

Maximum-Precision Markov Transition Table: Successive Daily Change in Closing Price of a Utility Stock

Paul R. Yarnold, Ph.D.

Optimal Data Analysis, LLC

Research seeking to increase the accuracy of traditional Markov analysis-based models, which assess the outcome (class) variable as a two-category variable, studies the use of over-time weighting schemes. This paper demonstrates how to maximize precision of the class variable by using ODA to weight each individual “observation” (event) in the transition table by its corresponding exact absolute change-in-value.

Central to Markov models used to investigate temporal behavior of ordered phenomena—such as credit risk¹ or risk of infection², is a transition table constructed as seen in Figure 1.

Figure 1: Transition Table for Ordered Event

	Time $i+1$	
Time i	<u>Down</u>	<u>Not Down</u>
<u>Down</u>	$D_i D_{i+1}$	$D_i ND_{i+1}$
<u>Not Down</u>	$ND_i D_{i+1}$	$ND_i ND_{i+1}$

The nominal class variable—Down vs. Not Down (alternatively, Up vs. Not Up), is the lowest-granularity, least sensitive metric which is possible to construct to indicate the change in value of an ordered outcome between successive measurements. In legacy Markov analysis the individual events are unit-weighted: each tally in the transition table represents “one point”. Although legacy statistical evaluation of unit-weighted transition tables uses chi-square analysis³ to assess the comparability of different

transition matrices, outcome convergence to steady state across replications, and number of processes underlying a transition table—by definition, ODA finds the *most accurate* models in this specific context⁴⁻¹³ as well as in other nominal methodological contexts.¹¹⁻⁶⁶

It is possible that a nominal (i.e., binary, dichotomous, two-class) outcome variable is insufficiently precise to capture more subtle yet theoretically and/or empirically meaningful changes in outcome—thus yielding suboptimal analytic accuracy attributable to inadequately-granular measurement.⁶⁷ Fortunately ODA software allows individual observations (events in the transition table) to be weighted by any positive value—facilitating transformation of the binary class variable into a more precise and potentially accurate/meaningful metric.^{12,13,68-71} This “proof- of-concept” paper shows how to weight events to create the maximum-possible-precision transition table given the precision of data available for analysis.

The application selected for exposition is stock daily closing price. To select the stock two alphanumeric characters (F, E) were entered via keyboard by a blindfolded laboratory technician on a computer connected to a stock site. Based in Akron, OH, FirstEnergy Corp (NYSE symbol FE) is an electric utility company which generates, distributes and transmits electricity, and is also involved in energy management and related services. Daily FE stock closing price was recorded for each trading day in the second-half of 2018 (July 2 - December 31) yielding a series of 121 closing price differences between successive days. Sample daily closing prices for FE stock used herein are given in Table 1, showing a day-over-day positive price change in July; the only two successive days in the series on which successive closing price was identical; and day-over-day negative price change in November (gain, unchanged and loss, respectively).

Table 1: Sample Daily Closing Price (\$) of FE Stock for the Second-Half of 2018

<u>Date</u>	<u>Closing Price</u>	<u>Difference</u>
July 2	\$36.22	
July 3	\$36.43	\$0.21
August 30	\$37.38	
August 31	\$37.38	\$0
November 5	\$37.48	
November 6	\$37.46	-\$0.02

This series was used to create a unit-weighted Markov transition table (Table 2). Data were assessed via non-directional ODA testing the exploratory hypothesis that data primarily fall into either diagonal.⁷² The ODA model indicated stationarity (Down at t_i predicts Down at t_{i+1} , and *vice versa*), but this result was not statistically significant ($p < 0.99$), achieving close to the same level of accuracy expected by chance (ESS=1.52; 0=chance; 100=no errors). Findings for the minimum-precision Markov transition table thus indicate that nominal daily change in FE closing price cannot be discriminated *vs.* a uniform random number.^{12,13}

Table 2: Transition Table for Unweighted Change in FE Stock Daily Closing Price

	Time $i+1$	
Time i	<u>Down</u>	<u>Not Down</u>
<u>Down</u>	25	29
<u>Not Down</u>	30	37

Next, every observation (event) in the transition table was weighted by the absolute value of the difference in closing price between the index (t_{i+1}) *vs.* prior (t_i) day: weights must be positive, so the sample was reduced by one event with a difference score of \$0 (Table 1).⁷³ The resulting ODA model indicated stationarity, yielding the identical transition table (Table 2) except the Down _{i} -Down _{$i+1$} tally fell to 24 (the event with a weight of \$0 was eliminated). For the weighted model, weighted sensitivity for Down (59.4) and for Not Down (55.7) at t_{i+1} exceeded unit-weighted findings: the resulting weighted ESS=15.2 is relatively weak¹¹⁻¹³ and not statistically significant (two-tailed $p < 0.22$).

Comments

Markov transition tables clearly are sensitive to measurement precision: FE stock was comparably likely to close Down *vs.* Not Down after closing Down *vs.* Not Down on the prior trading day, however empirically (not statistically) the absolute magnitude of change was greater on repeated Down days and repeated Not Down days.

The randomly selected stock, a utility company, meandered to and fro over six months of trading: utility stocks are reputedly stable and return a high dividend. It would be interesting to compare present results with findings obtained for daily trades, different weights (e.g., value = price X volume), and for stocks and investment instruments of different types¹.

Not done here to maximize the clarity of exposition, future research in this area should ipsatively standardize the serial weight prior to constructing a weighted transition table: this requires arithmetic manipulation to ensure all

weights exceed zero, and then later reversing the manipulation to obtain desired unit of change. This transformation maximizes ESS and inhibits paradoxical confounding in serial designs.⁷⁴⁻⁷⁹

Finally, another interesting avenue for future research involves discriminating specific types of weighted transition events, for example $D_i D_{i+1}$ vs. $D_i N D_{i+1}$ and $N D_i D_{i+1}$ vs. $N D_i N D_{i+1}$. Novometric CTA weighted by price or value could use temporally contiguous general and industry-specific leading indicator data, volatility, option trading, moving average, and so forth as potential attributes (“independent variables”) for naïve⁸⁰⁻⁸⁷ or causal inference analysis involving propensity score weighting.⁸⁸⁻⁹⁴

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⁷²ODA¹² and MegaODA⁶⁹⁻⁷¹ code used was:
INPUT festock.txt;
OUTPUT festock.out;
VARS i iplus1 absdiff;
CLASS iplus1;
ATTRIBUTE i;
INPUT festock;
MCARLO ITER 25000;
GO;

⁷³The ODA and MegaODA code was amended:
EXCLUDE absdiff=0;
WEIGHT absdiff;

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Author Notes

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