day.

Goal

The target of the project is to

- Develop an algorithm to identify "hot zones" where drivers should position themselves
- Create time-based recommendations that adapt to changing demand patterns
- Visualize results for easy implementation by drivers

The dataset represents latitude and longitude of 564k pickups in April 2014

Dataset description

- Dataset of April 2014 used with 564k lines

- 4 columns:
  - Date
  - Latitude
  - Longitude
  - Base : Internal code, not used in the analysis

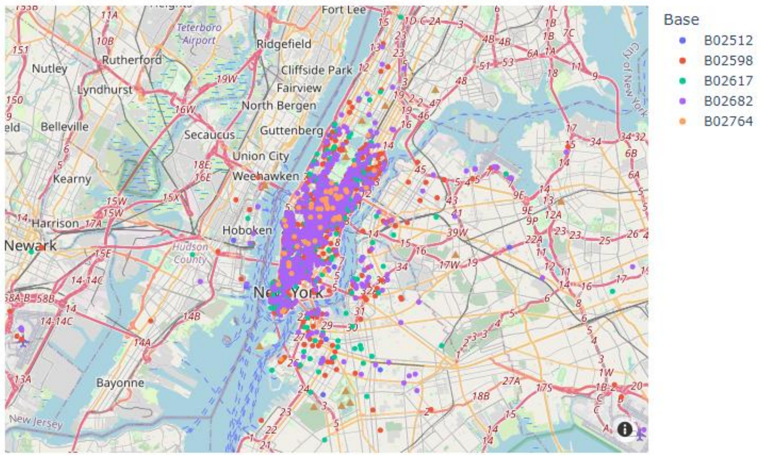
- Preprocessing limited to converting the date column into several sub-columns

- Focus on New York City inside this latitude and longitude line :
  - Latitude minimum = 40.4774
  - Latitude maximum = 40.9176
  - Longitude minimum = -74.2591
  - Longitude maximum = -73.7004

- Analysis done on the 30th of April 2014 at 5pm to limit the number of lines

Overview of the pickup location for a given hour oof a given day

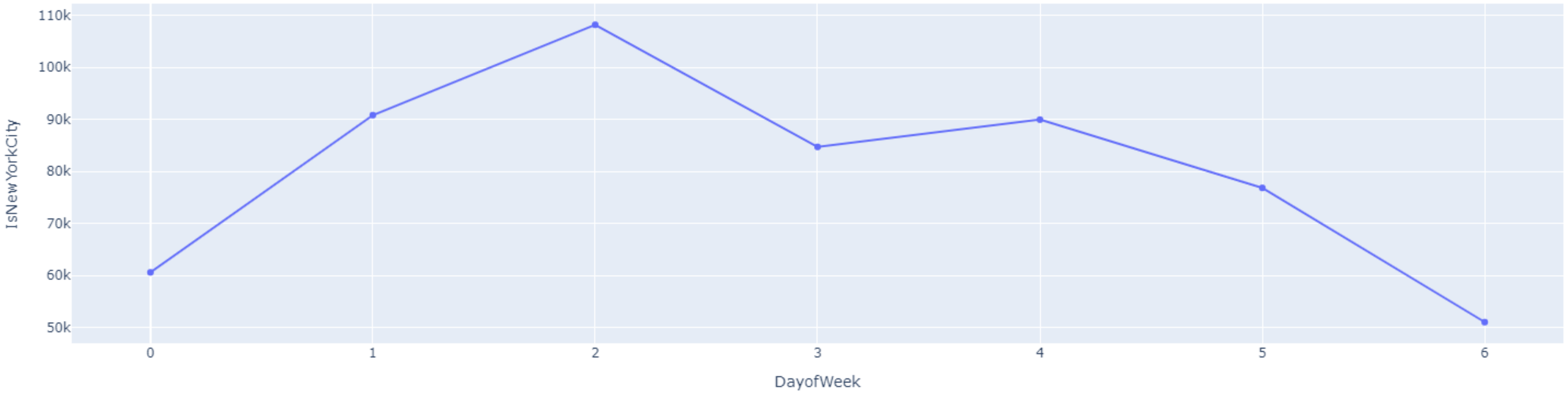
Pick up of the 30th at 5pm



Monday and Sunday are the lowest day while the peak in on Wednesday

Uber

Number of pickups per Day | April 2014, NYC only, 0 = Monday

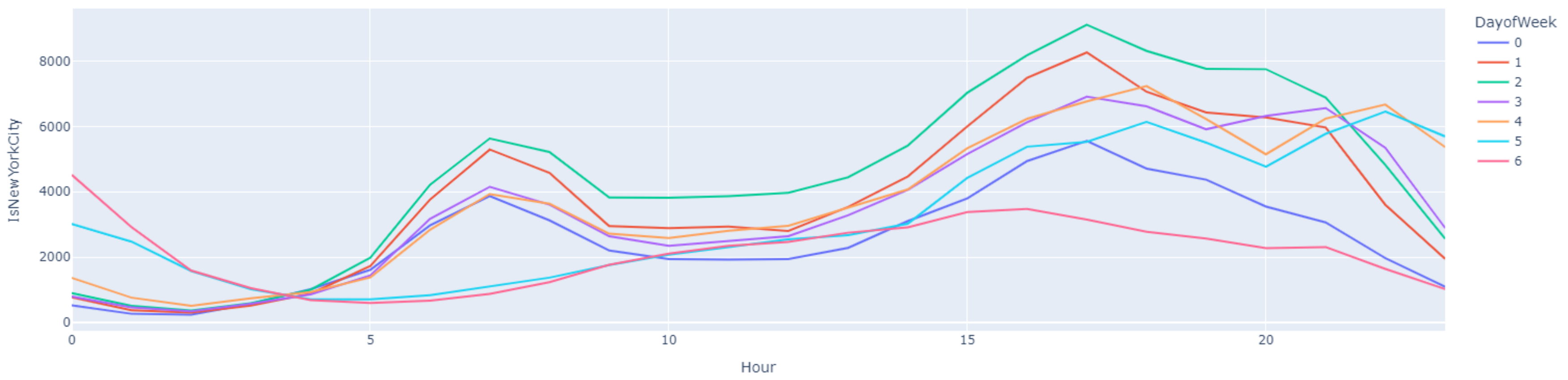


Monday Tuesday Wednesday Thursday Friday Saturday Sunday

During the week, there is a peak at 7am then between 5pm and 8pm while the night is busy during the weekend

Uber

Number of pickups per Hour depending on the day | April 2014, NYC only, 0 = Monday



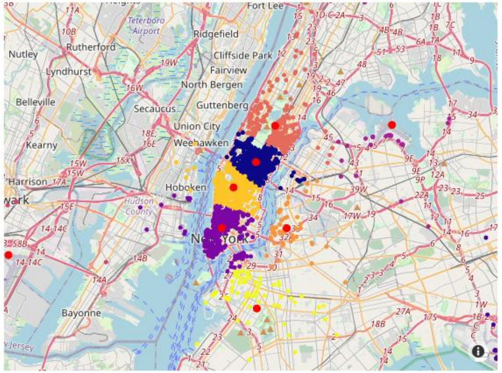
DBScan is used to calculate coordinates of hot zones at any given time

Kmeans Clustering

Description

- Elbow and silhouette methods to get the optimal number of clusters
- 9 clusters seems to be the best for April 30th

Cluster Overview

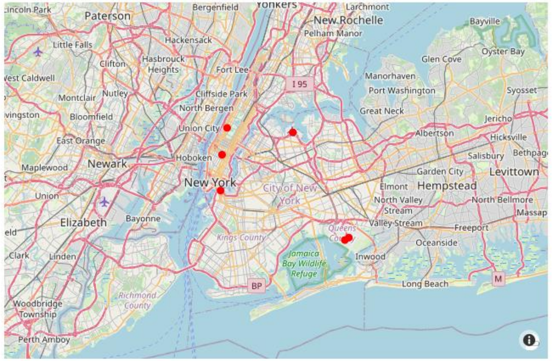


DBScan

Description

- DBScan used to handle different numbers of cluster depending on the time
- Parameters : Epsilon = 0.1 / Min Sample = 10
- 6 clusters + outliers

Cluster Center Overview



DBScan chosen for algorithm as the number of cluster adapts to the dataset

Hot zone are calculated and plotted for any given time with a DBScan clustering

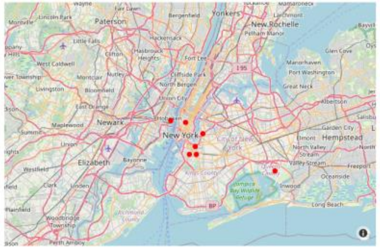
Uber

Plot_hot_zone function

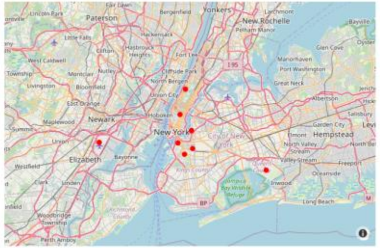
- Input : dataset, day of the week, hour, dbscan parameters
- For any given hours, would calculate the clusters center and plot them
- The output would be a map with the hot zones of this hour
- For a given day, the evolution of hot spots can be shown by looping over different hours

Evolution of hot zones for a Saturday at 12am, 6am, 12pm, 6pm

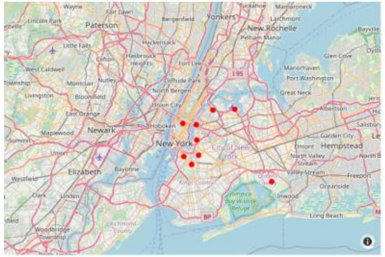
12am



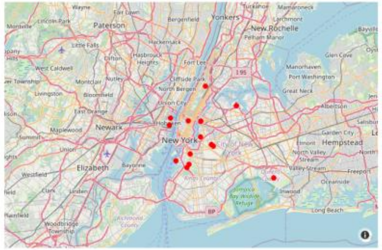
6am



12pm



6pm



Q&A

Agenda

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Project Reminder

AT&T

Project	• One of the main pain point that AT&T users are facing is constant exposure to SPAM messages. • AT&T has been able to manually flag spam messages for a time, but they are looking for an automated way of detecting spams to protect their users.
Goal	Your goal is to build a spam detector, that can automatically flag spams as they come based solely on the sms' content.

Transforming sentence to encoded list to feed the model

Dataset description

- Data structure
  - 1 target column : spam or ham (not spam)
  - 3 column with truncated messages
  - All 3 columns merges to get the total sentence
- 5,572 lines
- 13.41% of spam message

Data Preprocessing

Data cleaning

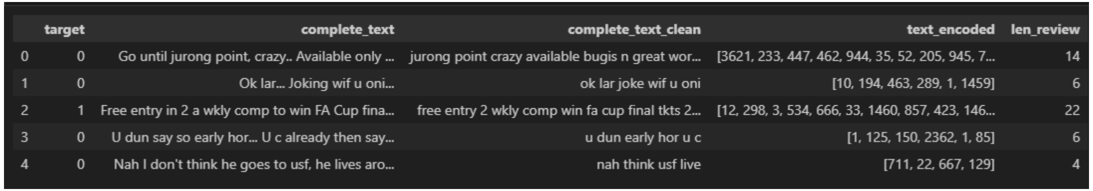
- Removing non-alphanumeric characters
- Converting to lower case

Spacy Cleaning

- Lemmatization of each sentence
- Stop Words removal

Tokenization and padding

- Tokenization : Conversion of each sentence to a list of number
- Padding : Scaling of each sentence to a 100-element list



	target	complete_text	complete_text_clean	text_encoded	len_review
0	0	Go until jurong point, crazy.. Available only ...	jurong point crazy available bugis n great wor...	[3621, 233, 447, 462, 944, 35, 52, 205, 945, 7...	14
1	0	Ok lar... Joking wif u oni...	ok lar joke wif u oni	[10, 194, 463, 289, 1, 1459]	6
2	1	Free entry in 2 a wkly comp to win FA Cup fina...	free entry 2 wkly comp win fa cup final tkts 2...	[12, 298, 3, 534, 666, 33, 1460, 857, 423, 146...	22
3	0	U dun say so early hor... U c already then say...	u dun early hor u c	[1, 125, 150, 2362, 1, 85]	6
4	0	Nah I don't think he goes to usf, he lives aro...	nah think usf live	[711, 22, 667, 129]	4

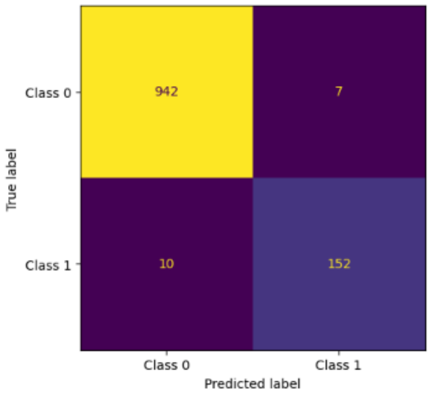
A neural network with GRU layers were chosen for deployment

	Description	Results
Embedding Model	• 1 Embedding layer • Max Pooling / Dropout / Dense final layers	• F1 Score : 0.940 • Recall : 0.907 • Accuracy : 0.985
GRU	• Gated recurrent units neural networks • 1 Embedding layer • 1 GRU layers with 128 units • Max Pooling / Dropout / Dense final layers	• F1 Score : 0.947 • Recall : 0.938 • Accuracy : 0.984
LSTM	• Long short-term memory neural network • 1 Embedding layer • 1 LSTM layer with 16 units • Max Pooling / Dropout / Dense final layers	• F1 Score : 0.941 • Recall : 0.923 • Accuracy : 0.983
Glove + LSTM	• Use of pre-trained embedding matrix • LSTM layers with 128 units • Max Pooling / Dropout / Dense final layers	• F1 Score : 0.851 • Recall : 0.746 • Accuracy : 0.966
BERT	• Use of BERT pre-trained model from 2018 • Use of preprocess and encoder BERT layers • Dropout and Dense final layers	• F1 Score : 0.933 • Recall : 0.894 • Accuracy : 0.983

Best Performance

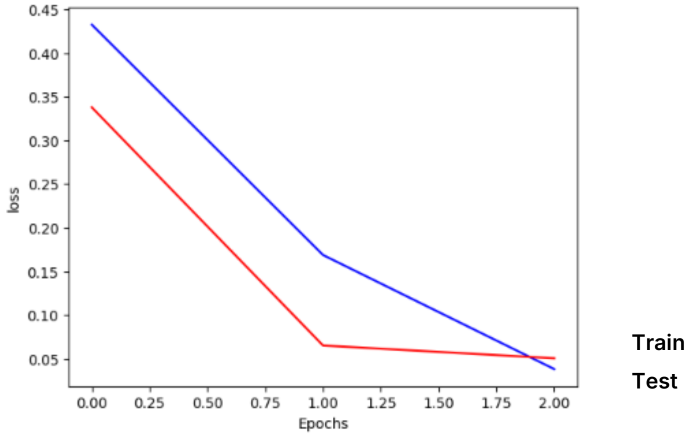
Only 10 spam wrongly categorized with a recall around 0.938

Confusion Matrix



0.938 recall, only 10 spams wrongly flagged categorized

Train and Test Accuracy per epoch



No overfitting

Q&A

Agenda

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Project Reminder

getaround

Project

- Main Getaround issue : late returns at checkout, which cause significant problem
- To address these issues, Getaround is implementing a minimum delay between consecutive rentals

Goal

This project has several objectives:

- Optimal Minimum Delay Threshold: Identify the ideal time buffer between consecutive rentals
- Pricing Optimization: Build a machine learning model to predict the optimal rental price based on car features and rental patterns.
- Data Analysis App: Create an interactive Streamlit dashboard to visualize the main analysis and simulate the impact of different threshold settings on rental availability and revenue.
- API: Create a RESTful API to make the pricing model accessible for production use, allowing for seamless integration with other systems.

Key Findings

getaround

Short time gaps between reservations represent a minor portion of business operations
- Out of 21k rentals, only 8% have a time gap below 12 hours between consecutive rentals
- On average, each car is rented fewer than 3 times, indicating moderate utilization
- Less than 400 rentals (approximately 2%) have a time gap below 1 hour from the previous rental

Late checkouts have limited impact on overall business operations:
- Only 218 rentals were affected by late checkouts, where the car was not available at the scheduled time
- The cancellation rate for affected rentals is around 17%, which is comparable to the average cancellation rate of 15%
- Most delays were under 30 minutes, likely due to minor traffic issues, which wouldn't typically justify a cancellation

A buffer of 30-60 minutes between rentals appears sufficient to minimize scheduling conflicts
- Given the current rental frequency, aggressive time optimization does not appear necessary
- Most delays are less than 1 hour, and this buffer would prevent most potential issues
- Approximately 2% of reservations would be affected by implementing this threshold

21k rentals, 80% on mobile and 15% cancelation rate

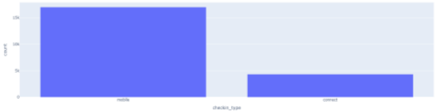
Dataset description

- There are 7 columns with 21,310 lines :
  - Rental ID
  - Car ID
  - checkin type : mobile or connect
  - state : canceled or ended
  - delay_at_checkout_in_minutes
  - previous_ended_rental_id : Only 9% data available on previous rental
  - time_delta_with_previous_rental_in_minutes

- Hypothesis : Let's assume than NaN is meaning than the previous rental was more than 12hour before or that there were no previous rental

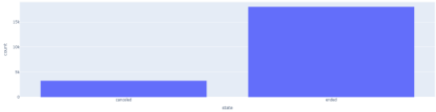
Distribution of main columns of the dataset

Checkin type



80% mobile rental

State



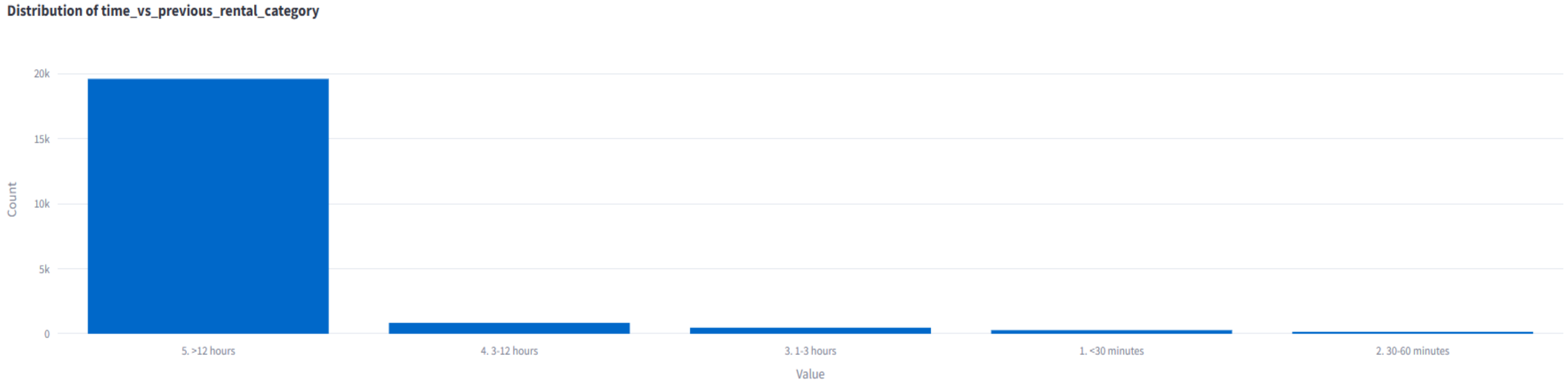
15% cancellation

Short time gaps between reservations represent a minor portion of business operations

getaround

Distribution of rental by time vs. previous rental |

When not data, it is assumed that delay is higher than 12 hours

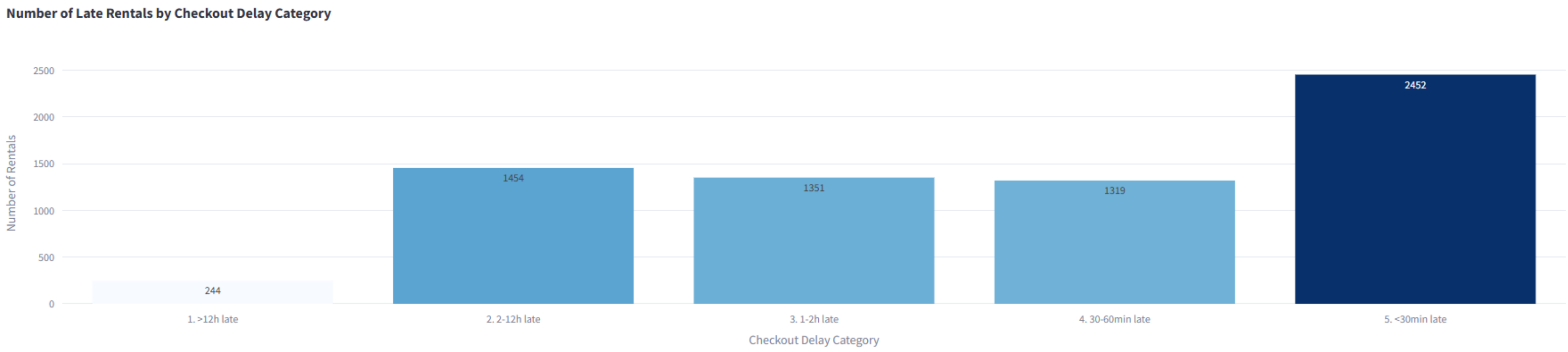


In #	*19,599*	*841*	*469*	*279*	*122*
In %	*92%*	*4%*	*2%*	*1%*	*1%*

Main delay is below 30 minutes and majority is below 60 minutes

getaround

Distribution of late checkout by time of delay

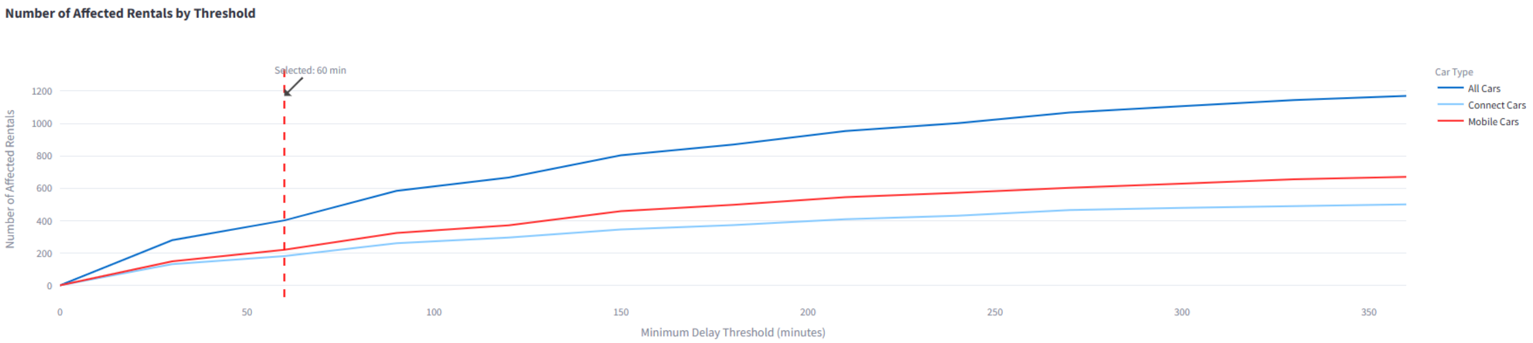


60 minutes seems a good threshold given the low number of rentals impacted

getaround

Distribution of late checkout by time of delay

Impact of 60-minute Minimum Delay



181 rentals would be impacted with a threshold of 60 minutes

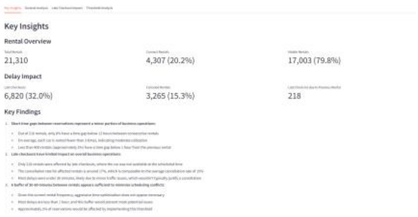
Streamlit App : 4 tabs for detailed analysis

getaround

Streamlit app overview

Streamlit

Tab 1 : Key Insights



Key Insights | General Analysis | Late Checkout Impact | Threshold Analysis

Key Insights

Rental Overview

Total Rentals
21,310

Connect Rentals
4,307 (20.2%)

Mobile Rentals
17,003 (79.8%)

Delay Impact

Late Checkouts
6,820 (32.0%)

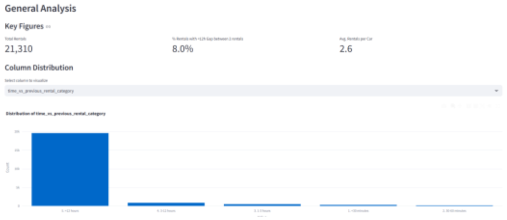
Canceled Rentals
3,265 (15.3%)

Late Check-ins due to Previous Rental
218

Key Findings

1. Short time gaps between reservations represent a minor portion of business operations:
   - Out of 21k rentals, only 8% have a time gap below 12 hours between consecutive rentals
   - On average, each car is rented fewer than 3 times, indicating moderate utilization
   - Less than 400 rentals (approximately 2%) have a time gap below 1 hour from the previous rental
1. Late checkouts have limited impact on overall business operations:
   - Only 218 rentals were affected by late checkouts, where the car was not available at the scheduled time
   - The cancellation rate for affected rentals is around 17%, which is comparable to the average cancellation rate of 15%
   - Most delays were under 30 minutes, likely due to minor traffic issues, which wouldn't typically justify a cancellation
1. A buffer of 30-60 minutes between rentals appears sufficient to minimize scheduling conflicts:
   - Given the current rental frequency, aggressive time optimization does not appear necessary
   - Most delays are less than 1 hour, and this buffer would prevent most potential issues
   - Approximately 2% of reservations would be affected by implementing this threshold

Tab 2 : General Analysis



General Analysis

Key Figures

Total Rentals
21,310

% Rentals with <12h Gap between 2 rentals
8.0%

Avg. Rentals per Car
2.6

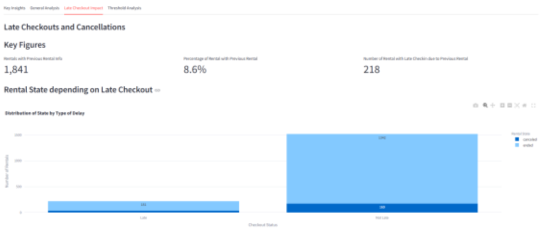
Column Distribution

Select column to visualize

time_vs_previous_rental_category

Distribution of time_vs_previous_rental_category

Tab 3 : Late Checkout Impact



Key Insights | General Analysis | Late Checkout Impact | Threshold Analysis

Late Checkouts and Cancellations

Key Figures

Rentals with Previous Rental Info
1,841

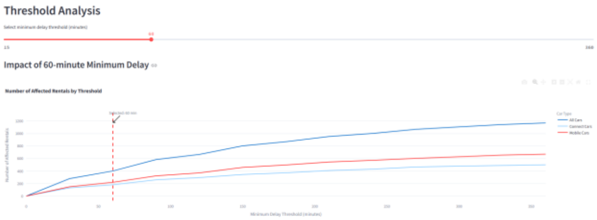
Percentage of Rental with Previous Rental
8.6%

Number of Rental with Late Checkin due to Previous Rental
218

Rental State depending on Late Checkout

Distribution of State by Type of Delay

Tab 4 : Threshold Analysis



Threshold Analysis

Select minimum delay threshold (minutes)

60

15 — 360

Impact of 60-minute Minimum Delay

Number of Affected Rentals by Threshold

4.8k lines of rental data to get a pricing prediction

getaround

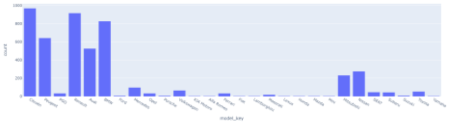
Dataset description

- 4,843 lines in the dataset and no missing data
- 15 columns
  - Car categorical information : model, fuel, color, type,
  - Car numerical information : mileage, engine power
  - Boolean information : GPS, air conditioning, automatic, connect, speed regulator, winter tires
  - target : rental price

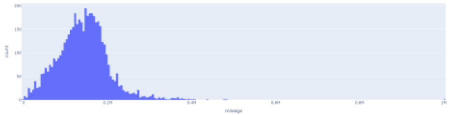
- Limited data cleaning
  - Removal of unused column
  - Flag as 'Others' the model with less that 5 occurrence in the dataset

Distribution of some columns of the dataset

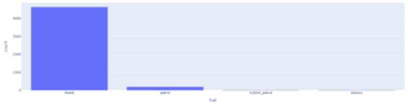
Model



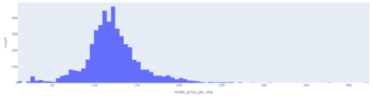
Mileage



Fuel



Price



Different Catboost model tested on MLFlow for a final R2 test of 0.78

Model used

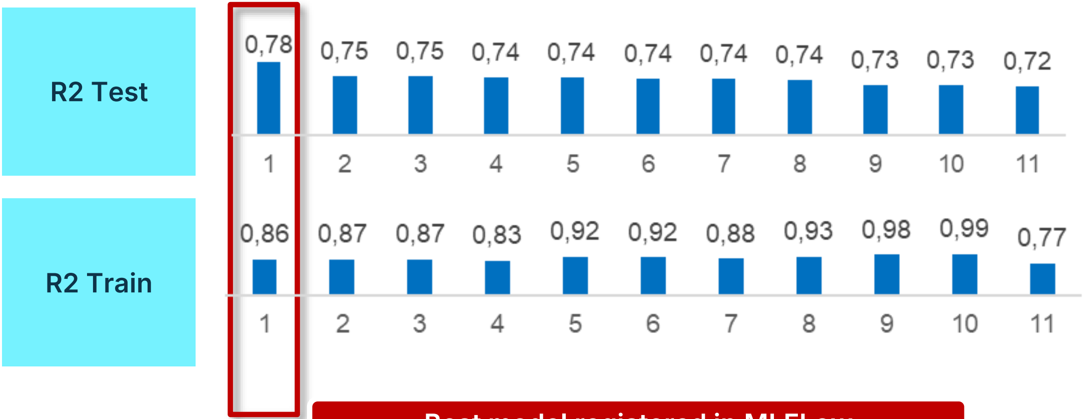
Preprocessing

- Numerical data : Standard Scaler
- Categorical : One Hot Encoder

Model

- Model used : Catboost Regressor
- Different experiments done on MLFlow
- Best model used for the API
- Parameters :
  - Depth
  - Iterations
  - Learning Rate

Experiments overview



Best model registered in MLFLow

Streamlit App : 4 tabs for detailed analysis

getaround

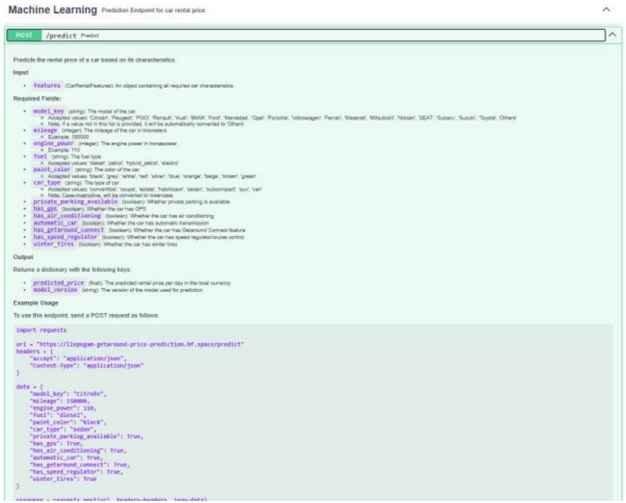
Streamlit app overview

Streamlit

Description

- Text input from the user
  - 13 value to enter
  - validation of data format
  - if model unknown, replace by Others
- Use of registered model stored in MLFlow
- API stored in Hugginface

Predict Endpoint


Machine Learning Prediction Endpoint for car rental price.

POST `/predict` Predict

Predicts the rental price of a car based on its characteristics.

Input

- `features` (CarRentalFeatures): An object containing all required car characteristics.

Required Fields:

- `model_key` (string): The model of the car
  - Accepted values: 'Citroën', 'Peugeot', 'PGO', 'Renault', 'Audi', 'BMW', 'Ford', 'Mercedes', 'Opel', 'Porsche', 'Volkswagen', 'Ferrari', 'Maserati', 'Mitsubishi', 'Nissan', 'SEAT', 'Subaru', 'Suzuki', 'Toyota', 'Others'
  - Note: If a value not in this list is provided, it will be automatically converted to 'Others'
- `mileage` (integer): The mileage of the car in kilometers
  - Example: 150000
- `engine_power` (integer): The engine power in horsepower
  - Example: 110
- `fuel` (string): The fuel type
  - Accepted values: 'diesel', 'petrol', 'hybrid_petrol', 'electro'
- `paint_color` (string): The color of the car
  - Accepted values: 'black', 'grey', 'white', 'red', 'silver', 'blue', 'orange', 'beige', 'brown', 'green'
- `car_type` (string): The type of car
  - Accepted values: 'convertible', 'coupe', 'estate', 'hatchback', 'sedan', 'subcompact', 'suv', 'van'
  - Note: Case-insensitive, will be converted to lowercase
- `private_parking_available` (boolean): Whether private parking is available
- `has_gps` (boolean): Whether the car has GPS
- `has_air_conditioning` (boolean): Whether the car has air conditioning
- `automatic_car` (boolean): Whether the car has automatic transmission
- `has_getaround_connect` (boolean): Whether the car has Getaround Connect feature
- `has_speed_regulator` (boolean): Whether the car has speed regulator/cruise control
- `winter_tires` (boolean): Whether the car has winter tires

Output

Returns a dictionary with the following keys:

- `predicted_price` (float): The predicted rental price per day in the local currency
- `model_version` (string): The version of the model used for prediction

Example Usage

To use this endpoint, send a POST request as follows:

```
import requests

url = "https://llepogam-getaround-price-prediction.hf.space/predict"
headers = {
    "accept": "application/json",
    "Content-Type": "application/json"
}

data = {
    "model_key": "Citroën",
    "mileage": 150000,
    "engine_power": 110,
    "fuel": "diesel",
    "paint_color": "black",
    "car_type": "sedan",
    "private_parking_available": True,
    "has_gps": True,
    "has_air_conditioning": True,
    "automatic_car": True,
    "has_getaround_connect": True,
    "has_speed_regulator": True,
    "winter_tires": True
}

response = requests.post(url, headers=headers, json=data)
```

Q&A

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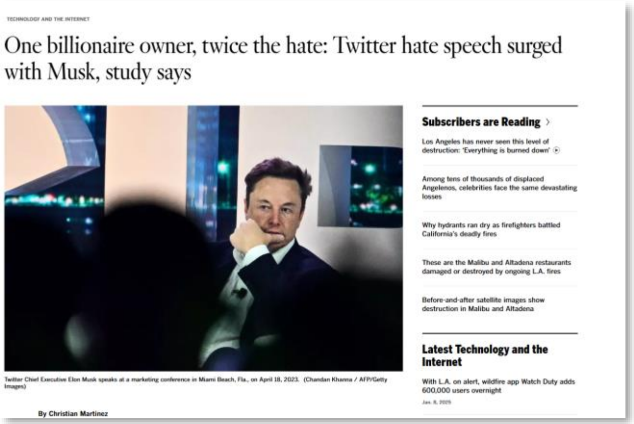
“Moderation is a propaganda word for censorship”

Elon Musk, interview with Don Lemon, March 2024

Big tech companies are reducing their focus on moderation leading to increase of hate speech



TECHNOLOGY AND THE INTERNET

One billionaire owner, twice the hate: Twitter hate speech surged with Musk, study says

Twitter Chief Executive Elon Musk speaks at a marketing conference in Miami Beach, Fla., on April 18, 2023. (Chandan Khanna / AFP/Getty Images)

By Christian Martinez

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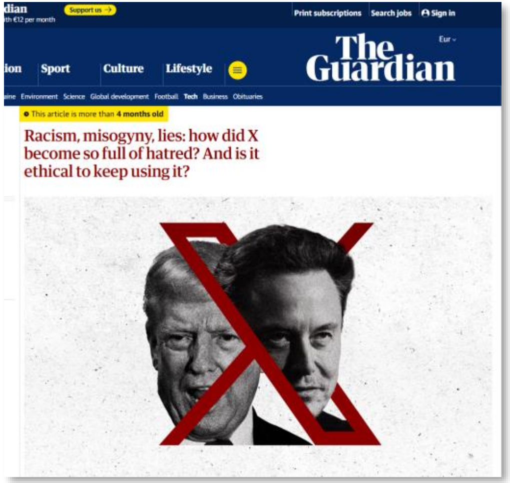

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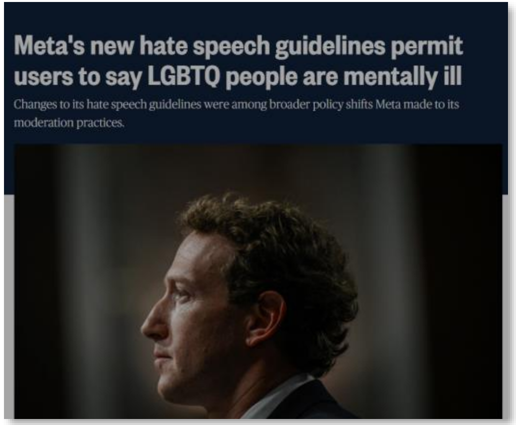
Racism, misogyny, lies: how did X become so full of hatred? And is it ethical to keep using it?



Meta's new hate speech guidelines permit users to say LGBTQ people are mentally ill

Changes to its hate speech guidelines were among broader policy shifts Meta made to its moderation practices.

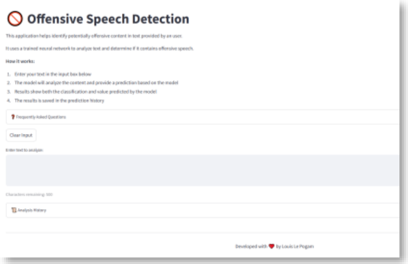
Objectives : build a fully deployed offensive speech detection model

Target

Build a model to detect offensive speech

Results

Deployed model with 73% accuracy and 68% recall



🚫 Offensive Speech Detection

This application helps identify potentially offensive content in text provided by an user.

It uses a trained neural network to analyze text and determine if it contains offensive speech.

How it works:

1. Enter your text in the input box below
2. The model will analyze the content and provide a prediction based on the model
3. Results show both the classification and value predicted by the model
4. The results is saved in the prediction history

Developed with ❤️ by Louis Le Pogam

4 steps to get a deployed model

	Description	Technology
1 Dataset	• Choose dataset to use in the training	Hugging Face
2 Model	• Build preliminary models to define the best design	colab
3 Fine-Tuning	• Fine-tune the model to find best parameters • Register prediction and preprocessing models	mlflow
4 Deployment	• Make the model available through an API • Create an app with Streamlit to use it	FastAPI Streamlit

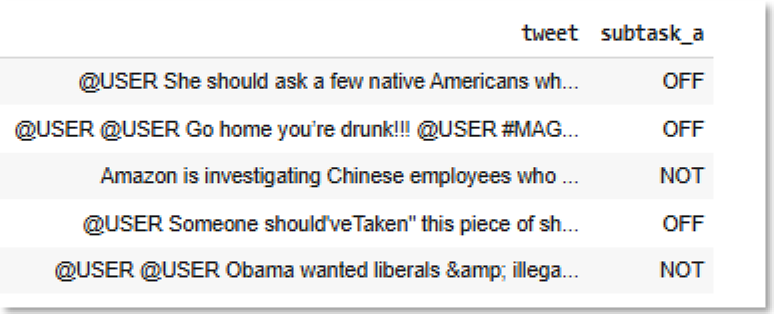
OLID dataset used for training, with 13.2k tweets, of which 33.2% are offensive

Source

- Catalog of abusive language data (PLoS 2020)
- Paper : *Vidgen B, Derczynski L (2020) Directions in abusive language training data, a systematic review: Garbage in, garbage out*
- Catalogue of datasets in different languages
- 25 languages available
- 59 datasets in English

Dataset used

- Name : The Offensive Language Identification Dataset (OLID)
- Paper : *Predicting the Type and Target of Offensive Posts in Social Media (2019)*
- Available data : Annotated tweets flagged offensive or not offensive
- Size : 13,240 tweets, of which 4,400 flagged as offensive (33.2% of total)
- Available on Hugging Face



tweet	subtask_a
@USER She should ask a few native Americans wh...	OFF
@USER @USER Go home you're drunk!!! @USER #MAG...	OFF
Amazon is investigating Chinese employees who ...	NOT
@USER Someone should'veTaken" this piece of sh...	OFF
@USER @USER Obama wanted liberals &amp; illega...	NOT

A neural network with GRU layers were chosen for deployment

	Description	Preprocessing	Results
GRU	• Gated recurrent units neural networks • 1 Embedding layer • 1 GRU layers with 64 units • Max Pooling / Dropout / Dense final layers	• Text cleaning : Punctuation and symbols removal, conversion to lowercase • Lemmatization and Stop Words removal • Encoding and Padding	• F1 Score : 0.63 • Recall : 0.66 • Accuracy : 0.74
LSTM	• Long short-term memory neural network • 1 Embedding layer • 2 LSTM layers with 64 units • Max Pooling / Dropout / Dense final layers	• Text cleaning : Punctuation and symbols removal, conversion to lowercase • Lemmatization and Stop Words removal • Encoding and Padding	• F1 Score : 0.61 • Recall : 0.58 • Accuracy : 0.75
BERT	• Use of BERT pre-trained model from 2018 • Use of preprocess and encoder BERT layers • Dropout and Dense final layers	• Text cleaning : Punctuation and symbols removal, conversion to lowercase • Lemmatization and Stop Words removal • BERT pre-trained preprocessed layer using directly text	• F1 Score : 0.59 • Recall : 0.57 • Accuracy : 0.73 • 3h training time

Chosen model

The model registered in MLFlow reached 68% recall and 73% accuracy

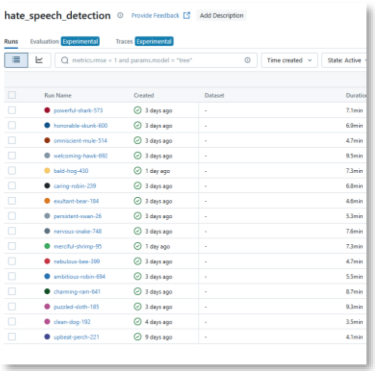
MLFlow Experiments

mlflow

Overview

- Change the number of units of each layers
- Add intermediate layers
- Increase or decrease the number or epochs for training

Experiments



hate_speech_detection ⓘ Provide Feedback Add Description

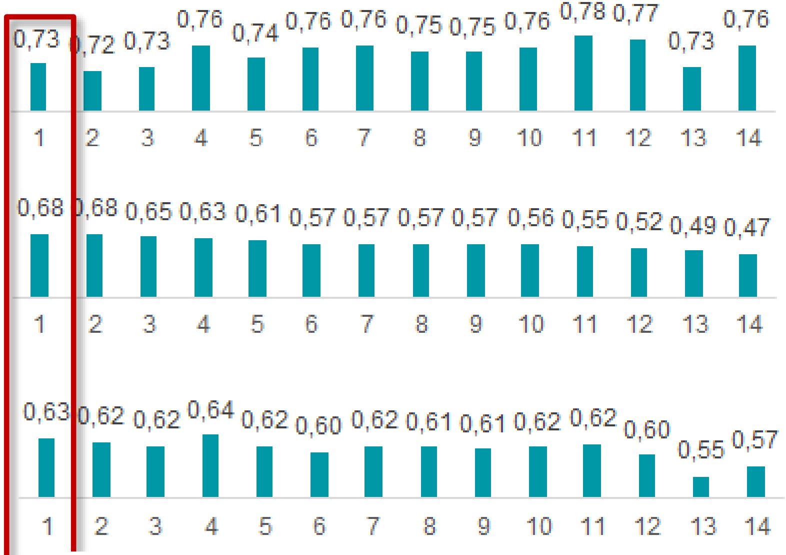
□	Run Name	Created	Dataset	Duratio
□	powerful-shark-573	3 days ago	-	7.1min
□	honorable-skunk-600	3 days ago	-	6.9min
□	omniscient-mule-514	3 days ago	-	4.7min
□	welcoming-hawk-692	3 days ago	-	9.5min
□	bald-hog-430	1 day ago	-	7.3min
□	caring-robin-239	3 days ago	-	6.8min
□	exultant-bear-184	3 days ago	-	4.8min
□	persistent-swan-26	3 days ago	-	5.3min
□	nervous-snake-748	3 days ago	-	7.6min
□	merciful-shrimp-95	1 day ago	-	7.3min
□	nebulous-bee-399	3 days ago	-	4.7min
□	ambitious-robin-694	3 days ago	-	5.5min
□	charming-ram-641	3 days ago	-	8.7min
□	puzzled-sloth-185	3 days ago	-	9.3min
□	clean-dog-192	4 days ago	-	3.5min
□	upbeat-perch-221	9 days ago	-	4.1min

Results

Accuracy

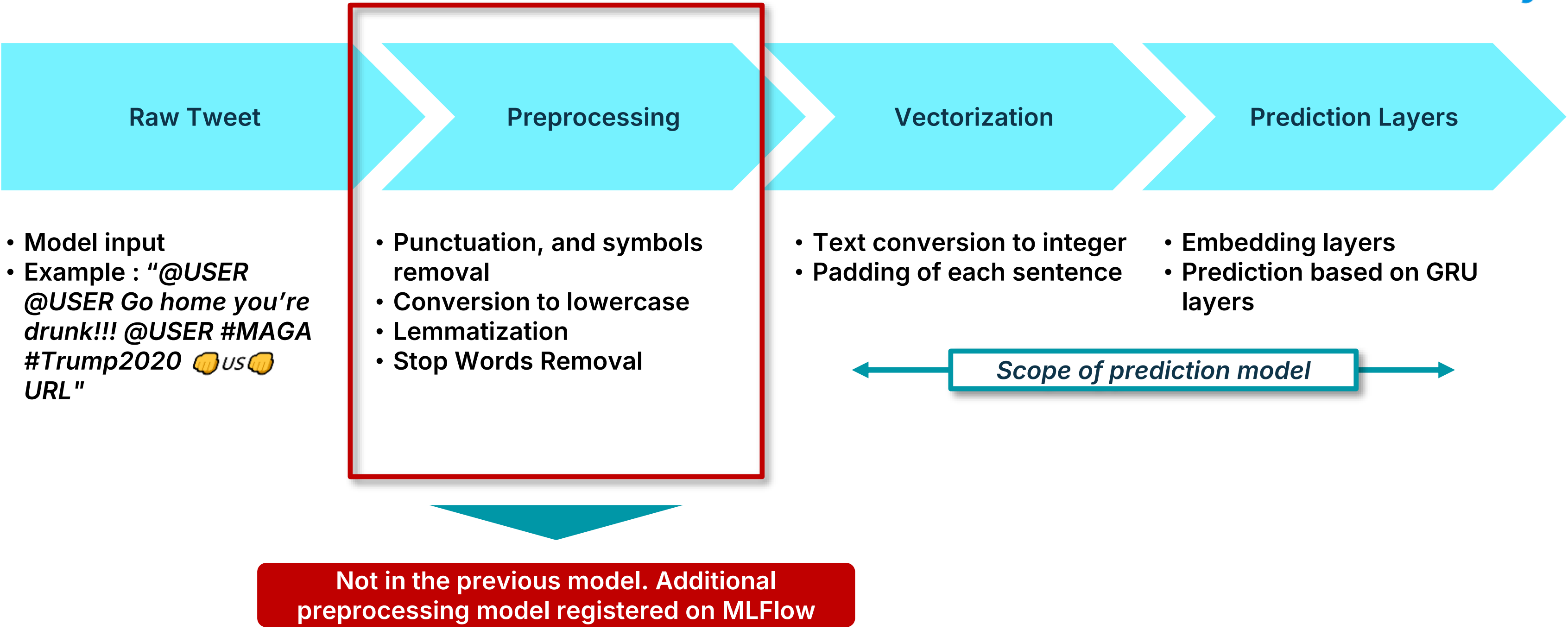
Recall

F1 Score



Model with highest recall registered in MLFlow

Additional preprocessing model was registered on MLFlow



Raw Tweet

- Model input
- Example : *"@USER @USER Go home you're drunk!!! @USER #MAGA #Trump2020 👊US👊 URL"*

Preprocessing

- Punctuation, and symbols removal
- Conversion to lowercase
- Lemmatization
- Stop Words Removal

Vectorization

- Text conversion to integer
- Padding of each sentence

Prediction Layers

- Embedding layers
- Prediction based on GRU layers

Scope of prediction model

Not in the previous model. Additional preprocessing model registered on MLFlow

The model were deployed through a Streamlit app use an API build with Fast API

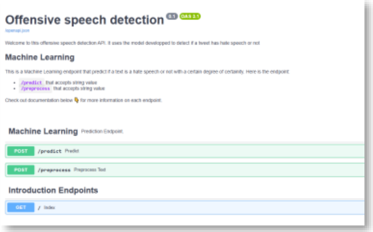
API

FastAPI

Description

- FastAPI API deployed on Hugging Face
- 2 endpoints using MLFlow models :
  - /preprocessing
  - /predict using the preprocessing model
- Prediction output
  - Prediction : “Offensive” or “Not Offensive”
  - Probability : Number between 0 and 1, the higher, the more offensive

Overview



Offensive speech detection 0.1 OAS 3.1

/openapi.json

Welcome to this offensive speech detection API. It uses the model developped to detect if a tweet has hate speech or not

Machine Learning

This is a Machine Learning endpoint that predict if a text is a hate speech or not with a certain degree of certainty. Here is the endpoint:

- /predict that accepts string value
- /preprocess that accepts string value

Check out documentation below 👇 for more information on each endpoint.

Machine Learning Prediction Endpoint.

POST /predict Predict

POST /preprocess Preprocess Text

Introduction Endpoints

GET / Index

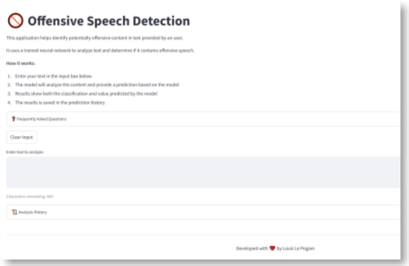
Detection App

Streamlit

Description

- Streamlit app deployed on Hugging Face
- Text entered as an input from the user
- Output from the model shown after validation
- Various explanation and FAQ
- History of research saved on a S3 bucket

Overview



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❓ Frequently Asked Questions

Clear Input

Enter text to analyze:

Characters remaining: 500

📜 Analysis History

Developed with ❤️ by Louis Le Pogam

Next Steps : Further improve the model and the app

	Improvements
Model	• Train the model on bigger dataset to improve the performance • Use remote training to use more ambitious models • Leverage on improvements in text detection and pre-trained model
App Performance	• Improve app performance to insure quicker prediction • Additional costs required to have access to better server
App UI	• Handle better exception and potential errors • Add additional endpoint and features (e.g. batch predict from a csv file)

Q&A

Thanks!