Risk score assessment for Twitch users/influencers.

The following document is part one in a series of two parts; part one discusses, in brief, the main objective and it’s background, and also lays out the foundation of the math used for the same. Part two talks in detail about some use cases, and specificity to Twitch.

Abstract

Financial, banking, and portfolio management institutions use risk to calculate and predict the credibility of customers which thus allows the accountability of the resources provided to them. Risk in that scenario would depend on a multitude of factors relating to monetary or financial transactions, for example relationship with banks, payment of debt, value of transactions etc. Risk in general terms would usually depend on parameters which, if overlooked, can potentially cause damage to the institution. However, a significant part of risk assessment is to also avoid damage in the long run i.e predicting future performance of customers.
A venture capitalist looking forward to a worthwhile endeavor in the social media/streaming business should be aware of risk in that realm much like the same way as finance. However, risk can be a bit tricky in the realm of social media.

Risk assessment by banks and financial institutions in a way is biased because they don’t take into account the fact that their customers have an incentive to boost their score, which in turn acts as a feedback loop between institutions and their customers. These institutions, nevertheless, produce some of the most accurate results. This paradox leads to a simple conclusion: a well established institution of any kind--whether it be financial or social media---does not need to worry about incentives. Incentives come with a cost of abandonment; Twitter does not need incentives because people have been using it for very a long time--and quite ironically, despite its actions on its users, they aren’t willing to leave that platform anytime soon--- but Parler’s users can potentially abandon the platform if it were to overlook incentives.

Thus, a good model for assessing risk for social media influencers and streamers would not only look at incentive, but also cater it’s parameters to best suit the needs of the business model.

The score index

The Twitch API allows fetching eligible viewers from a campaign, and in general for the total follower count of a streamer. These two parameters would be key to calculating risk for this model. The objective is to also identify the streamers with high follower count and popularity(top 1%). So, for even being considered, users first have to pass a filter which churns out only those users that have their follower and average viewer count above a minimum threshold. The value of the threshold again would depend on use case and business model so it's hard to quote a rigid value. However, it is required that the maximum value of the index scale br atleast greater than 200% of the threshold.

$$index = \lambda \cdot \frac{(value - threshold)}{scale}$$

Where λ = multiplier(a value that's dependent on need)

It should be noted that the above value is just a preliminary index, meaning it's only calculated for the first half of the problem.

The prediction

Once we have a list of users with their preliminary scores assigned, it's time to make actual predictions as to whether this user is really credible. A prediction in this sense would be knowing ahead of time if the user's follower count will likely go up, down, or stay the same. The prediction would obviously come with some uncertainty which the model has to acknowledge and expect. The prediction can only be made so far ahead of time, and should only included if it contains minimum error margin.

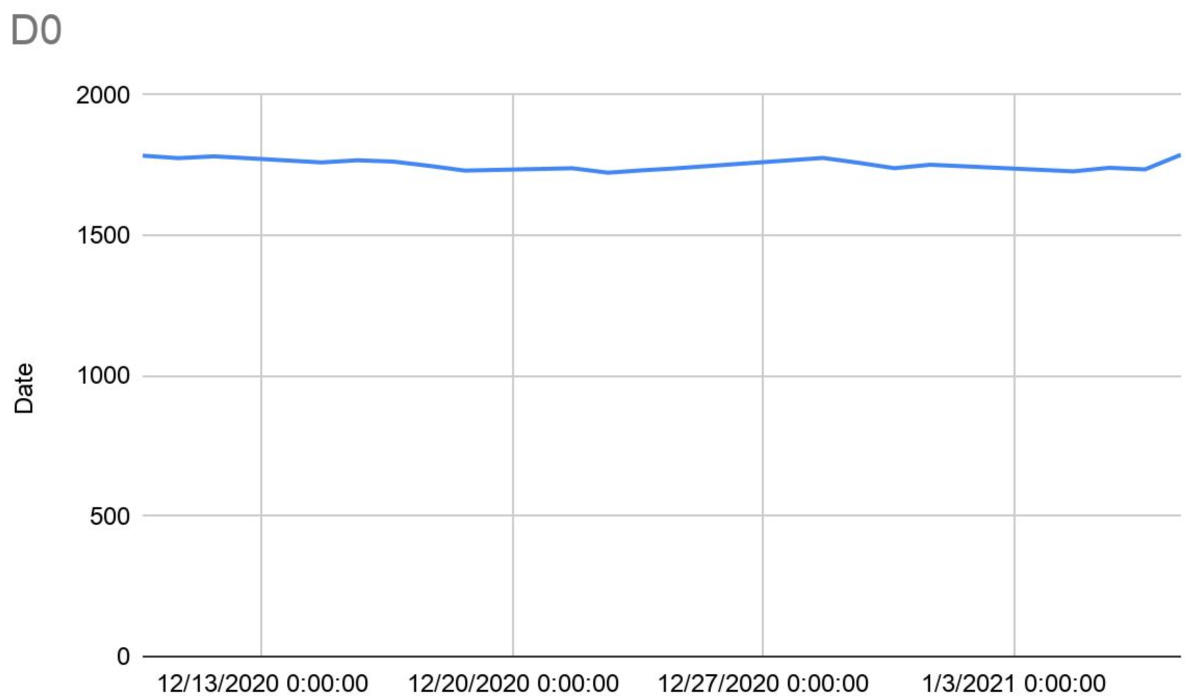
The D5 rule: fifth derivative rule

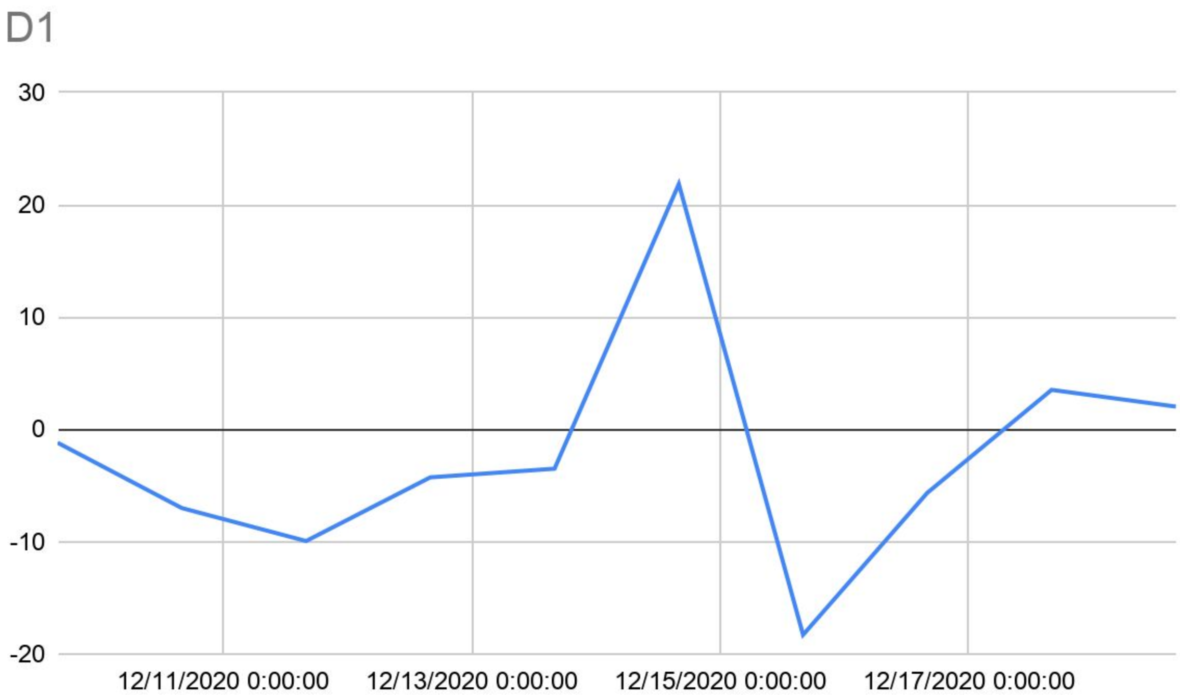
According to this rule, given a data set of abstract data, and given enough data in the set. Sketching the data in a cartesian coordinate system, and calculating the fifth derivative of the given data set, if we follow the trendline generated by the fifth derivative curve then we can sketch out how the graph will behave down the line.

Given a map $F = \{x \Rightarrow y : y = datapoint, x = range\}$

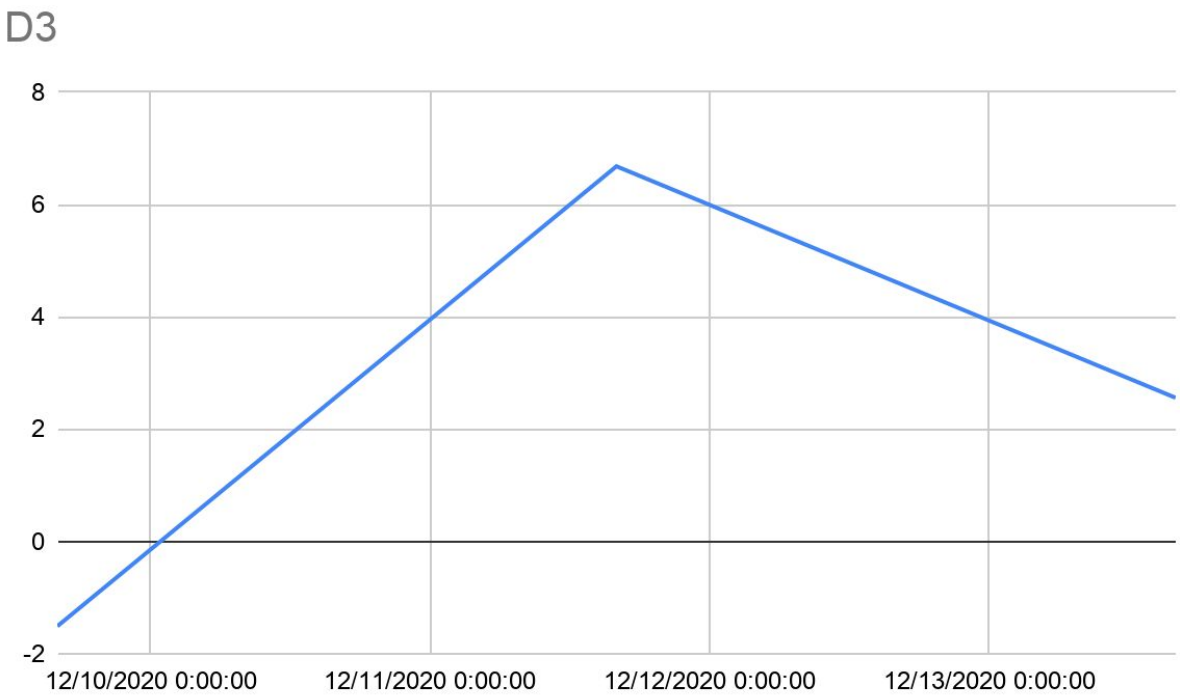
$$D_1 = \{x \Rightarrow y'(x) : x = reduced\ range\ for\ D_1\}$$
$$D_2 = \{x \Rightarrow y''(x) : x = reduced\ range\ for\ D_2\}$$

$$D_3 = \{x \Rightarrow y'''(x) \ : \ x \ = \ reduced\ range\ for\ D_3\}$$
$$D_4 = \{x \Rightarrow y''''(x) \ : \ x \ = \ reduced\ range\ for\ D_4\}$$
$$D_5 = \{x \Rightarrow y'''''(x) \ : \ x \ = \ reduced\ range\ for\ D_5\}$$





D1
30
20
10
0
-10
-20
12/11/2020 0:00:00
12/13/2020 0:00:00
12/15/2020 0:00:00
12/17/2020 0:00:00



The justification for using fifth derivative is the following:
Differentials measure changes in curves and values, and by definition the higher the order of derivative, the less prone it is to change (the slower it changes). Think of it as a massive wrecking ball moving with high speed; the higher the momentum of that ball is (momentum = mass * velocity), the slower it will slow down if someone tries to stop it. The reverse effect is a free falling ball, the faster it's velocity changes, the faster it takes for it to fall to the ground.

Acceleration is second order derivative of position, and velocity is its first order derivative. So, any slight change to in position would account for little to no change in the acceleration, visa versa any moderate change in acceleration would cause significant change(of same manner) in the position. If at a moment in time, the rate of change of acceleration is slowing down (quite slowly), then it will take some more time for position to halt too. In summary, given the trendline in rate of change of acceleration, we've predicted to a high degree of accuracy the nature of the position in a later moment in time.

In the earlier section, we imposed a condition that the score index should be atleast 200% above the threshold. The reason for that is if, in the future, a bizarre change occurs in the fifth derivative of the dataset, it will take some time for that to reflect in the dataset itself. This period--the warning period as i'd like to call it-- will signal a high risk rate.

Limitations to the rule

To generate the fifth derivative of a dataset, and to actually still have enough data points left to follow the trend curve, a lot of data is required in the initial set. One of the fundamental prepositions of calculus is that large curves are divided into infinitesimally small sections. Which means that in an ideal case, we should have a continuous dataset, however, real world data is neither continuous, nor infinite. This constraint of the model makes errors inevitable. The solution is to have as many data points as possible to minimize any potential error uncertainty. To put it in perspective, if the fifth derivative curve consists of atleast 10 data points then the initial dataset should contain atleast 10×2^5 data points.

The expansion of the 5th derivative curve can only allow us to predict trend lines and not actual behaviour of the curve. In calculus, infinitesimally small changes occur in smooth curves, and in practice the changes are not that small, and we're only guessing the trend line so the model is only going to be as accurate as the data it's been provided. However, many other techniques can be implemented down the line to make sure of that.

Anomaly detection

Although they cause more uncertainty, anomalies are a huge part of the internet and should be taken into account while trying to predict the D5 trend line. Anomalies in this case are any type of abnormal or bizarre behaviour that can be observed in the follower, viewer count, or changes in those values. For example if user A has about 10 followers on day 1, but suddenly 100,000 on day 2, that would count as an anomaly. As bizarre as it might sound, these kind of behaviours have often occurred in the past (a viral video, a tweet, or a meme), and are significantly likely. Now, if this phenomenon is a part of the system itself, the next question is how do you distinguish between them and actual anomalies. To answer this question, I turned my attention to the November 3rd presidential election.

The 2020 presidential candidate Joe Biden's poll performance contained some of the most bizarre anomalies(from a statistical point of view) that anyone had ever seen. Among the many allegations of voter fraud that the Trump campaign made towards Biden's campaign, some of the leading forensic experts and mathematicians also called out this phenomenon for "failing to follow Benford's law". Benford's law states that any large span on an average follows a certain distribution of the base digits that make up the data-- the digit 1 would appear about 55% of the time, 2 would appear 2 would appear 27.9 % and so on. This law can be used as a clue to detect that something is inappropriate with the data you're dealing with. Biden's voter count failed to follow Benford's law because the average frequency of digits was nowhere near 30% (as set by the Benford's limit).

Even Though anomalies are normal on the internet(and in the earlier scenario, digital voting machines), too much deviation of the law can be a clear tell tale sign that something fishy is

going on under the hood. Au contraire, if the D5 trend curve were to be selected in such a manner as to undermine Benford's law by a huge margin, then the model would produce inappropriate and false results.
In summary, to make sure that the model produces most accurate results, we also need to take into account that the D5 trend curve follows Benford's law as closely as possible.

Final remarks

The above sections layout the fundamentals of the model that would be used for risk assessment in the following two parts:

Part one concluded with a rigid formula to calculate preliminary score index that would be scaled appropriately. And part two talked about D5 trend line to make further predictions about the performance of the users.

In the next part of this document, I will include some real world examples where the above model is used to assess risk for some stock market data. And also some examples relating specifically to Twitch where i try to make a risk assessment for some Twitch users by tweaking the parameters of this model to best suit the needs of the model and optimize the accuracy of the same. I would also try to sum up the above two separate indices into one compound index that will encapsulate both the preliminary index and prediction outcome.