PREDICTING STRENGTH OF MATCHED SETS OF TEST SPECIMENS

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ABSTRACT

Five different methods for *a priori* estimating bending strength of wood and wood composite specimens are compared in this paper. They are: (1) edge-matching, (2) matching specimens by normal distribution, (3) matching specimens by log-normal distribution, (4) simple linear regression, and (5) multiple linear regression. It was found that the square root of mean square error (RMSE) of percent difference (PD) of predicted modulus of rupture (MOR) is the key measure in comparing the five methods. Multiple linear regression was found to be the best method to predict MOR of a specimen in an edge-matched set. Finally, how to create the prediction limits for mean MOR of a subgroup of specimens is discussed. The prediction limits for predicting MOR make it possible to quantitatively determine the effect of various treatments of wood materials.

Keywords: Predicting strength, edge-matching, distribution, regression, prediction limits.

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INTRODUCTION

The creation of a set of bending specimens whose strength can be accurately predicted is essential in the studies of fatigue, creep-rupture, and damage accumulation in wood. In these studies, a stress ratio defined as the applied stress divided by the stress known to cause failure in a conventional short-term strength test is needed but can only be approximated because the strength of any specimen is known only after a destructive test. Numerous methods for estimating strength nondestructively of solid wood and wood composites have been reported in the literature: (1) edge-matching which assumes that mechanical properties (e.g., modulus of elasticity (MOE) and modulus of rupture (MOR) of an edge-matched pair) are similar (McNatt 1970); (2) matching specimens by the order of failure (Johns and Madsen 1982); (3) matching specimens by underlying failure distribution (Gerhards 1988); (4) matching specimens by matched distribution of MOE (Foschi and Barrett 1982) or by distributions of MOE and strength ratio (the hypothetical ratio of the strength of member to the strength it would have if no weakening defects were present) (Soltis and Winandy 1989); (5) averaging in which the predicted strength is assumed to be the average test strength of all control specimens (Gerhards 1976); (6) simple averaging wherein the average strength of two neighboring side-by-side control specimens is used as the prediction value (Tichy 1976); (7) predicting MOR by using correlation between MOR and MOE (Schniewind 1967) or correlation between MOR and both MOE and density (Sekino and Okuma 1985); (8) adjusted regression in which the regression model and properties of the pair matching specimen are used to predict the static strength (Gerhards 1976); and (9) end-matching which assumes that mechanical properties (e.g., modulus of elasticity (MOE) and modulus of rupture (MOR) of an end-matched pair) are similar (Tichy 1976).

In all the above methods, two matched sets of specimens were required; one set was used as a control set and subjected to the static test, and the other was used as a test set for a treatment. The static strengths of the control set and times-to-failure of the test set were determined. But different assumptions were used for each method to predict strength for the test set. Methods (1) and (9) assumed that MOE and MOR of the matched pair are similar. In method (2), the static strengths of the control set and times-to-failure of the test set were ordered from lowest to highest. It was assumed that a specimen that was ranked n^{th} in times-to-failure had the same static strength as the n^{th} static strength ranked in the control set. In method (3), distributions of both the static strengths of the control set and times-to-failure of the test set were created. Given a time-to-failure, the percentile in the time-to-failure distribution could be found, and it was assumed to be the same in the static strength distribution, and so the static strength was determined based on the same percentile. Although the predicted MOR in method (3) remained in the same rank as in method (2), the magnitudes of the predicted MOR were not the same. The ideas used in method (4) were the same as in method (3) except that the distribution of MOE was used instead of the time-to-failure distribution. Methods (5) and (6) used averaging technique to estimate the strength of test specimens. In method (7), it was assumed that relationships between MOR and MOE (or MOE and density) in both sets were the same. Therefore, the static strength of a specimen in the test set could be determined by using the regression function created from the control set. Based on method (7), method (8) added the MOR, MOE, and density properties of the pair-matched specimen in the regression equation. All methods required that one of each matched pair be tested to failure in a conventional short-term test.

For small structural sizes of lumber, Gerhards (1976) determined how closely the bending or tensile strength of one specimen could be predicted by a closely matched specimen. Two matching criteria were examined: tangential matching, where the specimens were chosen side-by-side along approximate tangents to the growth rings; and radial matching, where they were similar along a radius. Four previously discussed alternatives for predicting static strength, namely methods (1), (5), (7), and (8) were compared. The standard deviation of σ_s/σ_p ratios (defined as actual strength divided by predicted strength) and the maximum deviation of individual σ_s/σ_p ratios were used as two indexes to compare the four alternatives. Method (7) was found to be the best (with a coefficient of variation of 11.6%) to predict strength of bending specimens while method (8) was the best (with a coefficient of variation of 14.4%) to predict tension specimens' strength. The maximum deviation (worst case) was used to estimate the range of predicted static strength of an individual specimen. Such deviation was so large that it could mask the effect of a treatment, e.g., to enhance fire performance of wood. Therefore, the standard deviation was used as a basis to select the sample size (ASTM 1994) necessary to detect an average effect of the treatment on strength.

Tichy (1976) conducted similar research for commercial oriented strandboard (OSB). Percent error, which was defined as predicted MOR minus actual MOR as a percent of actual MOR, was used as the index instead of σ_s/σ_p ratio. Four alternatives discussed previously, namely methods (1), (6), (8), and (9), were compared. The differences between methods (1) and (9) were small. The method (6) of simple averaging was found to be the best (with a standard deviation of only 4.4%, as compared to over 10% for the other two methods) for OSB. There was no discussion of the prediction range of MOR for individual specimens.

The primary objectives of this research were: (1) to evaluate five different methods for strength prediction that are commonly used for solid wood by quantitatively comparing them by (a) square root of mean square error (RMSE) of percent difference (PD) of predicted MOR and (b) the correlation coefficient between the actual and predicted MOR; (2) to determine the best model for predicting MOR; (3) to determine prediction limits of a given stress ratio for individual specimens; and (4) to determine prediction limits for mean MOR of a group of specimens.

MATERIALS AND PRIMARY DATA

Four test groups were formed; two groups of small beams of sawn southern pine (SP1 and SP2), one group of oriented strandboard (OSB), and one group of plywood (PLY). SP1 and SP2 were cut from southern pine 2×4s (nominal 2 in. (50.8 mm) in thickness and 4 in. (101.6 mm) in width obtained from a local supplier). All 2×4s were conditioned for about three months at 22.2°C (72°F) and 36% relative humidity. For SP1, 660.4-mm (26-in.)-long clear straight-grain sections were crosscut from the 2×4 lumber. An edge-matched pair of specimens was obtained by ripping the clear section lengthwise. The resulting edge-matched specimens were randomly separated into two sets (A and B). There were 24 pairs in group SP1 (24 specimens measured 38.1 by 38.1 by 660.4 mm in SP1A and SP1B each). Specimens were tested under center-point load with a rate of displacement of 2.54 mm/min and support span of 609.6 mm; flexural MOE and MOR were determined for each specimen. Group SP1m is the same as group SP1, except that four outlier pairs were culled (discussed later).

For the SP2 group, the 2×4s were crosscut, and edge-matched pairs were made as with group SP1. Additionally, each pair was visually checked to ensure that both specimens had no boxed heart (no pith appears on the cross section) and had as similar a growth ring pattern as possible. There were 22 pairs in group SP2. Each specimen measured 38.1 by 38.1 by 660.4 mm. MOE and MOR were determined for each specimen under four-point load with a simple span of 609.6 mm. Two load points spaced 203.2 mm apart were centrally located on the span. All specimens were

TABLE 1. *Averages and coefficients of variation (in parentheses) of physical properties of test specimen.*

Group	Set	Number of specimens	TTF[a] min	Moisture content %	Density (kg/m^3)[c]	MOE (10^9 Pa)[d]	MOR (10^6 Pa)[d]
SP1	A	24	6.5 (27.7)	8.21 (4.64)	600.6 (11.5)	13.86 (15.61)	114.6 (15.36)
	B	24	6.3 (25.4)	8.27 (5.28)	597.5 (10.2)	13.58 (14.27)	111.2 (12.79)
SP1m[b]	A	20	6.6 (27.3)	8.16 (4.90)	596.9 (11.6)	13.77 (12.17)	115.2 (12.97)
	B	20	6.4 (26.6)	8.26 (5.73)	595.4 (11.0)	13.65 (13.92)	110.6 (13.72)
SP2	A	22	5.0 (20.0)	7.38 (5.93)	650.0 (13.6)	16.64 (12.74)	120.9 (18.95)
	B	22	4.9 (20.4)	7.39 (5.39)	647.7 (13.6)	16.73 (13.89)	118.4 (19.24)
OSB	A	67	2.0 (10.0)	8.86 (1.96)	578.7 (3.5)	4.81 (9.21)	21.8 (16.0)
	B	67	1.0 (14.0)	9.21 (2.28)	578.6 (2.9)	4.88 (9.31)	21.2 (16.9)
PLY	A	32	5.2 (23.1)	10.04 (4.13)	605.0 (6.4)	12.41 (18.30)	77.1 (17.71)
	B	32	5.0 (22.0)	10.06 (3.84)	605.9 (6.2)	12.47 (19.62)	76.2 (20.37)

[a] Time-to-failure.
[b] Group SP1m is the same as group SP1 except that 4 pairs were culled.
[c] 1 kg/m^3 = 0.0624 pcf.
[d] 1 Pa = 1.45 × 10^{-4} psi.

tested with pith side down under load control at a rate of 33.4 N/sec (7.5 lb/sec).

The OSB group (Bradtmueller 1992) was prepared from commodity boards, 23/32 inches (18.3 mm) in thickness, as commonly used for floor panels in residential and light commercial construction. The adhesive used in the OSB was an aqueous solution of phenol-formaldehyde. In accordance with ASTM D1037 (ASTM 1996) for center-point testing, specimen length and width were defined as 488.9 mm and 76.2 mm, respectively. Four edge-matched pairs per panel were cut from 18 panels, with the longitudinal direction of specimens parallel to the aligned face fiber direction. All specimens were conditioned to equilibrium moisture content in a climate controlled chamber maintained at approximately 26.7°C and 65% RH. MOE and MOR were determined for each specimen under center-point bending with a support span of 438.1 mm. A rate of deflection of 5.6 mm/min was used for set A and 8.9 mm/min for set B.

For the PLY group, 64 specimens were cut from 11 panels of commercially manufactured southern pine plywood. The 15/32-in. (11.9 mm) thick panels were 32/16 span rated. The specimen length and width were defined as 609.6 mm and 50.8 mm, respectively. MOE and MOR were determined for each specimen under center point bending load with a support span of 553.7 mm and a rate of displacement of 6.6 mm/min.

Like SP1, the edge-matched specimens from the other groups were separated randomly into two sets (A and B). The general properties of the various test groups are summarized in Table 1.

METHODS

The "A" sets were arbitrarily selected to be the control sets of the specimen pairs. They were loaded to failure using conventional short-term tests as discussed. Next, the MOR of the specimens from the "B" sets was predicted using several techniques, which will be discussed later, based on model parameters/characteristics of their matched mates from the "A" sets. Then, the specimens from all "B" sets were tested to failure using identical procedures as their matched mates from the "A" sets (except that different loading rates were used for OSB groups) and their actual strengths calculated. Finally, the predicted strengths of "B" specimens were compared with their actual strengths. By making these comparisons, the evaluation of the effectiveness of the various prediction strategies was made.

Two measures of effectiveness were used. One was the correlation coefficient between

TABLE 2. *RMSEs of percent difference and correlation coefficients of predicting MOR with different methods.*

	Edge-matching		Normal dist.		Lognormal dist.		Linear		Multiple linear	
	RMSE[a]	Coeff[b]	RMSE[a]	Coeff	RMSE[a]	Coeff	RMSE[a]	Coeff	RMSE[a]	Coeff
SP1	17.1	0.46	12.2	0.67	10.5	0.67	12.6	0.67	6.9	0.85
SP1m	10.3	0.79	11.2	0.71	11.5	0.71	10.5	0.71	6.8	0.89
SP2	11.7	0.91	8.5	0.92	8.9	0.92	8.8	0.92	8.0	0.93
OSB	19.4	0.34	11.5	0.79	11.6	0.78	11.3	0.79	11.2	0.79
PLY	16.7	0.67	12.0	0.84	12.3	0.84	11.8	0.84	11.8	0.84

[a] Square root of the mean of the squares of percent differences.
[b] Correlation coefficients between predicted MOR and actual MOR.

predicted and actual MOR. The other was PD of predicted and actual MOR defined as

$$PD = \frac{\hat{R} - R}{\hat{R}} \times 100 \qquad (1)$$

where $\hat{R}$ and R are predicted and actual MOR, respectively. The PD defined here is not the same as the percent error defined by Tichy (1976). The reason why the predicted MOR is used as the denominator is that in determining the effect of a treatment of wood, the actual MOR of specimens in the test set is unknown. If both $\hat{R}$ (predicted MOR) and PD in Eq. (1) are estimated from the control set, then the prediction range ($|\hat{R} - R|$)can be determined.

Five different methods were used to estimate MOR. It is important to keep in mind that all five methods are variations on the analysis of data from physically edge-matched test specimens. The five methods are:

(1) Edge-matched specimens; mechanical properties (MOE, MOR) of an edge-matched pair are assumed to be the same.
(2) Matching specimens by normal distribution: distributions of mechanical properties (MOE, MOR) of edge-matched sets (A and B) are assumed to be normal and the same.
(3) Matching specimens by lognormal distribution: distributions of mechanical properties (MOE, MOR) of edge-matched sets (A and B) are assumed to be lognormal and the same.
(4) Simple linear regression: the simple regression relationships between MOR and MOE (E) of edge-matched sets (A and B) are assumed to be the same. The simple linear model can be stated as follows:

$$R_i = \beta_0 + \beta_1 E_i + \epsilon_i \qquad (2)$$

where ϵ_i is a random error; the model parameters β_0 and β_1 are determined by regressing the data of set A, and are assumed to be applicable to set B. Then, given the MOE (E_i) of a specimen in set B, the corresponding MOR (R_i) is determined using Eq. (2).
(5) Multiple linear regression: the regression relationships between MOR and both MOE (E) and density (D) of edge-matched sets (A and B) are assumed to be the same. The multiple linear model is stated as follows:

$$R_i = \beta_0 + \beta_1 D_i + \beta_2 E_i + \epsilon_i \qquad (3)$$

where β_0, β_1 and β_2 are model constants, are determined by regressing the data of set A, and are assumed to be applicable to set B. Then, given MOE (E_i) and density (D_i) of a specimen in set B, the corresponding MOR (R_i) is determined using Eq. (3).

RESULTS AND DISCUSSION

Square root of mean square error (RMSE) and correlation coefficients for predicting MOR using different methods are summarized in Table 2. The edge-matching method is the simplest way to create a set of specimens for predicting MOR. When comparing MOR of the two sets in group SP1, it is found that the correlation coefficient is 0.46 and RMSE of

PD is 17.1%. After graphing the data, four outliers were observed. When checking the corresponding specimens, it was noticed that the growth ring patterns on the ends of two specimens in a matched pair were not symmetric, and one specimen was much closer to the pith than the other. This resulted in large differences of MOR. When these four pairs were culled, the results (SP1m in Table 2) improved significantly. The RMSE of PD was 10.3% and the correlation coefficient was 0.79. In the SP2 group, every edge-matched pair was visually checked so that the growth ring patterns of the two specimens were as symmetric as possible. The results were close to that obtained for group SP1m. For OSB and plywood, the edge-matching method was not as good as for solid southern pine.

It is not surprising that the correlation coefficients between predicted and actual MOR are almost the same when using the simple linear regression method and the distribution method (both normal and lognormal). This is because the underlying assumption for the two methods is that MOR is correlated with MOE. In comparing them with the corresponding results of the edge-matching method, it is observed that the correlation coefficients and RMSEs of PD using linear regression and distribution methods are improved for SP1, OSB, and plywood; however, the correlation coefficients are about the same for groups SP1m and SP2.

When density is added to form a multiple linear regression model to predict MOR, the results are improved markedly for the southern pine groups. It is interesting to observe that multiple linear regression does not improve the predictability between the SP1 and SP1m groups (the RMSEs are about the same). The reason is that the different growth ring patterns on the end of four outlier pairs show different densities. Usually, a specimen that has annual rings closer to the pith has less density. Therefore, the use of the multiple regression method would eliminate the necessity for the visual inspection of growth ring characteristics, which was used in the formation of the SP1m group from the SP1 group.

Up to this point, two statistical measures are used to determine the best method for creating sets of specimens with *a priori* "known" strengths. The measures are RMSE of PD and the correlation coefficient (r) between the predicted and known MOR. For the SP2 group, the correlations are very similar (0.91 to 0.93) for all methods, but the RMSE of PD varies (11.7 to 8.0). Therefore, the question is which measure should be used in selecting the best method?

In the studies of fatigue and damage accumulation of wood, the stress ratio σ is defined as:

$$\sigma = \frac{\sigma_a}{\sigma_{ult}} \tag{4}$$

where σ_a is the applied stress and σ_{ult} is the actual MOR of the bending specimen. In reality, however, σ_{ult} is unknown. If a specimen is destroyed in determining its strength, it is obviously not available for the desired test. Therefore, the denominator must be predicted by using the methods discussed above.

From Eq. (4), the PD of the estimated stress ratio is the negative of PD of the predicted MOR:

$$\frac{d\sigma}{\sigma} \times 100 = -\frac{d\hat{R}}{\hat{R}} \times 100 = -PD \tag{5}$$

Thus, based on the results obtained from analysis of $d\hat{R}/\hat{R}$, a prediction interval for $d\sigma/\sigma$ can be determined.

The 95% prediction limits for a new observation depend on the RMSE. In contrast, the correlation coefficient cannot be used to quantitatively determine the accuracy of the prediction. Furthermore, the sensitivity of correlation coefficient is lower than one of the RMSEs because the correlation coefficients are very similar, while the RMSEs vary for all methods. Therefore, we use RMSE as the primary measure for determining which method is best. From Table 2 it is clear that the multiple linear regression model consistently

TABLE 3. *Average PPSEs and correlation coefficients of predicting MOR by using different control sets.*

	Multiple linear model created from set A				Multiple linear model created from set B			
	Set A		Set B		Set A		Set B	
	PPSE[a]	Coeff[b]	PPSE	Coeff	PPSE	Coeff	PPSE	Coeff
SP1	8.05	0.88	8.11	0.85	7.52	0.88	7.55	0.85
SP1m	7.45	0.86	7.59	0.89	7.08	0.86	7.18	0.89
SP2	7.51	0.85	7.62	0.93	6.47	0.83	6.5	0.96
OSB	10.89	0.76	10.7	0.79	11.4	0.76	11.08	0.79
PLY	11.24	0.82	11.24	0.84	12.15	0.81	12.16	0.84

[a] Percent prediction standard error.
[b] Correlation coefficients between predicted MOR and actual MOR.

yields the smallest RMSEs and hence is the best prediction method for all three wood-based materials.

The prediction limits for 95% confidence for a new observation ($\hat{R}$) using multiple linear regression with two explanatory variables (density and MOE) are (Neter et al. 1996):

$$\hat{R} \pm t(0.975; n - 3)s\{R_{new}\} \tag{6}$$

where $\hat{R}$ is a predicted MOR; n is the sample size; t is the critical value from the Student t-distribution; and $s\{R_{new}\}$ is the variance of predicting the new R and its square root is calculated as:

$$s\{R_{new}\} = RMSE\sqrt{1 + X_h'(X'X)^{-1}X_h} \tag{7}$$

where X (its transpose is X') is the matrix composed of all independent variables of the regression group and is given as

$$X = \begin{bmatrix} 1 & D_1 & E_1 \\ 1 & D_2 & E_2 \\ \vdots & \vdots & \vdots \\ 1 & D_n & E_n \end{bmatrix} \tag{8}$$

and X_h (its transpose is X_h') is the matrix corresponding to the new observation with independent variables D_h and E_h and is given as

$$X_h' = [1 \quad D_h \quad E_h] \tag{9}$$

The $s\{R_{new}\}$ is slightly different for each new observation because of a different X_h. To use the relative error of prediction, an alternative term called percent prediction standard error (PPSE) is introduced which is defined as

$$PPSE = \frac{s\{R_{new}\}}{\hat{R}} \times 100 \tag{10}$$

Then Eq. (6) becomes

$$\hat{R} \pm \hat{R}t(0.975; n - 3)/100 \tag{11}$$

The PPSE of predicting MOR for an individual specimen can be obtained from an appropriate statistical analysis program. The average PPSEs and correlation coefficients of predicting MOR using multiple linear models are summarized in Table 3. Both sets were alternately used as the control set to create the regression model, which was used to predict MOR for the other set. When the control set was determined, average PPSEs from both control and test sets were about the same. This is expected since the X matrix used to calculate the $s\{R_{new}\}$ in Eq. (7) is the same for both sets. However, average PPSEs were quite different for the same set when a different set was used as the control set. This occurs because a different X matrix was used to calculate the $s\{R_{new}\}$.

When either of the matched sets is randomly selected as the control set, Eqs. (6) or (11) can be used to create the prediction limits for the MOR of an individual specimen. As an example of the application of this method, the average 95% prediction limits of a stress ratio of 0.80 are estimated as follows. From Table 3, the smaller average PPSE for predicting MOR is found to be 7.52% (using the regression coefficients from set "B" to predict MOR of set "A" in SP1 group). Since there are 24 specimens in the SP1 group, *t(0.975, 21)* is

TABLE 4. *Average properties, predicted mean MORs and their PPSEs of subgroups in SP1 group.*

Subgroup #	Number of specimens	Density (kg/m³)[c]	MOE (10^9 Pa)[d]	MOR (10^6 Pa)[d]	PPSE[b] %
1	4	523.1	11.48	92.7	5.3
2	4	560.3	12.79	103.1	4.2
3	4	572.3	13.58	108.1	4.0
4	4	589.2	14.65	114.9	3.8
5	4	705.1	13.11	122.6	4.2
6	4	653.6	17.52	135.7	4.0
Average	4	600.6	13.86	112.9	4.3
COV[a]	0	11.1	15.0	13.4	12.6

[a] Coefficient of variation.
[b] Percent prediction standard error.
[c] 1 kg/m³ = 0.0624 pcf.
[d] 1 Pa = 1.45×10^{-4} psi.

2.080 (Neter et al. 1990). The average prediction limits for MOR of a specimen in test set of SP1 group are then $\hat{R} \pm \hat{R} \times 0.156$ from Eq. (11). Then from Eq. (5) the average 95% prediction limits for determining the stress ratio are $\sigma \pm \sigma \times 0.156$. When a target stress ratio is set at 0.80, the average prediction interval is 0.67 to 0.93.

Although the best prediction model is used, the prediction interval for the MOR of a single specimen is still relatively too large in the study of damage accumulation in wood. If the mean MOR of a subgroup of m specimens is predicted, then $s\{\bar{R}_{new}\}$ in (7) can be estimated by:

$$s\{\bar{R}_{new}\} = RMSE\sqrt{\frac{1}{m} + \bar{X}_h'(X'X)^{-1}\bar{X}_h} \quad (12)$$

where

$$\bar{X}_h' = [1 \quad \bar{D}_h \quad \bar{E}_h]. \quad (13)$$

$\bar{D}_h$ is the average density and $\bar{E}_h$ is the average MOE of the subgroup of specimens.

For the previous example, the twenty-four specimens of SP1 are ranked in order of their predicted maximum load (from lowest to highest). Then six subgroups are formed by picking the first four specimens as group 1, the second four as group 2, and so forth. Thus $m = 4$. The average properties, mean predicted MOR, and PPSE for the mean MOR of the subgroups are given in Table 4. The PPSEs for predicting the mean MOR of the subgroups are significantly smaller than that for an individual specimen (7.5%). Assume that the average PPSE is 4.3%. Then the 95% prediction limits for determining the average stress ratio of 0.8 of the subgroup of 4 specimens are $0.8 \pm .08 \times 2.08 \times 0.043$. The corresponding prediction interval is 0.73 to 0.87. If a smaller interval is needed, then a larger population in the subgroup is required.

CONCLUSIONS

The multiple linear regression created from a control set is found to be the best predictor of MOR of a specimen in an edge-matched set. The PPSE of predicting MOR can be used to create associated prediction limits. Based on the small-clear southern pine and panel products tested in this study, the prediction interval (with 95% confidence) for predicting MOR of one specimen is so large that the predicted stress ratio is not recommended for use in studies of fatigue and damage accumulation in wood. Therefore, a subgroup of m specimens whose predicted maximum loads are as close as possible are suggested for use in such studies. The average predicted MOR of the subgroup can be more accurately determined, and its prediction interval reduced significantly.

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