# Determination of Half-Life in Mutation Process of Polymerase Basic Protein 1 Family from Influenza a Virus

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- Keywords: Bioinformatics, Amino-Acid Pair Predictability, Differential Equation, Evolution, Influenza A Virus, Polymerase Basic Protein 1.
- Abstract: The evolutionary process of a protein family is usually an up and down fluctuating curve when it presents in the x, y coordinates, where the x-axis is time and y-axis is an evolutionary feature of proteins. This irregular curve characterizes its patterns with various periodicities and unexplainable time frames. In the past, we used the fast Fourier transform (FFT) to find these periodicities in hemagglutinin, a surface protein from influenza A virus. However, FFT cannot distinguish the up and down fluctuations without periodicity. In this study, we employ the analytical solution of a system of differential equations from our previous studies to determine the half-life of evolution of the polymerase basic protein 1 (PB1) from influenza A virus from 1918 to 2009. We (i) converted 2352 PB1 into the predictable portion, (ii) presented these predictable portions according to their sampling times with respect to subtypes, (iii) employed the analytical solution to fit the predictable portions versus time profile, (iv) used several statistical measures to determine the goodness-of-fit, and (v) obtained the half-life of evolutions with respect to subtypes. Although our study sheds some insight onto the PB1evolution, much work is needed to better understand the virus evolution.

# **1** INTRODUCTION

It is widely acceptable and well known that mutations in protein push the protein evolution forward (Levine, 2020, Lyons, Lauring, 2018, Bloom, Arnold. 2009). In the x, y coordinates, the x-axis and y-axis are time and a protein feature, which represents its evolution. Based upon this evolution-time profile, one can easily perceive some particular aspects of a protein evolution. In this x, y coordinates, the y-axis is can be any protein feature subject to mutations. In other words, a mutation changes a given protein feature, which leads to a different value in the y-axis.

In such x, y coordinates, the evolutionary process can be a line up and down irregularly, no matter whether it presents in alphabets, which are form of protein, or in numeric values, which are converted using any of 540-plus conversion methods (Kawashima *et al.*, 2008, Wu, Yan, 2008).

It is useful and meaningful to find the patterns in such irregular up and down evolution-time profile. In the past, our research group used the fast Fourier transform to find the periodicity in the evolution of hemagglutinins from influenza A virus (Wu, Yan, 2005. 2006). However. the evolution of hemagglutinins does not have a unique periodicity, but many periodicities, because the fast Fourier transform can decompose a combined periodicity into many components. Therefore, it would be more useful and meaningful to pursue another aspect of evolution, the half-life of irregular up and down evolutionary line in the x, y coordinates.

In the past, our research group developed a system of differential equations to describe the evolution of influenza A virus hemagglutinins (Wu, Yan, 2009), matrix protein 2 (Yan *et al.*, 2009), matrix protein 1 (Yan *et al.*, 2010), polymerase acidic protein (Yan, Wu, 2010), nucleoprotein (Yan, Wu, 2011), and neuraminidase (Yan, Wu, 2021). We prefer three terms of the analytical solution as  $y(t) = A_1 e^{-k_{1t}} cos(\alpha_1 t + \phi_1) + A_2 e^{-k_{2t}} cos(\alpha_2 t + \phi_2) + A_3 e^{-k_{3t}} cos(\alpha_3 t + \phi_3) + C$ , where y is the protein feature of

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evolution, A,  $\alpha$  and k are parameters, t is the time,  $\varphi$  is a phase difference, and C is a constant.

In this study, we are interested in the polymerase basic protein 1 (PB1) from influenza A virus. PB1 is a subunit of RNA-dependent RNA polymerase complex, which is associated with the transcription and replication of the influenza A viral genome (Engelhardt, Fodor, 2006, Nayak *et al.*, 2004). PB1 is important for the efficient propagation of the virus in the host and for its adaptation to new hosts (Brower-Sinning *et al.*, 2009) and considered as a determinant of the pathogenicity of the 1918 pandemic virus (Watanabe *et al.*, 2009). Besides, PB1 is the major target for both CD4(+) and CD8(+) T-cell responses (Assarsson *et al.*, 2008). Because of this importance, we wish to find some patterns in PB1 evolution.

#### 2 MATERIALS AND METHODS

# 2.1 Data

5125 full-length PB1s of influenza A virus sampled from 1918 to 2009 were obtained from the influenza virus resources (Influenza virus resources, 2021). After excluded identical sequences (Furuse *et al.*, 2009), 2352 PB1s were used in this study.

# 2.2 PB1 Evolution

In *x*, *y* coordinates, we use the time in the *x*-axis and the amino-acid pair predictability (AAPP) of each PB1 as protein evolution feature in the *y*-axis, and AAPP was computed with the following example. ABL31752 PB1 from human H5N1 influenza virus, strain A/Indonesia/CDC836/2006(H5N1), comtains 757 amino acids. The first and second amino acids can be counted as an adjacent amino-acid pair, the second and third as another pair, the third and fourth, until the 756th and 757th, thus there are totally 756 adjacent amino-acid pairs.

This PB1 has 51 serines (S) and 59 threonines (T), if the permutation can predict the appearance of amino-acid pair ST: it must appear 4 times  $(51/757\times59/756\times756=3.97)$ . Actually it does appear four times, so the pair ST is predictable. In contrast, this PB1 has 33 phenylalanines (F) and 50 glutamic acids (E), if the permutation can predict the appearance of amino-acid pair FE: it must appear twice  $(33/757\times50/756\times756=2.18)$ . But, it appears six times in realty, so the pair FE is unpredictable. In this way, all amino-acid pairs in ABL31752 PB1 can

be classified as predictable and unpredictable, which are 26.98% and 73.02%.

In the second example, ABL31774 PB1 from human influenza virus isolated in 2006 has only one amino acid different from ABL31752 PB1 at position 598. However, its predictable and unpredictable portions are 25.40% and 74.60%. Thus, AAPP distinguishes one PB1 from another in terms of numbers rather than alphabets that represent amino acids.

In this manner, we can use 26.98% to represent ABL31752 PB1 and 25.40% to represent ABL31774 PB1 in the *y*-axis of *x*, *y* coordinates. This method is applied to all 2352 PB1 in this study.

#### 2.3 Half-Life of Evolution and Statistics

We use the analytical solution shown in Introduction to fit the AAPP-time profile to get the half-life. The t-test was employed to compare the difference between uphill and downhill half-life, and P < 0.05 is considered significant. The fitting was conducted using SigmaPlot (SPSS Inc., 2002).

## **3 RESULTS AND DISCUSSION**

Figure 1 shows the evolution of 2352 PB1s over 90 year for the NA subtypes. Graphically, Figure 1 has the following meanings: the solid curve in the top panel presents the evolution of 2352 PB1s from 1918 to 2009, and each point is the mean value of predictable portions of all PB1s in a given year with its standard deviation (vertically grey line). The dotted line is the fitting by three-term of analytical solution. Similarly, the same meanings can be applied to other panels. In top panel, the time starts from 1918, when the Spanish pandemic occurred, for N1 subtype. However, this is not the case for the rest NA subtypes. Therefore, the imbalanced data may compromise us to use the analytical solution to fit these AAPP-tine profiles to find out the half-life of evolution. Thus, we conducted three statistical tests to determine the goodness-of-fit when we use a three-term analytical solution to treat these evolutionary curses.



Figure 1: Evolution of influenza A virus PB1 family from 1918 to 2009 in terms of predictable portion of AAPP in different NA subtypes. The data present as mean±SD. The dotted lines are fitted curves using analytical solution.



Figure 2: Residual over time for different NA subtypes.

Figure 2 demonstrates the goodness-of-fit for fitting of data in Figure 1 by observing whether there is a trend in plotting residual over time. Actually, we cannot see any monotonic trend in any panel in Figure 2 although there is a tendency that the longer the time involved, the more the fluctuations. Nevertheless, we observed the relatively large fluctuations around 1980s.



Figure 3: Evolution of influenza A virus PB1s from 1918 to 2009 in terms of predictable portion of AAPP in all PB1s and different HA subtypes. The data present as mean±SD. The dotted lines are fitted curves using analytical solution.

Figure 3 illustrates the evolution of 2352 PB1s over 90 year for the HA subtypes. Graphically, Figure 3 is completely similar to Figure 1, therefore, all the implications in Figure 1 are applicable to Figure 3. In Figure 3, we can see several dramatically sharp decreases in AAPP while there is only one such fall in Figure 1, suggesting the difference between HA and NA subtypes.

Figure 4 exactly is the same as Figure 2, i.e. to observe any trend of residuals over time for the goodness-of-fit. Similarly, we cannot notice any monotonic trend in all the panels in Figure 4, suggesting a goodness-of-fit. Again, we can see some fluctuations around 1980s. Both Figures 3 and 4 ran our first statistical test.



Figure 4: Residual over time in all and different HA subtypes.

Figure 5 pictures the second statistical test, that is, residuals versus fitted values. Here, we are still looking for whether there is any trend between two variables. Indeed, there is no any visible trend although sometimes clusters formed.

Figure 6 manifests the third statistical test, say, residuals versus actual values. Similarly, we wish to find whether there is any trend in these panels. In good agreement with the above two statistical tests, we cannot find out any monotonic trend although the residual increases as actual value increases in some cases, which are generally attributed to the unbalanced data because of difficulty in collecting samples of influenza A virus. Collectively, these three statistical tests confirmed goodness-of-fit when using three exponential terms of analytical solution.

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	H9 subtype	H10 subtype	N1 subtype	N2 subtype
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	N3 subtype	N6 subtype	N8 subtype	N9 subtype
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Figure 5: Residual versus fitted value of predictable portion for all and different subtypes of PB1.

The solid curves in Figures 1 and 2 present the change in predictable portions of the PB1s over time. Their fluctuation renders us to find the downhill and uphill half-life, which then serves as initial values for fitting. With decaying exponential, the half-life is  $t_{1/2}=ln(2)/k=0.696/k$ , where  $k=(ln_{ypeak}-ln_{ytrough})/t_{interval}$ , which is the downhill half-life. Hereafter, we can compute the uphill half-life in the similar way. Consequently, we can find the parameters in the three terms of analytical solution in Table 1.

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(%) ₽	H4 subtype	H5 subtype	H6 subtype	H7 subtype	-4
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-4	H9 subtype	H10 subtype	N1 subtype	N2 subtype	-4
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-4	N3 subtype	N6 subtype	N8 subtype	N9 subtype	-4
	26 27 28 29	27 28 29 30 31	25 26 27 28 29 30 31	27 28 29 30 3	1

Figure 6: Residual versus actual value of predictable portion for all and different subtypes of PB1.

In Table 1, the third term in the analytical solution cannot be found by fitting for H4, H6, H9 and H11. This phenomenon may not be surprising because the samples of those subtypes are quite imbalanced. On the other hand, this also indicates the limitation in fitting although the goodness-of-fit

looks good. In reality, these parameters lack physical meanings in biological sense. This is the drawback of application of mathematical methods in biological and medical fields because it is always very hard to relate a model parameter to a biological and medical meaningful indicator.

Table 1: Parameters for	analytical solution.
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Subtype	$A_1$	<i>k</i> 1	$\alpha_{l}$	<b>\$\$\$</b> 1	$A_2$	<i>k</i> <sub>2</sub>	$\alpha_2$	<b>\$\$</b> 2	A3	<b>k</b> 3	α3	<b>\$</b> 3	С	$R^2$
All	-15.28	0.97	0.55	1.80	-0.28	0.00	2.01	-5.96	-0.23	0.00	0.89	6.75	27.41	0.53
H1	5.67	0.00	-0.04	0.52	-8.17	0.87	1.36	-3.56	0.40	0.00	1.04	-1.53	21.95	0.69
H2	13.48	0.35	0.45	3.94	2.22	0.00	0.58	6.48	-1.19	0.00	1.78	1.93	27.78	0.85
Н3	-0.67	0.02	0.68	4.76	-1.52	0.04	-0.25	3.35	0.57	0.02	0.90	4.13	27.14	0.60
H4	1.13	0.13	1.71	-1.84	1.95	0.15	0.39	4.10					27.63	0.84
Н5	3.75	0.17	1.52	-0.82	-2.37	0.11	0.42	0.85	3.34	0.12	1.32	-3.08	27.32	0.71
H6	4.10	0.33	2.02	-0.70	0.27	0.00	1.31	-1.57					26.91	0.98
H7	-14.93	0.86	2.02	-3.36	-2.18	0.00	0.49	1.78	-1.58	0.00	0.72	3.09	28.02	0.98
Н9	-0.60	0.03	2.35	14.1 3	-5.35	0.81	1.26	0.61					27.10	0.92
H11	-3.80	0.12	0.19	4.94	-0.92	0.00	1.27	-0.38					29.07	0.84
N1	-0.46	0.00	1.08	1.07	-0.39	0.00	0.63	0.16	11.2 6	0.53	5.59	-0.54	27.25	0.54
N2	2.38	0.22	1.95	-2.76	2.82	0.07	-0.26	-4.15	0.31	0.03	1.21	-8.55	26.97	0.60
N3	-2.74	0.00	0.64	7.03	2.55	0.00	0.68	6.51	2.04	0.15	-1.21	-6.86	27.71	0.76
N6	-29.25	0.99	1.99	-0.31	-0.26	0.00	2.08	1.69					27.80	0.98
N8	2.17	0.06	1.08	0.30	1.01	0.04	1.55	8.05	1.88	0.05	0.46	-0.22	28.40	0.52
N9	0.73	0.00	1.50	-0.40	-0.81	0.00	-0.31	3.37	0.66	0.02	0.87	1.82	28.40	0.94

Table 2. Half-life between uphill and downhill in influenza A virus PB1.

Subtype	Uphill half-life (years)			Dov	t test		
	Number	Mean	SD 7	Number	Mean	SD	P value
All PB1	11	50.34	15.94	12	38.34	16.25	0.09
H1	11	46.64	19.90	13	41.82	19.28	0.55
H2	10	36.73	15.45	8	36.73	15.45	0.64
Н3	6	44.83	31.65	6	39.30	19.13	0.72
H4	3	30.42	18.69	5	49.72	22.93	0.27
Н5	7	42.67	16.68	10	54.99	22.18	0.23
H6	7	36.76	15.51	7	41.66	25.39	0.67
H7	5	32.68	18.57	6	44.19	18.30	0.33
Н9	4	52.40	26.01	6	56.27	19.33	0.79
H11	6	38.21	13.15	4	36.63	14.85	0.86
N1	10	50.74	19.01	11	40.19	15.97	0.18
N2	8	34.09	15.07	10	38.09	12.77	0.55
N3	6	64.18	29.62	6	42.95	13.58	0.14
N6	8	56.55	20.38	7	58.74	28.13	0.87
N8	5	23.63	16.89	7	26.79	19.00	0.77
N9	6	48.69	21.35	7	45.96	24.09	0.83

Table 2 lists the half-life with statistical comparison, As no statistical difference was found between uphill and downhill half-lives, we can see that the half-life is ranged smaller in HA subtype than that in NA subtype, especially for the uphill half-life. Yet, the standard deviations (SD) are actually quite large, suggesting the sampling number is not large. This demonstrates another difficulty in modeling, that is, the experimental data always do not meet the demand from modelers. Therefore, do we need to design an experiment according to experimenters or modelers?

The pandemic/epidemic mechanism is extremely complicated, and the current Covid-19 is the best proof that we know too little to implement any efficient and effective measures to stop the spread of coronavirus. Because of rich data in influenza virus, the detailed and comprehensive studies on influenza virus nevertheless can enrich our knowledge on influenza virus, which can extrapolate to coronavirus.

### 4 CONCLUSIONS

In this study, we attempted to determine the half-life of PB1 from influenza A virus in terms of its evolutionary process. This is accomplished by using a three-term analytical solution of a system of differential equations obtained in our previous studies. In this way, we hope to reveal another aspect of virus evolution, however how to interpret the meaning of model parameters still requires more studies in the future.

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