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Decomposition for Judgmental Forecasting and Estimation

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ABSTRACT

Forecasters often need to estimate uncertain quantities, but with limited time and resources. Decomposition is a method for dealing with such problems by breaking down (decomposing) the estimation task down into a set of components that can be more readily estimated, and then combining the component estimates to produce a target estimate. Estimators can effectively apply decomposition to either multiplicative or segmented forecasts, though multiplicative decomposition is especially sensitive to correlated errors in component values. Decomposition is most used for highly uncertain estimates, such as ones having a large numerical value (e.g., millions or more) or quantities in an unfamiliar metric. When possible, multiple estimations should be used and the results aggregated. In addition, multiple decompositions can be applied to the same estimation problem and the results resolved into a single estimate. Decomposition should be used only when the estimation can make component estimates more accurately or more confidently than the target estimate.

Keywords: algorithmic decomposition, judgmental forecasting, numerical estimation

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Imagine that you are sitting in a little cafe on Leopoldstrasse in Munich, sipping on a cup of coffee and a bit of schnapps. Your companion mentions an interest in starting a new publication dedicated to fanciers of exotic animals. Being a person of some financial means, you often find yourself engaged in discussions in which business propositions are put before you and your interest is solicited. With guarded enthusiasm, you consider your companion's casual proposal. Certainly there are people with strong interest in exotic animals, but the real question is what is the commercial potential of such an enterprise. To evaluate this prospect, you need to estimate some numbers: for example, how many people are interested in exotic animals, and how many of those would subscribe to such a publication? Your companion poses these questions directly to you, and you reply that you have no idea what the size of such numbers might be. However, on reflection, you realize that you do have some idea, though the range of possibilities seems enormous on first thinking. For example, if the publication was intended for the U.S. market, then the population of the U.S. would serve as an upper bound on the potential subscriber base. Further thought might reduce that number to only those over the age of 18, assuming that younger individuals would not have the money to own and maintain exotic animals. Clearly, you have some knowledge, but it is incomplete and not yet well organized. These situations are fairly common, particularly when generating numerical forecasts for which historical or other background information is scarce or unavailable, is not available within the time frame required, or is available only at greater cost than can be afforded. In these cases, forecasters are left to divine their best estimate based on what knowledge they have. If this is the situation, how should you go about generating a numerical estimate?

This chapter contains a set of principles to guide someone making a numerical estimate from partial or incomplete knowledge. All of the principles concern the use of decomposition to break the estimation problem down into more manageable or tractable subestimates, which one can make either more accurately or more confidently than the target quantity. As Howard Raiffa (1968) pointed out, ". . . decompose a complex problem into simpler problems, get one's thinking straight in these simpler problems, paste these analyses together with a logical glue, and come out with a program for action for the complex problem" (p. 271). Though Raiffa's advice was intended to aid decision making, his wisdom also applies to numerical estimation.

A further consideration concerns the precision of the estimate. An estimator could require a point estimate of a quantity. This might be the case when the estimate is to be quickly combined with other information in a larger problem. Alternatively, an estimator may want to assess a probability distribution over the quantity in question, if the distributional properties of the required quantity are what is needed. Both of these issues will be discussed in the principles.

Given sufficient time and resources, one might approach an estimation problem quite differently from the way one would approach the problem with minimum resources. For example, one would not attempt to produce a serious (and applicable) estimate of China's nuclear weapons capability by the year 2010 on the back of an envelope at a cafe. However, with some knowledge about the topic, one might make an estimate for a purpose having a relatively low cost for errors, such as stimulating conversation. A continuum exists in the amount of effort that would go into producing an estimate of something. The more important the "something," the more effort, cost, and sophistication would go into it. The principles in this chapter apply when one needs to estimate a quantity, but time and resources to produce an estimate are restricted and an aid is required to support judgment.

THE DECOMPOSITION DECISION

Practitioners faced with the problem of estimating an uncertain quantity must decide whether to use some form of decomposition or to rely instead on their unaided (and unstructured) intuition. The principles outlined below will help make this decision, particularly how to use decomposition given the uncertainties one has about the magnitude of the target quantity. A second decision concerns the form that decomposition should take. This decision is somewhat more difficult, in part because decomposition can take alternative forms for a particular problem, and in part because much less research has been done on the effectiveness of different forms of decomposition for equivalent estimation problems. The principles below address this decision by indicating potential gains or losses in efficiency and estimation accuracy that might result from decompositions that take on certain features, such as multiple component estimates. These will be discussed more fully as part of each of the principles set out below.

Example of a Typical Algorithmic Decomposition

To clarify what is meant in this context by the use of decomposition to aid estimation of an uncertain quantity, assume that an estimator was interested in the number of pieces of mail handled by the United States Postal Service last year. Obviously, someone in the U.S. Postal Service would have this information. For whatever reasons, however, we do not have it available when it is required. In such a case, the estimator could resort to using some form of decomposition like the one below taken from MacGregor, Lichtenstein and Slovic (1988):

How many pieces of mail were handled by the U.S. postal service last year?

A. What is the average number of post offices per state?
B. What is the number of states?
C. Multiply (A) times (B) to get the total number of post offices.
D. How many pieces of mail per day are handled by the average post office?
E. Multiply (C) times (D) to get the total pieces of mail per day for all post offices.
F. How many days are there in a year?
G. Multiply (E) times (F) to get the number of pieces of mail handled in a year by the U.S. postal service.

This is an *algorithmic decomposition*, in that it identifies specific component estimates that, when combined according to the arithmetic steps in the algorithm, will yield an estimate of the quantity in question. In this case, there are four component estimates: Step A, the average number of post offices per state; Step B, the number of states in the United States; Step D, the number of pieces of mail handled daily by the average post office; and Step F, the number of days in a year. Clearly, we can make some of these estimates more easily and confidently than others. The remaining steps of the algorithm are arithmetic operations performed on the component values. Sometimes these steps produce new intermediate values that are the result of combining component estimates. For example, in the algorithmic decomposition above, the first two estimates are multiplied to yield an estimate of the total number of post offices in the United States. We could estimate this quantity directly rather than using decomposition, in which case the form of the decomposition would be different.

PRINCIPLES OF DECOMPOSITION

A set of principles can be used to help structure the process of making estimates of uncertain quantities. The principles presented are those that are identified and supported by empirical research studies that have directly evaluated the use of decomposition for numerical estimation problems. The principles are presented in the form of advice, with an indication of research supporting each principle. The quality of the research evidence is evaluated, and is better for some principles than for others.

- **Use some form of decomposition, rather than none.**

This is the most general principle that applies in estimation situations, particularly when it is difficult to assess the level of uncertainty about the value of the quantity in question. Essentially, estimators will improve their accuracy by decomposing the estimation problem into subproblems that they can more easily or confidently estimate. They should then combine component estimates according to some algorithm or set of operations (generally, arithmetic) to obtain an estimate of the desired quantity. To implement the principle, the estimator should prepare a formal decomposition of the estimation problem in a form similar to that shown for estimating the number of pieces of mail handled by the U.S. postal service in a year.

Evidence: The research evidence in support of this very general principle is enormous and cannot be adequately covered here. Over four decades of research in human judgment and decision making show that decomposition improves judgmental performance over unaided or holistic judgment. For example, early studies of clinical judgment showed that a linear model of a clinical judge outperforms the human judge, largely because intuitive judgments are less reliable than decomposed ones (e.g., Meehl 1957; Goldberg 1968, 1970).

In most judgment situations, some type of decomposed model, even if it is not the best from a prescriptive standpoint, will do better than intuition (e.g., Slovic & Lichtenstein 1971; Dawes & Corrigan 1974; Dawes 1975, 1979). For example, Bonner, Libby and Nelson (1996) used both list-type and mechanical-aggregation decision aids to test improvements to auditors' assessments of conditional probabilities. They found that the mechanical-aggregation (decomposition) aid improved conditional probability judgments, even when a list-type aid (e.g., list relevant factors) was used beforehand. However, the list-type aid did not improve judgmental performance significantly when applied after the decomposition aid. Decomposition improved list-type aid performance, but not vice versa. In the context of improving survey research methodologies, Menon (1997) found that using decomposition to aid recall (i.e., probes for specific times or occasions that behaviors might have occurred) generally improved accuracy of estimation. Improvement in estimation accuracy was greater for *irregular* behaviors than for regular ones. Decomposition appeared to work because it stimulates episodic recall for irregular behaviors.

Kahneman, Slovic and Tversky (1982) and Edwards and von Winterfeldt (1986) give excellent overviews of decomposition and related issues in human judgment and decision making. Plous (1993) also gives a very readable synopsis.

With regard to the specific problem of numerical estimation of an uncertain quantity, a number of studies support the principle. One set of evidence pertains to multiplicative decomposition, in which a problem is broken down into multiplicative elements such as shown for estimating the number of pieces of mail handled by the U.S. postal service in a year.

Exhibit 1 summarizes three studies on the performance of multiplicative algorithmic decomposition compared to unaided or global estimation. The measure of comparative accuracy is the error ratio, computed as the ratio of the estimated value to the true or correct value, or the reverse, such that the result is greater than or equal to

1.0. The entries in Exhibit 1 for each of the three studies summarized are the number of different estimation problems included in the study, the median error ratio by problem for both global and decomposed estimation, and the error reduction or difference in error ratio between global and decomposed estimation. Median error ratios reported in Exhibit 1 are taken across problems. The error ratio for each problem was computed by taking the median error ratio across all individual estimators. Thus, the data summarized in Exhibit 1 is a median of medians. For example, the ADG study used five estimation problems, and the median error ratio of the five problems was 10.3 for global estimation and 3.4 for decomposed estimation for an error reduction of 6.9.

Exhibit 1
Summary of Error Ratios

Study [a]	Number of problems	Median Error Ratios		Error reduction
		Global	Decomposition	
ADG	5	10.3	3.4	6.9
MLS	16	5.8	2.9	2.9
M&A	10	13.9	8.9	5.0

[a] ADG = Armstrong, Denniston & Gordon (1975), adapted from Table 1.
MLS = MacGregor, Lichtenstein & Slovic (1988), adapted from Tables 4 and 6.
M&A = MacGregor & Armstrong (1994), adapted from Table 4.

The positive values for error reduction in all three studies indicate the superiority of decomposed estimation over global estimation. In general, these results suggest that across a wide range of almanac-type problems, an estimator might expect decomposition to lead to an improvement in estimation accuracy by a factor of approximately 5.0. However, for many of the quantities respondents estimated in these studies, the true value of the target quantity was highly uncertain.

Evaluation of the evidence: the evidence that decomposition aids numerical estimation is quite strong, and research makes a strong case that decomposition improves estimation accuracy. However, we lack a theory of decomposition that can be used to determine the particular form of decomposition to use from features or characteristics of the problem. Published work thus far has used decompositions of the researchers, and do not reflect a more general theory of decomposition. Likewise, the evidence thus far on the efficacy of decomposition as an aid to numerical estimation is almost entirely based on the performance of estimators using decompositions which they did not devise, but were instead produced for them to use. In some early pilot studies by the author of this paper, university-age students had difficulty generating their own algorithmic decompositions when given only simple instructions and an example to guide them. MacGregor and Lichtenstein (1991) gave their research subjects (again, university students) a written tutorial on how to construct algorithmic decompositions for the purpose of verifying an estimate of a quantity they had been given. Only 13.5 percent of those who received the tutorial were unable to construct a meaningful decomposition for verifying a target quantity. The concept of algorithmic decomposition apparently has sufficient intuitive plausibility and meaning that people can produce at least some type of problem structuring even without a general theory, though they may need some tutelage to apply the general principle to a specific estimation context.

- **Choose the form of decomposition (i.e., multiplicative versus additive) according to the nature of the estimation problem and your knowledge of the relationship between problem components.**

In applying decomposition to an estimation problem, one must choose what form of decomposition to use. The evidence presented for the first principle was based on multiplicative decomposition. Another form of decomposition used in forecasting is segmentation, in which one breaks a problem down into additive components. Segmentation is applicable when a problem can be broken down into independent components, for each of which one can identify distinct causal factors, generally based on a theory about the overall relationship between the components (Armstrong 1985 reviews applications). For example, in forecasting future consumption of alcoholic beverages, consumption in different beverage categories (e.g., beer, wine, liquor) may be influenced by different causal factors (e.g., seasonality, socioeconomic status of consumers). Consequently, an estimator could segment the problem according to beverage type, estimate consumption for each beverage category independently, and add the estimates for each segment.

In general, segmentation has proven an effective approach for aiding estimation in forecasting problems. For example, Armstrong and Andress (1970) used segmentation to predict the volume of gasoline sold at filling stations. They first used a method based on segmentation to classify a sample of cases. They then used the resulting classification scheme to predict gasoline sales volume for a new sample. Average error for the segmentation approach was 41 percent, compared to a 58 percent average error for a linear regression model. Dunn, William and Spiney (1971) likewise found that forecasts aggregated from lower-level modeling (i.e., additive decomposition) were superior to a top-down approach in forecasting demand for telephones. In a study of time-series forecasting of product demand, Dangerfield and Morris (1992) found that they obtained better model-based time-series forecasts by aggregating forecasts produced for individual items to produce an overall estimate for a product class (i.e., BU or "bottom up"), than by producing a single forecast for the class itself (i.e., TD or "top down").

Gordon, Morris and Dangerfield (1997) found a similar result for model-based forecasts, but found that the accuracy of judgmentally produced time series extrapolations was no different for the BU and TD approaches. However, Edmundson (1990) found that time series forecasting can be dramatically improved by using a computer software aid to decompose a time series into its three classical components: trend, cycle, and noise. Judgmental forecasts of overall trends based on viewing trend components were more accurate than extrapolations from hardcopy plots of the holistic series.

In a different estimation context, Connolly and Dean (1997) studied the use of segmented decomposition in estimating probability distributions for completion times in a software writing task. They compared part-task distributions to distributions for the whole task. They found that, overall, distributions were "overtight," with too many actual completion times in the one percent and 99 percent tails of the judged distributions. Estimates aggregated from part-task estimates did not generally do as well as whole-task (holistic) estimates. However, the picture was inconsistent. They concluded that "the choice between holistic and decomposed estimates may thus be contingent on task, estimator, and method factors, and not a single best approach for all circumstances" (pgs. 1042 to 1043).

Evaluation of the evidence: Although additive decomposition apparently improves model-based forecasts, it seems not to have comparable effects on judgmental forecasts. In part, this is due to differences in the contexts in which additive decomposition has been studied: Gordon *et al*. (1997) and Edmundson (1990) examined judgmental performance in time series forecasting, while Connolly and Dean (1997) used additive decomposition to aid people's assessments of their actual behavior. Indeed, the Connolly and Dean results may say more about the potential biasing effects of decomposition on the psychological processes associated with memory and recall for actual events than about the effects of decomposition on judgmental forecasts.

Unfortunately, no studies to date directly compare additive decomposition with multiplicative decomposition for the same forecasting or estimation problems. Such studies would indicate more directly which decomposition form is more conducive to judgmental accuracy. Until we have such studies, we can only speculate that additive decomposition may prove less risky than multiplicative decomposition because it may under some circumstances reduce the opportunity for correlated errors. The evidence thus far has demonstrates that additive decomposition is generally superior to no decomposition for problems for which it is appropriate. Even when using additive decomposition for model-based forecasting, one must use judgment to determine the specifics of the decomposition and to determine the individual subclass models that will provide forecasts for aggregation. The choice of additive versus multiplicative decomposition will be based on the estimator's judgment and the characteristics of the forecasting problem. We need further research to identify problem characteristics that might make one form of decomposition preferable another.

- **Use decomposition when uncertainty is high; otherwise use global or holistic estimation.**

One can improve estimation accuracy by using decomposition only for problems for which the target quantity is highly uncertain. For point estimations of an uncertain quantity, the estimator should first assess the level of uncertainty associated with the estimation problem and then choose either holistic estimation or decomposition. The estimator should not use decomposition to refine estimates of numbers that have low uncertainty. In using decomposition for low uncertainty problems, one risks propagating errors in estimation during recomposition.

Multiplicative decomposition is based on the assumption that errors in estimation are uncorrelated and therefore will tend to cancel each other out. However, decomposing a low uncertainty problem increases the likelihood that one or more of the component estimates will have greater uncertainty than the uncertainty associated with the target quantity. Should this occur, errors in estimation may not cancel each other adequately, thereby leading to a less accurate estimate than the holistic estimation.

To apply the principle, one must first gauge the level of uncertainty at which decomposition becomes appropriate. MacGregor and Armstrong (1994) offer the following guidelines based on their comparison of the improvements in accuracy obtained when they applied decomposition in high versus low uncertainty contexts:

> "First, assess whether the target value is subject to much uncertainty by using either a knowledge rating or an accuracy rating. If the problem is an important one, obtain interquartile ranges. For those items rated above the midpoint on uncertainty (or above 10 on the interquartile range), conduct a pretest with 20 subjects to determine whether the target quantity is likely to be extreme. If the upper quartile geometric mean has seven or more digits, decomposition should be considered. For these problems, compare the interquartile ranges for the target value against those for the components and for the recomposed value. If the ranges are less for the global approach, use the global approach. Otherwise, use decomposition." (p. 505)

According to these guidelines, one should conduct an assessment of the level of uncertainty associated with the estimation problem. One approach is to estimate the possible range of the quantity in question and then calculate the ratio of the value at the third quartile (75^{th} percentile) to that at the first quartile (25^{th} percentile). In general, one can consider target quantities of seven or more digits to be highly uncertain and decomposition should be used to make these estimates. However, factors other than size can contribute to uncertainty. For example, unfamiliar numbers will have more uncertainty than familiar ones. Likewise, quantities expressed in units that are not natural can also increase uncertainty. One's assessment of uncertainty should be guided by all these factors.

A second way to apply this principle is to assess a probability distribution over the quantity in question. This approach may be useful if the distributional properties of the quantity are of value, or if one wishes a direct assessment of the uncertainty associated with the quantity in terms of the quantity's metric.

Evidence: Exhibit 2 summarizes research evidence in support of this principle with regard to point estimation. Here, the results are repeated from the same three studies shown in Exhibit 1, but with the estimation problems divided into two groups—extreme and not extreme.

Exhibit 2
Summary of Error Ratios – Not Extreme vs. Extreme Estimates

Study [a]	**Number of problems**	**Median Error Ratios**		**Error reduction**
		Global	**Decomposition**	
Not Extreme				
ADG	1	5.4	2.3	2.1
MLS	5	1.8	2.3	-0.5
M&A	4	3.4	10.5	-7.1
Extreme				
ADG	3	18.0	5.7	12.3
MLS	6	99.3	3.0	96.3
M&A	6	26.9	8.5	18.4

[a] ADG = Armstrong, Denniston & Gordon (1975), adapted from Table 1.
MLS = MacGregor, Lichtenstein & Slovic (1988), adapted from Tables 4 and 6.
M&A = MacGregor & Armstrong (1994), adapted from Table 4.

For this analysis, extreme problems are ones whose target values have seven digits or more (i.e., ≥ 10^7), while not extreme problems have four digits or fewer (i.e., ≤ 10^4). Again, differences between median error ratios for global versus decomposed estimation indicate accuracy of the two methods. For not extreme problems, decomposition generally decreases accuracy. Only for the one not-extreme estimation problem studied by ADG, however, did decomposition produce a more accurate estimate than global estimation. A different picture emerges for extreme or high uncertainty problems: decomposition provided markedly more accurate estimates than global estimation, with error reduction in some cases approaching a factor of 100. In general, using decomposition for high uncertainty problems can lead to improvements in estimation accuracy over global estimation by a factor of 12 to 15 or more.

Henrion, Fisher and Mullin (1993) had research subjects assess probability distributions over seven continuous quantities (e.g., "What was the total number of turkeys sold in the U.S. in 1974?") using holistic estimates and decomposition. They found no improvement in either estimation accuracy or calibration for decomposed assessments compared to holistic assessments. On the other hand, Hora, Dodd, and Hora (1993) found that probability distributions for continuous quantities were better calibrated when assessed using decomposition than when assessed using holistic methods. Kleinmuntz, Fennema and Peecher (1996) found that point assessments of probabilities were better calibrated when the assessments were decomposed in terms of conditional events. Decomposition appears in some circumstances to improve probability assessments, both point assessments and probability distributions. However, research to date has not consistently demonstrated its superiority and more research is needed along these lines.

Evaluation of the evidence: The evidence for the superiority of decomposition for high uncertainty problems is fairly strong. However, a key problem is identifying high uncertainty cases. Thus far, in only one study (MacGregor & Armstrong 1994) have researchers independently manipulated the factor of uncertainty; they intentionally maximized the range of uncertainty to demonstrate the effect, should it have existed. In middle ranges of uncertainty, say problems in the 10^5 or 10^6 range, the effects of decomposition are not yet known. Moreover, no one has done research directed toward understanding how different methods of assessing the uncertainty associated with an estimation problem could influence that assessment. This is a critically important point that bears strongly on whether one chooses to use decomposition in an estimation situation or to fall back on holistic estimation.

A second issue concerns the advisability of abandoning decomposition altogether for low uncertainty problems. The research to date shows that decomposition either does not improve accuracy very much in these cases or actually decreases accuracy. However, before we conclude that decomposition is contraindicated in low uncertainty situations, we need more research to determine why such problems do not seem to benefit from decomposition as do high uncertainty situations. Applying decomposition to low uncertainty problems may have advantages other than yielding numerical estimates. For example, decomposition could improve understanding of the estimation problem and thereby identify information needs that we would otherwise miss. A critical issue here is the confidence one can justifiably attach to an estimate made by decomposition — the research thus far suggests that we can place more confidence in decomposed estimates made for high uncertainty problems than for low uncertainty ones.

- **When estimating quantities for which decomposition is appropriate, use multiple decomposition approaches to estimate component values.**

One can improve the performance of decomposition by using multiple estimation approaches to produce multiple estimates of component values. In principle, multiple estimates of component values should lead to a more precise result for the overall decomposition when recombined, because the estimate of the component values themselves will be more accurate than otherwise. A multiple estimation approach may also be useful when the estimator is unsure about the best way to decompose the problem.

To implement this principle, first decompose the problem. Then, for component quantities that are highly uncertain, produce estimates using both global and decomposed estimation. Revise the two component estimates in light of one another to yield a final component estimate. Repeat this procedure for all appropriate component estimates, and then recompose the overall decomposition to produce an estimate of the target quantity.

Evidence: Though this principle is intuitively compelling and seems to be directly implied by the general efficacy of decomposition, very little empirical research evidence supports it. In one study that concerns the use of multiple component estimates in decomposition, MacGregor and Lichtenstein (1991) compared the accuracy of estimates made by using “extended decomposition” with that of estimates based on regular decomposition for one high uncertainty estimation problem — the number of pieces of mail handled by the U.S. Postal Service in a year. This estimation problem was previously used in the study of decomposition by MacGregor, Lichtenstein, and Slovic (1988). The decomposition below illustrates the form of decomposition research subjects used in the study.

How many pieces of mail were handled by the U.S. postal service last year?

A. What was the average number of post offices per state?
B. How many post offices are there in a small state?
C. How many post offices are there in a large state?
D. Revise your estimate in (A) of the number of post offices per state, considering your estimates in (B) and (C).
E. How many states are there?
F. Multiply (A) and (E) to get total number of post offices in the U.S.
G. How many people are employed in the U.S. postal system?
H. How many people are employed by the average post office?
I. Divide (G) by (H) to get the number of post offices in the U.S.
J. Revise your estimate of (F), considering your estimate in (I).
K. How many pieces of mail per day does the average U.S. post office handle?
L. Multiply (J) by (K) to get total pieces of mail handled in the U.S. per day by the U.S. Postal Service.
M. How many days are there in a year?
N. Multiply (L) by (M) to get the total number of pieces of mail handled by the U.S. Postal Service in a year.

In this problem, subjects used two decompositions to estimate the number of post offices in the U.S. In the first decomposition (Steps A through F), they made a global estimate of the average number of post offices per state and estimates of the number of post offices in a small state and in a large state. Research subjects then reconciled their original estimate (global) in light of their estimates for small and large states to produce a revised final estimate of the number of post offices in a state; then multiplied that by an estimate of the number of states in the U.S. (which most subjects estimated accurately!) to obtain a value for the total number of post offices in the U.S.

In a second decomposition (Steps G through J) to estimate the number of post offices in the U.S., subjects first estimated the number of people employed in the U.S. postal system and then divided that by their estimate of the number of people employed in an average post office. They compared and reconciled the two estimates of the number of post offices in the U.S. (Step J) to produce a final estimate. Both component estimation procedures were included as steps in the algorithmic decomposition procedure, leading to a final estimate of the target quantity.

Exhibit 3 compares the estimation accuracy of the “extended algorithm” procedure as applied to the Post Office problem with both regular decomposition and global estimation. Error ratios are shown for global estimation, algorithmic decomposition and extended decomposition, as well as for the two component values of the extended decomposition estimated by multiple means.

Exhibit 3
Summary of Estimation Performance for Post Office Problem *

	Error Ratios [a]					
***Component*:**	**Initial Estimate**	**Revised Estimate**	**Extended Decomposition**	**Regular Decomposition[b]**	**Global Estimate[b]**	**Error Reduction[c]**
PO's per state	–1.37	–1.37				
Total PO's	–1.57	–2.38				
Mail per day	+4.96	+5.97				
Final Estimate			–1.21	–8.84	–89.4	7.63

* Adapted from MacGregor & Lichtenstein (1991).
a Signs preceding error ratios indicate underestimation (–) and overestimation (+).
b From MacGregor, Lichtenstein & Slovic (1988).
c Error reduction for extended decomposition relative to regular decomposition.

For this problem the extended decomposition was superior to both global estimation and to regular algorithmic decomposition. The extended decomposition procedure improved accuracy over the regular algorithmic decomposition by more than a factor of seven, and over global estimation by a factor of 89. While revised estimates were generally more in error than initial estimates, the errors were opposite directions, leading to a cancellation of overall error and an improvement in estimation performance. MacGregor and Lichtenstein (1991) also studied a low uncertainty problem using the extended algorithm procedure—the number of forested square miles in the state of Oregon. However, both regular and extended algorithm procedures resulted in less accurate estimates than did global estimation, a result that is in line with other research that suggests the inadvisability of using decomposition in low uncertainty situations (see also Harvey, 2001, with regard to uncertainty assessment).

Evaluation of the evidence: The evidence for this principle is limited. First, only one estimation problem consistent with the principles I suggest has been studied using this form of decomposition. Thus, we cannot generalize these results to other problems. As with decomposition in general, extended decomposition can be performed in more than one way and other decompositions could have been used within the general decomposition MacGregor and Lichtenstein chose. Furthermore, the methods used were of two types: an algorithmic method and a method based on the distributional properties of a quantity in question. No one has examined how these two methods interact or what their other judgmental properties might be. Practitioners should be cautious in attempting extended decompositions. They should carefully consider the principles discussed above. For example, applying decomposition to component estimates that are of low uncertainty could result in greater error than using global estimates for components.

- **When estimating quantities for which decomposition is appropriate, rely on more than one estimator.**

For multiple estimators (experts) to work on a decomposition, they can each work a given decomposition, thereby producing multiple estimates of the target quantity. A second approach is for multiple estimators to provide component estimates, with the median estimate for each component in the problem decomposition then used to yield a single estimate of the target quantity.

Evidence: MacGregor, Lichtenstein and Slovic (1988) provided evidence for both of these approaches to using multiple estimators. They asked multiple estimators to work the same problem decomposition to estimate the number of cigarettes consumed per year in the U.S. (Exhibit 4).

The variation apparent in Exhibit 4 is typical of the variation in decomposed estimates for the six high uncertainty problems MacGregor, Lichtenstein and Slovic studied. Here, the distribution of estimates is plotted on a logarithmic scale, with the proportion of subjects shown on the vertical axis. The median error ratio for the decomposed estimate (8.86) was a dramatic improvement over the median error ratio for unaided estimate (393.3). However, perhaps most noticeable in Exhibit 4 is the tremendous variation in values for the target quantity produced by individual estimators, even in the decomposition condition. The improvement in estimation accuracy for decomposition was, in part, due to multiple estimators and an averaging of their errors of estimation. Though the median error ratios for unaided and decomposed estimation differed markedly, the two distributions do have considerable overlap: some estimators in the unaided condition produced more accurate estimates of the target value than did estimators in the decomposition condition. However, multiple estimators enhanced the improvement in estimation performance for decomposition.

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Exhibit 4. Distributions of log estimates for the estimation problem, "How many cigarettes are consumed a year in the US?" (Source: MacGregor, Lichtenstein, & Slovic, 1988)

A second approach to using multiple estimators is to obtain multiple estimates of component values. The median estimate for each component is then used in a problem decomposition. MacGregor, Lichtenstein and Slovic (1988) examined the efficacy of this decomposition bootstrapping approach. For six estimation problems having high uncertainty, the median error ratio for bootstrapped problems was 2.78 compared to 2.98 for regular decomposition, an error reduction of +.20. For the cigarette problem shown in Exhibit 4, however, the improvement was somewhat greater: the error ratio for decomposition was 2.0 compared with 1.19 for the bootstrapped condition, an error reduction of +.81.

Evaluation of the evidence: We need to pay further attention to the potential for multiple estimators to improve estimation accuracy. The research results described are from a single published study, although other data sets are available for which one could analyze the effects of multiple estimators (for problems and for components). The results described above suggest strongly that multiple estimators improve estimation accuracy and that multiple estimates of component values may yield even further improvement.

- **Use decomposition only when you can estimate component values more accurately than the target quantity.**

This principle is derived from the general conditions that make decomposition appropriate, namely that one knows more about the parts of a problem than about the whole. If this is not the case, decomposition will not improve accuracy or performance. Estimators should assess their uncertainty about the target value in question, construct an algorithm to estimate the target value according to the above principles, and then assess their uncertainty concerning the components of the algorithm. If they are more uncertain about the component values than about the target value, then they should revise the decomposition until they can estimate all the component values more confidently than they can the target quantity.

Evidence: Evidence for this principle is in part theoretical. Andradottir and Bier (1997) have provided theoretical evidence indicating the importance of precision in component estimates. They concluded that "forecasters would thus be well advised to choose conditioning events for which reasonably precise estimates can be obtained . . . even if these are not the events that most strongly influence the quantity in question" (p. 278). No one has done empirical studies to specifically examine estimation problems in which component estimates are less accurate than global estimates for an uncertain quantity. However, MacGregor, Lichtenstein and Slovic (1988) found that, of 22 component estimates research subjects produced in decomposed estimation problems, 21 of the estimates were more accurate than global estimates of the target quantities. Two of the estimation problems MacGregor and Armstrong (1994) used included the population of the United States as a component estimate; error ratios for that component were less than for global estimates of the target quantities. And finally, in Exhibit 3 from MacGregor and Lichtenstein (1991), we see that all error ratios for component estimates in the extended decomposition case are considerably less than the error ratio for the global estimate of the quantity in question. Empirically at least, research subjects generally produce component estimates for algorithmic decompositions they are given that are less in error than are global estimates of the quantities the decompositions are intended to estimate.

Evaluation of the evidence: Reports on much of the research on the efficacy of algorithmic decomposition have given relatively short shrift to the quality and accuracy of component estimates. Indeed, most researchers who seem to have assumed that component estimates would be more accurate than global estimates found that often they actually were, and have compared estimates produced by global and decomposed means. This focus on the bottom line means that we know more about the overall performance of decomposition than we do about judgmental performance within the decomposition itself. Also, we have no evidence on how estimators might revise the structure of a decomposition should they find they made estimates of components with less confidence than a global estimate of the target quantity.

IMPLICATIONS FOR PRACTITIONERS

Under some circumstances, decomposition leads to more accurate estimates than direct or holistic estimation, particularly when uncertainty about the target quantity is high and uncertainty about its component quantities is lower. Under these conditions, the estimator is generally better off using decomposition than not. As to how to decompose the problem, estimators are left to their own imaginations and creativity. In all the research thus far conducted on the efficacy of decomposition, decomposition of the problem was guided by no explicit decomposition theory; investigators studied decompositions that seemed plausible to them.

If one is concerned that a particular decomposition might lead to a biased estimate, they are encouraged to generate multiple decompositions and generate estimates of a target quantity from each one. Alternatively, one can ask multiple individuals to generate their own decompositions and produce multiple estimates of the target quantity. The resulting algorithms and estimates could both be compared and critiqued.

It is critical for practitioners to be aware that judgmental decomposition for forecasting and estimation will produce no better result than the quality of the component estimates. These estimates are, essentially, unaided and are subject to the sources of bias that plague all such estimates, including anchoring too strongly on an initial value and overconfidence in estimation accuracy.

A broader question concerns the role of judgmental decomposition for numerical estimation as part of forecasting in general. The situations in which judgmental decomposition is most likely to be applied are those in which no other source of information is available within the time or costs permitted. In many practical settings, databases and the like are available and should be consulted and used in preference to judgmental estimation. Practitioners should avoid uncritical acceptance of numerical estimates produced judgmentally through either decomposition or direct estimation. A potential (though untested) safeguard against uncritical acceptance may be to argue explicitly (either with oneself or with another) why a numerical estimate produced by decomposition might be too high or too low, either because knowledge or information is missing, or because of the structure of the decomposition itself (Arkes, 2001).

IMPLICATIONS FOR RESEARCHERS

To date, the research on judgmental decomposition for numerical estimation has focused largely on demonstrating its superior accuracy to unaided estimation, and on identifying situations in which decomposition is appropriate in terms of the level of the estimator's uncertainty about the target value. Much more limited research has been focused on the efficacy of multiple decompositions and on decompositions within decompositions. Future research should examine how alternative decompositions of estimation problems influence perceived and actual accuracy of estimates.

A critical element lacking in existing research is a theory to guide the form that decomposition should take. Likewise, virtually no research has examined how estimators naturally approach decomposition problems, the kinds of decompositions they produce, and what training or guidance they need to produce their own decompositions.

SUMMARY

In general, decomposition is an effective strategy for improving the quality of judgmental forecasts. The forecaster who must use judgment to produce a forecast should generally proceed by decomposing the forecasting problem. The forecaster should choose the form of the decomposition, additive versus multiplicative, according to the nature of the forecasting problem and the known causal factors associated with the problem, and their relationships. Multiplicative decomposition should be used only when uncertainty is high and avoided when uncertainty is low. If possible, one should use multiple approaches to estimating components of the decomposition, reconciling the resulting estimates in light of one another. If available, one should use multiple estimators or forecasters as well.

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