

9-2019

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Technical Report: UTEP-CS-19-100

Recommended Citation

Urenda, Julio; Hernandez, Manuel; Villanueva Rosales, Natalia; and Kreinovich, Vladik, "How User Ratings Change with Time: Theoretical Explanation of an Empirical Formula" (2019). *Departmental Technical Reports (CS)*. 1380.

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How User Ratings Change with Time: Theoretical Explanation of an Empirical Formula

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Abstract

In many application areas, it is important to predict the user's reaction to new products. In general, this reaction changes with time. Empirical analysis of this dependence has shown that it can be reasonably accurately described by a power law. In this paper, we provide a theoretical explanation for this empirical formula.

1 Formulation of the Problem

For many industries, it is important to predict the user's reaction to new products. To make this prediction, it is reasonable to use the past records of the user's degree of satisfaction with different similar products.

One of the problems with such a prediction is that the user's degree of satisfaction may change with time: the first time you see an exciting movie or read an exciting book, you feel very happy, when you see this movie the second time, you may notice holes in the plot or outdated (and thus, somewhat clumsy) computer simulation.

Because of this phenomenon, for each user, the ratings of the same product decrease with time. In other words, instead of the simplified formula $r = r(u, p)$ that describes how the ratings depend on the user u and on the product p , a more accurate estimates can be obtained if we take this dependence into account and use a more complex formula

$$r = r(u, p) + c_u(t),$$

where a decreasing function $c_u(t)$ – which is, in general, different from different users – change with time.

To test different ratings models, in the 2000s, Netflix had a competition in which different formulas were compared. The winning model (see, e.g., [3]) used an empirical formula

$$c_u(t) = \alpha_u \cdot \text{sign}(t - t_u) \cdot |t - t_u|^{\beta_u}, \quad (1)$$

where t_u is the mean date of rating, and α_u and β_u are parameters depending on the user. (Actually, it turned out that the value β_u is approximately the same for all the users.)

The question is: why this formula works well, while possible other dependencies on time do not work so well?

2 Our Explanation

First technical comment. The formula (1) does not uniquely determine the functions $r(u, p)$ and $c_u(t)$: we can add a constant to all the ratings $r(u, p)$ and subtract the same constant from all the values $c_u(t)$ and still get the same overall ratings r .

To avoid this non-uniqueness, we can, e.g., select $c_u(t)$ in such a way that $c_u(t_u) = 0$; this is, by the way, exactly what is done in the formula (1). This equality is easy to achieve: if we have a function $c_u(t)$ for which $c_u(t_u) \neq 0$, then we can consider new functions $\tilde{c}_u(t_u) \stackrel{\text{def}}{=} c_u(t) - c_u(t_u)$ and $\tilde{r}(u, p) \stackrel{\text{def}}{=} r(u, p) + c_u(t_u)$. Then, as one can easily see, we have

$$\tilde{r}(u, p) + \tilde{c}_u(t) = r(u, p) + c_u(t),$$

i.e., all the predicted ratings remain the same.

In view of this possibility, in the following text, we will assume that

$$c_u(t_u) = 0.$$

First idea: the description should not depend on the unit for measuring time. We are interested in finding out how the change in ratings depends on time. In a computer model, time is represented by a number, but the numerical value of time depends on what starting point we choose and what unit we use for measuring time. In our situation, there is a fixed moment t_u , so it is reasonable to use t_u as the starting point and thus use $T \stackrel{\text{def}}{=} t - t_u$ to measure time instead of the original t .

In the new scale, the formula describing how ratings change with time takes the form $C_u(T)$, so that $c_u(t) = C_u(t - t_u)$. The condition $c_u(t_u) = 0$ takes the form $C_u(0) = 0$.

In terms of the new time scale, the empirically best formula (1) leads to the following expression for $C_u(T)$:

$$C_u(T) = \alpha_u \cdot \text{sign}(T) \cdot |T|^{\beta_u}. \quad (2)$$

While there is a reasonable starting point for measuring time, there is no fixed unit of time. We could use years, months, weeks, days, whatever units make sense. If we replace the original measuring unit with a new unit which is λ times smaller, then all numerical values of time are multiplied by λ . So, instead of the original value T , we get a new value $\tilde{T} = \lambda \cdot T$.

Since there is nothing special in selecting a measuring unit for time, it makes sense to require that the corresponding formulas not change when we make a different selection.

This has to be related to a change in how we measure ratings. Of course, we cannot simply require that the formula for $C_u(T)$ be invariant under the change $T \rightarrow \lambda \cdot T$. Indeed, in this case, we would have $C_u(\lambda \cdot T) = C_u(T)$ for all λ and T . Thus, for each $T_0 > 0$, by taking $T = 1$ and $\lambda = T_0$, we would be able to conclude that $C_u(T_0) = C_u(1)$ – i.e., instead of the desired decreasing function, we would have a constant function $C_u(T) = \text{const}$.

This seeming problem can be easily explained if we take into account how similar scale-invariance works in physics. For example, the formula $v = d/t$ that describes how the average velocity v depends on the distance d and time t clearly does not depend on what measuring unit we use for measuring distance: we could use meters, we could use centimeters, we could use inches. However, this does not mean that if simply change the measuring unit for distance and thus replace the original value d with the new value $\lambda \cdot d$, the formula remains the same: for the formula to remain valid, we also need to accordingly change the unit for measuring velocity, e.g., from meters per second to centimeters per second.

Similarly in our case, when we describe the dependence of rating on time, we cannot just change the unit for time, we also need to change another unit – which, in this case, is the unit for ratings.

But does this change make sense? At first glance, it may seem that it does not: we ask the user to mark the quality of a product (e.g., of a movie) on a certain fixed scale (e.g., 0 to 5), so how can we change this scale? Actually, we can. Users are different. Some users use all the scale, and mark the worst of the movies by 0, and the best by 5. What happens when a new movie comes which is much better than anything that the user has seen before? In this case, the user has no choice but to give a 5 to this movie as well – wishing that the scale had 6 or 7 or even more. Similarly, if a movie has a very negative experience with a movie, a much worse one than anything that he or she has seen before, this user places 0 and wishes that there was a possibility to give -1 or even -2 .

Other users recognize this problem and thus, use only, e.g., grades from 1 to 4, reserving 0 and 5 for future very bad and very good products. Some professors grade the student papers the same way, using, e.g., only values up to 70 or 80 out of 100, and leaving higher grades for possible future geniuses.

In other words, while the general scale – from 0 to 5 or from 0 to 100 – is indeed fixed, the way we use it changes from one user to another one. Some users use the whole scale, some “shrink” their ratings to fit into a smaller sub-scale. A natural way to describe this shrinking is by an appropriate linear transformations – this is how, e.g., we estimate the grade of a student who for legitimate reasons had to skip a test worth 20 points out of 100: if overall, the student earned 72 points out of 80, we mark it as $\frac{72}{80} \cdot 100 = 90$ points on a 0 to 100 scale.

Depending on what scale we use for ratings, the corresponding rating values change by a linear formula: $r \rightarrow \tilde{r} = a \cdot r + b$. In particular, for the difference between the ratings, we get

$$r_1 - r_2 \rightarrow (a \cdot r_1 + b) - (a \cdot r_2 + b) = a \cdot (r_1 - r_2).$$

So, when we change the unit for measuring time by a λ times smaller one, we may need to according re-scale our difference $C(T)$ between the ratings. Thus, we arrive at the following precise formulation of the desired invariance.

Formal description of unit-independence. We want to select a function $C_u(T)$ for which, for each $\lambda > 0$, there exists a value $a(\lambda)$ for which

$$C_u(\lambda \cdot T) = a(\lambda) \cdot C_u(T). \quad (2)$$

It is also reasonable to assume that the function $C_u(T)$ continuously change with time – or at least change with time in a measurable way.

What can we conclude based on this independence. It is known (see, e.g., [1]), every measurable (in particular, every continuous) solution to the equation (2) for $T > 0$ has the form

$$C_u(T) = \alpha_u^+ \cdot T^{\beta_u^+}, \quad (3)$$

for some α_u^+ and β_u^+ .

Similarly, for $T < 0$, we get

$$C_u(T) = \alpha_u^- \cdot |T|^{\beta_u^-}, \quad (4)$$

for some α_u^- and β_u^- .

These formulas are similar to the desired formula (1), but we still have too many parameters: four instead of the desired two. To get the exact form (1), we need one more idea.

Second idea: the change in rating should be the same before and after t_u . It is reasonable to require that for each time interval $T > 0$, the change of rating should be the same before and after t_u , i.e., the change of ratings between the moments $t_u - T$ and t_u should be the same as the change of ratings between the moments t_u and $t_u + T$.

The change of ratings between the moments $t_u - T$ and t_u is equal to

$$c_u(t_u) - c_u(t_u - T) = -(c_u(t_u - T) - c_u(T)) = -C_u(-T).$$

The change of ratings between the moments $t_u + T$ and t_u is simply equal to

$$c_u(t_u + T) - c_u(t_u) = C_u(T).$$

Thus, the above requirement means that for every $T > 0$, we should have

$$-C_u(-T) = C_u(T).$$

Substituting the expressions (3) and (4) into this formula, we conclude that for each T , and taking into account that $|-T| = T$, we have

$$\alpha_u^+ \cdot T^{\beta_u^+} = -\alpha_u^- \cdot T^{\beta_u^-}.$$

Since this must be true for all T , we must have $\alpha_u^+ = -\alpha_u^-$ and $\beta_u^+ = \beta_u^-$.

Thus, for both $T > 0$ and $T < 0$, we indeed have the formula (1), with $\alpha_u = \alpha_u^+$ and $\beta_u = \beta_u^+$. The formula (1) is explained.

Acknowledgments

This work was supported in part by the US National Science Foundation grants 1623190 (A Model of Change for Preparing a New Generation for Professional Practice in Computer Science) and HRD-1242122 (Cyber-ShARE Center of Excellence).

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