# Predicting the Popularity of Reddit Memes with Deep Learning

**Viet Hung Pham**
Budapest University of Technology and Economics
phamv@edu.bme.hu

**József Pintér**
Budapest University of Technology and Economics
pinterj@math.bme.hu

**Bálint Turi-Kováts**
Budapest University of Technology and Economics
tkbalint@math.bme.hu

## Abstract

Memes are a form of media which are gaining attention on the internet lately. The purpose of this project is to build deep learning models to be able to predict as accurately as possible whether a meme is popular or not, also known as dank in internet slang. These memes have a higher chance of being shared by others, becoming viral in the process. Identifying them is an machine learning problem with ever-increasing importance. In this paper, we use cutting-edge deep learning methods, convolutional neural networks and vision transformer models to achieve high accuracy metrics. We compare these models, then conduct hyperparameter optimization to get the desired result.

# Mémek népszerűségének előjelzése mélytanulási módszerekkel

## Kivonat

Internetes mémeket egyre többet látni elmúlt években, egyre fontosabb szerephez jutnak a kommunikáció során. Ebben a cikkben mély tanulási modelleket építünk, amelyekkel minél pontosabban szeretnénk meghatározni, egy bizonyos mém sikeres lesz-e, vagy sem. Az ilyen mémeket többen osztják meg, több emberhez jutnak el, felismerésük egyre fontosabb feladat. Különféle mély tanulási modellekkel, konvolúciós neurális hálókkal és vision transformer modellek segítségével igyekszünk minél pontosabban osztályozni. A modellek et összehasonlítjuk, majd hiperparaméter-optimalizálással próbáljuk elérni a kívánt célt.

## 1 Introduction

Media in the twenty-first century is constantly changing, as the internet plays an ever-increasing role in everyone's life. People share more and more humorous images or animations, commonly referred to as memes. Similarly to jokes spreading through word of mouth, memes can also spread from person to person. If a single meme manages to partake in such a journey, it is considered viral, because everyone seemed to have infected by it. An internet slang synonym of the word cool, dank memes is a term used to describe absurd, bizarre, yet viral variants and types of memes.

Memes can originate from a lot of places. The most common place for a meme to show up is a social media site. The creator of the meme attempts to get attention by posting their work and the public reacts on it. Depending on the website, these memes can usually be seen by the public and voted on, resulting in some sort of a popularity index.

In this paper, we look at memes from the memes subreddit of the social media site called Reddit. Users can submit content to communities, called subreddits, while others can vote on them. Upvotes and downvotes are possible and after some time, the most popular posts appear toward the top of the list. With 17 million users as of December 2021, /r/memes is not only in the 50 most popular subreddits, it is also one of the most comprehensive collection of memes on the internet.

## 2 Background

As memes are a fairly new phenomenon, most early related work discussed trends like word-of-mouth (1) and viral marketing (2; 3), before insights into internet memes (4) were analyzed.

In the past, viral internet memes were predicted based on social media factors (5), or models were designed to interpret the transmission of memes through the Internet (6). Worth noting that most papers study data in text form, which can be hashtags (7) or quotes (8).

Our main help and the closest related work investigated meme popularity of 129,326 memes from March 2020, with the goal of connecting viral memes with the coronavirus outbreak and restrictions (9).

## 3 Data description

This study is based on web scraped data from Reddit. The website allows for Application Programming Interface usage, so we registered these APIs to automate the process of downloading a massive amount of pictures and metadata. Although this has resulted in a significant amount of broken images we eventually found ways to clean the dataset.

### 3.1 Exploratory analysis

At this point, 258,315 memes were scraped between February 2011 and October 2021. For every image we stored the image itself, as well as the id, title, score and date as metadata. It is easy to see the frequency of the memes throughout the year. As we can observe on the plot, there are no instances from 2013. It turns out the Reddit API cannot scrape anything from 2013. We conducted a few sanity checks and they paint a fair picture: early on memes were scarce and less popular, because Reddit itself was less often visited. Then through the years the popularity and submissions also increased, which can also be seen in **Figure 2**.

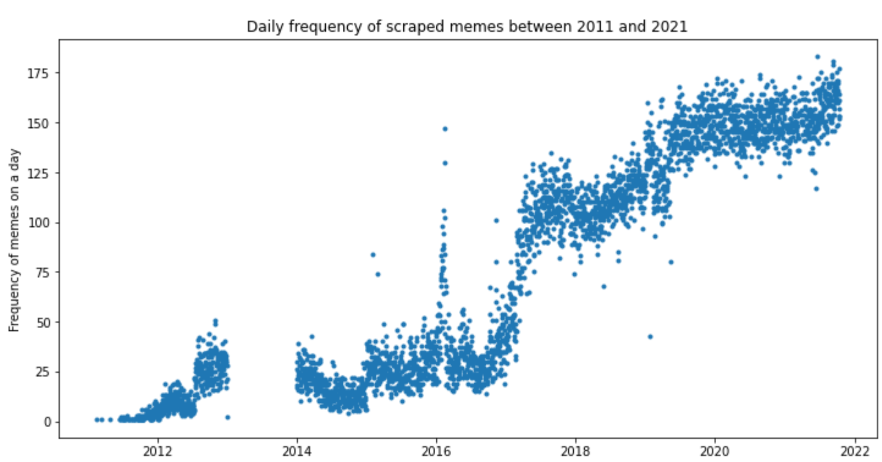


Figure 1: The distribution of memes by submission date

We also calculated the target variables. in this binary classification exercise, we decided that a meme is considered dank, if it is in the top five percentile in terms of score, in the one-week rolling window around the day the meme was published. Following this, we ended up with 13,142 dank memes, 5.09% of the dataset.

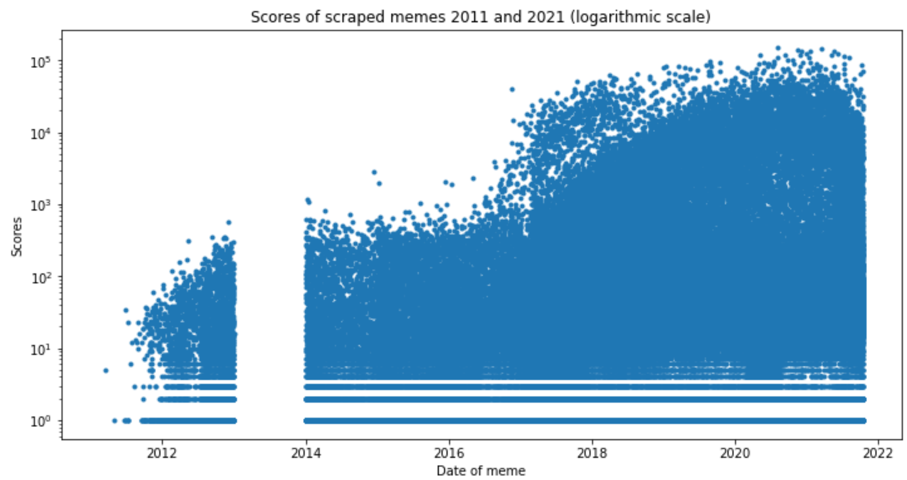


Figure 2: The distribution of memes by submission date

### 3.2 Preprocessing and data cleaning

Images were distributed into train-valid-test folders with each containing sub-folders called **0** (not viral) and **1** (viral). Some issues with images were detected and action was carried out according to that which included:

- Converting images with other color channels other than RGB
- Removing GIFs, broken images and memes exceeding PIL's limit pixel sizes

The dataset ended up having the following distribution:

- Training set: **235504** memes with label 0 and **12638** memes with label 1
- Validation set: **4741** memes with label 0 and **259** memes with label 1
- Test set: **4760** memes with label 0 and **240** memes with label 1
- Total number of memes are **258142**

## 4 Modeling and evaluation

We aim to predict whether a meme becomes viral or not. This is a supervised learning problem, a binary classification problem to be exact. The inputs are the data about the meme, while the output is the popularity measured as a binary variable (1: viral, 0: not viral). Important to mention that the class distribution is not balanced, approximately 5% of the dataset was recognized as viral meme data.

### 4.1 Modeling

Both Convolutional Neural Network (CNN) and Vision Transformer (ViT) models were deployed to provide predictions on the popularity of the meme, whether it is viral or not. The latter are a brand new method for image classification detailed in (10) and (11). Tensorflow/Keras was used for implementing CNN models (ResNet and Xception) and one ViT model (ViT B32) and another ViT model (Hugging Face Google ViT base-patch16) was carried out in PyTorch. Top layers of those models were removed and replaced by custom Dense layers and an output layer of a single neuron with sigmoid activation. Furthermore, pre-trained imagenet weights were also used. In transfer learning, only the top custom layers weight would change during the training, the rest would be frozen.

### 4.2 Optimiziation

Data augumentation, rescaling were conducted on the dataset. As it is a imbalanced classification problem, there were several options to deal with this situation. Class weighting were opted for this project. Class Weighting for models written in Keras were **0.5268** for label 0 and **9.8173** for label 1 according to balanced class weights. For models conducted in PyTorch **0.1** for label 0 and **1** for label 1. Not much hyperparameter optimisation were done because of the sheer size of the dataset so one epoch of learning holds for about 25-35 minutes.

### 4.3 Evaluation

| Model | Accuracy | Precision | Recall | F1-score | PR-AUC |
|---|---|---|---|---|---|
| ResNet | 0.6540 | 0.0815 | 0.6042 | 0.1436 | 0.0913 |
| ResNet w/ fine-tuning | 0.8996 | 0.1124 | 0.1583 | 0.1315 | 0.0882 |
| Xception | 0.8092 | 0.0839 | 0.3000 | 0.1311 | 0.0832 |
| ViT B32 | 0.6064 | 0.0740 | 0.6250 | 0.1323 | 0.0929 |
| Google ViT w/ fine-tuning | 0.8803 | 0.1106 | 0.2208 | 0.1474 | 0.1021 |

Table 1: Different scores on the test dataset

ResNet with fine-tuning were carried out after the vanila ResNet by unfreezing the top layers (in our case the top 164 layers out of 564 layers). The Google base-patch16 ViT from Hugging Face's repository was fine-tuned only on half of the training dataset (due to lack of time), still it was the best performing modell. The result represented in **Table 1** was not particularly impressive but 80-90% improvement from a random model when comparing based on PR-AUC. Accuracy in this imbalanced binary classification is not appropriate measure for model performance. We believe with proper hyperparameter optimisation the relevant metrics can be vastly improved.

## 5 Conclusion

In this work, we used deep learning methods to predict the popularity of internet memes web scraped from the social media site Reddit with the aim of identifying individual or groups of memes with the potential to become viral.

Due to the scope of the project and the deadlines which had to be bet, several limitations had to be imposed. As already mentioned, hyperparameter optimisation could be deployed in a wider scale. We did not manage to include optical character recognition or sentiment analysis on the text found on memes, as initial results turned out to be too inaccurate to be used in the models, and the time frame did not allow for in-depth research on this topic. As a future step, we would also like to include topicality by comparing memes to the current headlines of the New York Times. Both the image actuality (e.g. typical Di Caprio meme, or Troll Face meme) and text actuality of memes can be taken into consideration. For the former, database of the site Know Your Memes can be harnessed where memes are categorised based on their imagery. For this purpose we have also trained a model which can distinguish between 100+ categories of memes with an accuracy of 95%. Other class imbalance offsetting methods such as SMOTE and different class weighting could also be deployed.

In the near future, we are planning to carry on with further developing our models using the above-mentioned techniques to gain improvements on model stability and relevant metrics.

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