THE FORECASTING CLASSIFICATION GRID: A Typology for Method Selection

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ABSTRACT

Given the large variety of forecasting methods, researchers have developed different ways of classifying these methods. However, none of these methods meet the criteria of a good typology, i.e. concise, exclusive and exhaustive. Based on a review of the current classification methods, the paper proposes a forecasting classification grid based on two distinct dimensions, i.e. judgmental opinions and empirically evaluated ideas, and naive and causal forecasting. Being concise, exclusive and exhaustive, this new classification method provides a systematic way to organize different forecasting methods.

INTRODUCTION

Forecasting is used in many contexts including predicting the weather, the economy, the advancement of technology, the effect of medicine on a patient, and even changes in fashion. Numerous forecasting methods have been developed and applied in these areas, ranging from judgmental opinions to complex econometrics models. For the variety of forecasting methods, researchers have developed different ways of classifying these methods. Classification of forecasting methods helps to organize and better understand different methods, and more importantly provides a guidance of choosing different forecasting methods under different contexts. A good classification should be concise, exclusive and exhaustive. However, none of the current classifications meets all of these requirements.

This paper reviews the current classification of forecasting methods and proposes a new classification that is concise, exclusive and exhaustive. Each current classification method is reviewed and evaluated according to Brucks' (1986) criteria of a good typology. Built on the current classifications, the paper proposes a new classification and discusses how various forecasting methods fit within the new classification scheme.

CLASSIFICATION SCHEMES IN THE LITERATURE

Brucks (1986) stated that a good typology should have three objectives:

1) *The typology and coding scheme should be easy to use and seem logical to people who are using the coding scheme.*
2) *The typology should cover as many of the subjects' statements as possible while remaining relatively parsimonious.*
3) *The categories in the typology should be as distinct from each other as possible.*

In other words, a good classification system should be exhaustive, exclusive, and concise. Exhaustive means that the classification system should cover every potential option. Exclusive means that anything that belongs into one category should clearly not belong in another category. These criteria will be used to evaluate the various classification schemes that researchers have created to compartmentalize technological forecasting methods.

There are many ways to classify forecasts, all of them at least somewhat arbitrary. The ones more frequently used in the literature are discussed. The classification systems are listed in chronological order as this approach allows the reader to see how subsequent classifications built upon earlier research.

CETRON AND RALPH, 1971 – SUMMARY

Cetron and Ralph grouped forecasting techniques into five categories: intuitive methods, trend extrapolation, trend correlation, analogy, and dynamic predictive models. This classification system appeared to have been largely based upon the chapter headings of Lenz's 1962 landmark work on technological forecasting, but Cetron and Ralph did place some new methods within some of the classifications.

Intuitive methods include: individual forecasting, polls, panels, and the Delphi technique. Cetron and Ralph's reasoning for grouping these methods together was that all were based upon opinions. Ideally, these opinions were well-educated estimates made by experts, but they were all based upon the intuition of the forecaster.

Trend extrapolation is simply forecasting based upon the continuation of existing trends. It includes: simple extrapolation, substitution, and modified curve-fitting. Cetron and Ralph found that the general opinion in 1971 was that trend extrapolation was widely used due to its ease-of-use rather than due to any accuracy advantages (echoing an observation made a decade earlier by Lenz in 1962). The two key assumptions of trend extrapolation are:

1) the factors which caused the prior pattern of progress will continue;
2) the combined effect of these factors will continue the same pattern of progress.

Since technological progress typically advances slowly, reaches a critical mass, accelerates exponentially, and then slows as it reaches limitations, one can expect a given innovation to fit a type of trend curve. Cetron and Ralph distinguished between five types of trend curves: linear with flattening, exponential with no flattening, s-shaped, double exponential, gradual-rapid-subsequent flattening.

In **trend correlation**, the forecaster assumes that "one factor is the primary causal influence in the advancement of the technological parameter of interest." Trend correlation analysis is optimal for situations where the development of a certain innovation lags the development of another innovation.

Analogy forecasting simply looks for another pattern that should be similar to the pattern to be forecast. These are typically classified as growth or historical analogies. Forecasters have used growth formulas (e.g., the rate of cell increase within a rat) and historical patterns (e.g., GE looked at fossil fuel and hydroelectric power development to successfully forecast nuclear power development).

Dynamic predictive models are based upon work initially done by Forrester (1958), the chair of Lenz's thesis. Lenz built upon Forrester's modeling structure to simulate the impact of important causal factors. Over time, these models became more sophisticated. Currently, these types of models are most frequently referred to as structural models.

CETRON AND RALPH, 1971 – STRENGTHS AND WEAKNESSES

Cetron and Ralph's original contributions are largely in the area of intuitive methods, in the addition of historical analogies to the analogy classification, and in incorporating previous research into a formal classification system. Their taxonomy is concise, but neither exhaustive nor exclusive. It is not exhaustive as it does not consider techniques such as forecasting by role-playing. It is not exclusive as their definition of trend correlation specifically incorporates causality. Thus, one could reasonably say that trend correlation – as defined by Cetron and Ralph – is a subset of their dynamic predictive model classification.

MARTINO, 1972 – SUMMARY

Martino discussed five types of forecasts: intuitive, consensus, analogy, trend extrapolation, and structural models.

Intuitive forecasts are obtained by simply asking an expert. Martino wryly noted that "even though an expert may be wrong, his intuitive forecast may still be the best forecast available." He then cited Ralph C. Lenz's quip that intuitive forecasting's real problem is it is "impossible to teach, expensive to learn, and excludes any process of review."

Consensus methods obtain results by asking multiple experts. These experts typically meet together, but this is not a requirement. The positive aspects of this method are:

- that any fact that is known to one expert becomes available to all;
- multiple heads are less likely to overlook something;
- chances are that biases will balance out;
- opportunities for experts to see how others think and thus revise estimates with new input.

The negative aspects of this method include:

- all the problems associated with group dynamics (the Delphi technique is a consensus method that tries to eliminate/reduce these problems);
- any misinformation known to one is known by all.

The **forecasting analogy method** compares a known event (historical event, physical/biological process, etc.) with the event to be forecasted. Growth curves are often used to predict the advance of some technology. The S-curve has been found in many living species for both individual and population growth curves. The adoption of many technological innovations follows a similar pattern - starting slow, followed by a rapid rise, then a leveling off that leads to obsolescence. "The major strength of this method is that it eliminates much of the subjectivity of either intuitive or consensus methods of forecasting. Its major weakness, however, is that the exact extent of the analogy between the model and the thing to be forecast is often not evident until it is too late to do any good" (Martino, 1972).

Trend extrapolation avoids the problem of estimating changes in specific S-curves. Instead of focusing on a single device - or technology - trend extrapolation considers a series of devices that perform the same function. Successive devices usually have major differences in performance (on the order of 100% or more), while improvements to a single device are usually on the order of a few percent.

Structural models create an analytical model of the technology-generation process. "A characteristic feature of such models is they tend to be abstractions; certain elements are omitted because they are judged to be irrelevant, and the resulting simplification in the description of the situation is intended to be helpful in analyzing it and understanding it" (Martino, 1972).

MARTINO, 1972 – STRENGTHS AND WEAKNESSES

Martino's classification system is concise and easily understood. His lexicon is a bit confusing, as intuitive forecasts do not consist of all intuitive forecasts, but merely those that are from the opinion of a single expert. He reserves the classification *consensus methods* for the opinions of multiple experts. As his boundaries are quite clear for all five categories, Martino's classifications are exclusive. One might question the need for dividing subjective techniques into two categories based upon whether a single or multiple number of experts contributed toward it. This distinction does not seem useful and Martino is the only one to have made such a division. Further, the preciseness with which Martino defined his two expert classifications actually precluded both of these categories from incorporating non-expert intuitive forecasting methods such as role-playing. Thus, Martino's taxonomy is not exhaustive.

BRIGHT, 1978 – SUMMARY

Bright developed and used eight categories of forecasting: intuitive forecasting, trend extrapolation, dynamic modeling, morphological analysis, normative forecasting, monitoring, cross-impact analysis, and scenarios. As one would expect from their names, Bright's **intuitive forecasting**, **trend extrapolation**, and **dynamic modeling** categories are virtually identical to their Cetron and Ralph (1971) counterparts: respectively, intuitive methods, trend extrapolation, and dynamic predictive models.

Bright's classification of **morphological analysis** was for techniques that created a matrix of all theoretically possible combinations of technological approaches and configurations. He admitted that for morphological analysis to be considered forecasting, "one must argue that morphological analysis identifies known technology and predicts future technology by displaying possibilities that are not yet in use or even explored." Zwicky used morphological analysis of the jet engine to conceptualize the terra-jet, the hydra-jet, and the ram-jet. However, granting Bright's assumption that morphological analysis allows one to identify future possibilities does not make morphological analysis a forecasting technique. Since morphological analysis does not mention the timing of a new innovation, but rather the potential for its existence, it falls short of Bright's own criteria for a forecast. This is not to say morphological analysis has no place in the forecasting discipline, but rather, morphological analysis may help the forecaster conceive of some new technology. Then the forecaster can determine the appropriate method to forecast the adoption of this innovation.

Bright categorizes forecasts that assume new technology will materialize to meet a specific need as **normative forecasting**. However, the distinction between a normative forecast and an exploratory forecast does not change how forecasts are done. Rather, it changes the rate-of-progress assumptions for the forecast and normative forecasts should obviously show a faster rate-of-progress than exploratory forecasts.[1] Thus, while it is important to understand the distinction between normative and exploratory forecasting, normative forecasting is a *type* of forecasting, not a *method* of forecasting.

Bright stated that **monitoring** is based upon assessing events in progress and included four activities:

1) Searching the environment for signals that may be the forerunners of significant technological change;
2) Identifying possible alternative consequences if these signals are not spurious and if the trends that they suggest continue;
3) Choosing those parameters, policies, events, and decisions that should be followed in order to verify the true speed and direction of technology and the effects of employing that technology;
4) Presenting the data from the first three steps in a timely and appropriate manner for management's use in decisions about the organization's reaction.

Bright (1978) believed the essence of monitoring is "evaluation and continuous review." Like the error in classifying normative forecasting, Bright's work confuses a goal of the forecast (monitoring) with the forecast itself. Monitoring is simply a way of using forecasts, but is not a forecast in itself. Indeed, monitoring more accurately describes a way in which one may wish to use forecasting techniques to incorporate data as it becomes available.

Bright stated that **cross-impact analysis** "attempts to do in fact what is implied in all forecasting -- to provide a prediction of future conditions with allowance for all the interacting forces that will shape that future." Cross-impact analysis is a technique for building a matrix from the opinions of experts. It has some similarities to the Delphi technique and Bright mentioned that cross-impact analysis could complement the Delphi technique. So, cross-impact analysis should be more properly considered as a technique within the intuitive forecasting classification.

Bright (1978) uses the term **scenario** to describe a detailed description of a possible future. "In effect, the planner concedes he cannot predict the 'real' future, so he looks at several possible futures with the idea of being prepared for any uncertainty (the usual military goal) or of coming up with a plan that best accommodates the variety of uncertainties ahead (the usual industrial goal)." This was indeed a new technique that does not readily fall into any of the previously discussed classifications. One might force it to fit into a loose definition of an intuitive forecast, but as Bright used them, scenarios were meant to cover the entire range of foreseeable options with little thought given to which scenario was most probable.

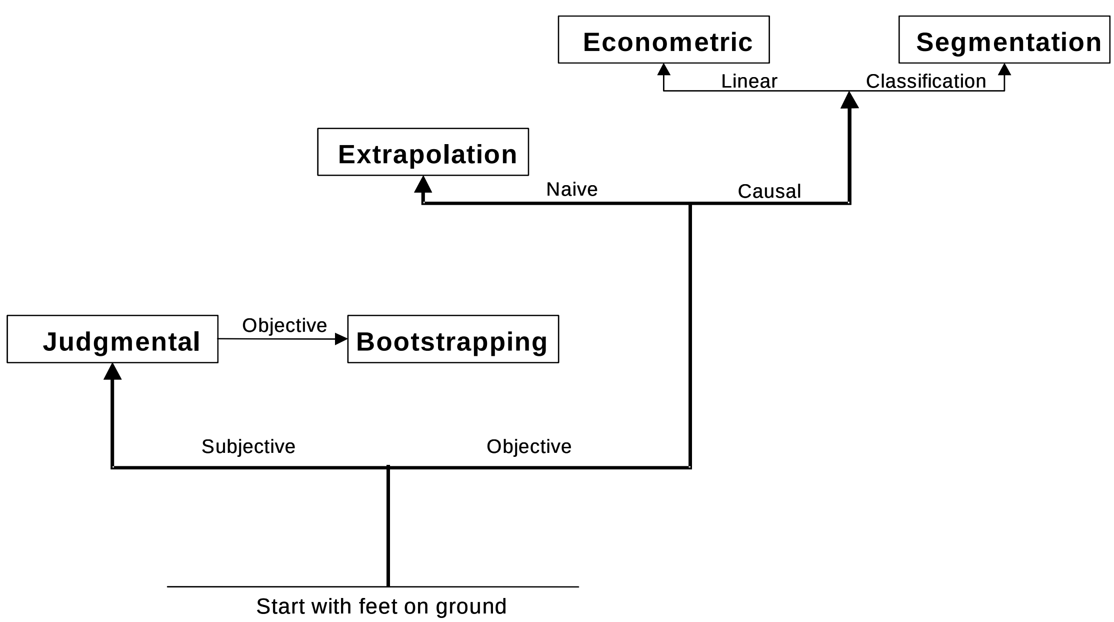
BRIGHT, 1978 – STRENGTHS AND WEAKNESSES

Bright was a strong advocate of the use of scenarios in forecasting and this was one of his main contributions to the field. He also distinguished between forecasts, predictions, and speculations. Bright (1978) defined a forecast as "a statement about a condition in the future, arrived at through a system of reasoning consciously applied by the forecaster and exposed to the recipient." He defined a prediction as "a statement about the future based on rationale, if any, that the predictor has not made known." And Bright defined speculation as "a statement about the future in which the predictor admits high uncertainty and/or admits lack of a highly supportive rationale." By these definitions, one cannot make an intuitive forecast, but merely an intuitive prediction or speculation. With eight classifications, Bright's taxonomy is hardly concise. However, three of Bright's categories – morphological analysis, normative forecasting, and monitoring are not actually forecasting classifications at all. In addition, the cross-impact analysis is a subset of his intuitive forecasting classification, so his classifications are not exclusive. His classification system is one of the more exhaustive systems and it would not take much redefining to incorporate newer techniques such as forecasting by role-playing into his scenario classification.

ARMSTRONG, 1985 – SUMMARY

Armstrong (1985) said that research for analyzing data has historically been organized along three continuums: subjective vs. objective, naive vs. causal, and linear vs. classification methods. He then placed five forecasting methods within these continuums to develop a methodology tree (Figure 1) that also provided guidance as to when various methods should be used. The heavier lines represent the key decisions that need to be made by the forecaster; the decisions in turn will help determine which methods should be used. Armstrong's five classifications were: judgmental, bootstrapping, extrapolation, econometric, and segmentation.

Figure 1: Forecasting Methodology Tree (Armstrong, 1985)



The subjective methods are those using implicit (i.e., vague) processes for data analysis. Naive methods only use data on the variable of interest; causal models use additional variables. Causal models ask "why?" and use these factors to make forecasts. “Linear” is used by Armstrong as meaning a formula and could include non-linear models. However, Armstrong also had a strong preference for linear models as they are both simpler and - in his experience - more accurate than non-linear models. The other side of the linear continuum is classification (segmentation) where the forecaster would group units that are expected to behave similarly (e.g., as a group, African-American voters vote Democrat).

Armstrong stated that there are three main decisions to be made when making a forecast. The primary decision is to select intuitive or objective methods. If objective methods are chosen, then Armstrong says another choice must be made between naive and causal approaches. And if a causal approach is selected, the forecaster must then decide between linear and classification approaches.

The **judgmental** classification in Armstrong’s lexicon is synonymous with his use of the term subjective. In his words, “These methods are also called implicit, informal, clinical, experienced-based, intuitive methods, guestimates, WAGs (wild-assed guesses), or gut feelings." This category may be considered equivalent to Cetron and Ralph’s (1971) intuitive methods. Likewise, Armstrong’s **extrapolation** classification is similar to Cetron and Ralph’s use of trend extrapolation. The only difference of note is that Armstrong included analogies within his extrapolation category.

Bootstrapping methods are ways of explicitly capturing the subjective processes used by an intuitive forecaster. Direct bootstrapping involves input from a forecaster on how an intuitive forecast was made. In many cases, the predictor is unable to produce an algorithm for producing his forecast. Indirect bootstrapping is used to reverse engineer the rules the forecaster is intuitively using, thus making these rules explicit.

All of the previous classifications schemes placed all explicit models into one category. Armstrong divided his into two categories: econometric and segmentation. The **econometric** classification is used for linear[2] representations of causal models that summarize existing knowledge within the models themselves. The **segmentation** methodology "attempts to find behavioral units that respond in the same way to the causal variables and to group these units.” For example, a very basic forecast about the initial acceptance of a new innovation may use a gender segmentation scheme and assume that five percent of males and three percent of females will adopt the innovation in the first year.

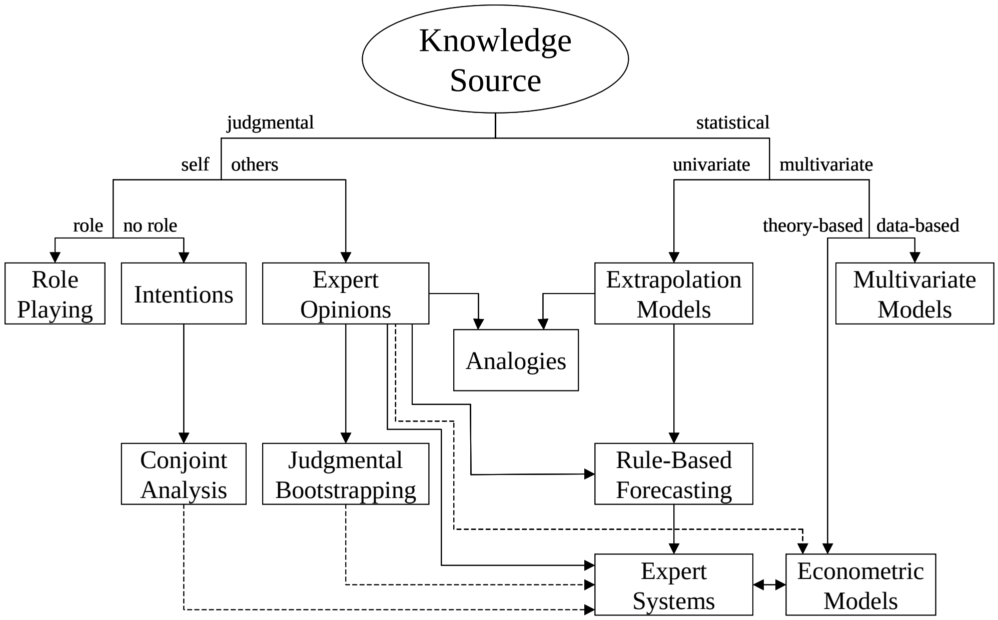
ARMSTRONG, 1985 – STRENGTHS AND WEAKNESSES

Armstrong’s Forecasting Methodology Tree provided guidance that better enabled a forecaster to understand what elements went into determining which forecasting method(s) to use. Armstrong’s suggestion and use of the naive/causal continuum was also quite useful and built upon the traditional subjective/objective distinction. However, his linear/classification distinction seems questionable. Not only does this distinction include a bias against non-linear methods, it seems to serve little purpose. For example, the resulting classifications – econometric and segmentation – are not exclusive (e.g., econometric models can easily incorporate multiple segments with their models). One might even say that segmentation is not a forecasting method per se; rather, segmentation techniques may be used to complement most forecasting methods. Forecasters may create forecasts from aggregate data or they may first segment the data, create individual forecasts for each segment, and then sum these forecasts. In addition, the models that result from bootstrapping might be viewed as econometric and/or segmentation models. Armstrong’s (1985) classification scheme is concise, but is neither exhaustive nor exclusive.

ARMSTRONG, 2001 – SUMMARY

Fortunately for the progress of forecasting, Armstrong did not stop with his initial Forecasting Methodology Tree. Armstrong's (2001) Methodology Tree is a significantly revised version of his earlier classification scheme. It also provides guidance to which method(s) should be used in a given situation.

Figure 2: Armstrong's Methodology Tree (2001)



Dashed lines represent possible relationships.

Armstrong (2001) believed there are eleven types of forecasting methods: role playing, intentions, conjoint analysis, expert opinions, judgmental bootstrapping, analogies, extrapolation methods, rule-based forecasting, expert systems, econometric models, and multivariate models. Armstrong placed these eleven categories into a Methodology Tree (see Figure 2) where the first branch separates judgmental methods from statistical methods. Judgmental methods are then subdivided into those that predict one's own behavior (self) and those where experts predict how others will behave (others). The self methods are further subdivided into roleplaying (where people are placed in a role and asked to act accordingly) and intentions (where people predict their own behavior in various scenarios). Conjoint analysis examines how different scenarios affect intentions. Along the "others" branch, expert opinions are used to make forecasts. Judgmental bootstrapping uses regression analysis to infer experts' rules for forecasting based upon the information that the experts use to make forecasts. Analogies are typically used when few, or no, observations are available (e.g., the introduction of a completely new innovation like holographic television). The statistical side of the methodology tree first splits into univariate and multivariate branches. The univariate branch is also known as "extrapolation methods" since it uses values of a series to predict other values. Rule-based forecasting is a type of expert system that integrates forecasting methodology with domain knowledge. Expert systems represent rules that the experts use. The multivariate branch subdivides into theory-based (econometric) and data-based (multivariate) models.

ARMSTRONG, 2001 – STRENGTHS AND WEAKNESSES

Armstrong's scheme is more useful than the schemes preceding it, as it provides guidance as to when to use various techniques. However, it is also a somewhat flawed typology. It is neither exhaustive, exclusive, nor concise. It is not exhaustive because certain classifications are not listed (e.g., where do non-expert opinions about the behavior of others go?). It is not exclusive since he has a classification for extrapolation models, yet all forecasts are extrapolations in one sense or another and some of his classifications are really subsets of a more general classification that he also listed. For instance, he stated that judgmental bootstrapping and rule-based forecasting were expert systems, yet he listed these as unique types along with expert systems. And with eleven non-exhaustive classifications, his system is hardly concise.

SUMMARY OF CLASSIFICATION SCHEMES

The existing classification schemes have made great contributions to the development of forecasting, especially technological forecasting. The earlier typologies (Cetron and Ralph 1971; Martino, 1972) were most useful in determining what was – and was not – forecasting. The later ideas (Armstrong, 1985, 2001) took a step forward by also providing guidance as to when certain classifications should be used. But these typologies are neither exhaustive, exclusive nor concise (Table 1).

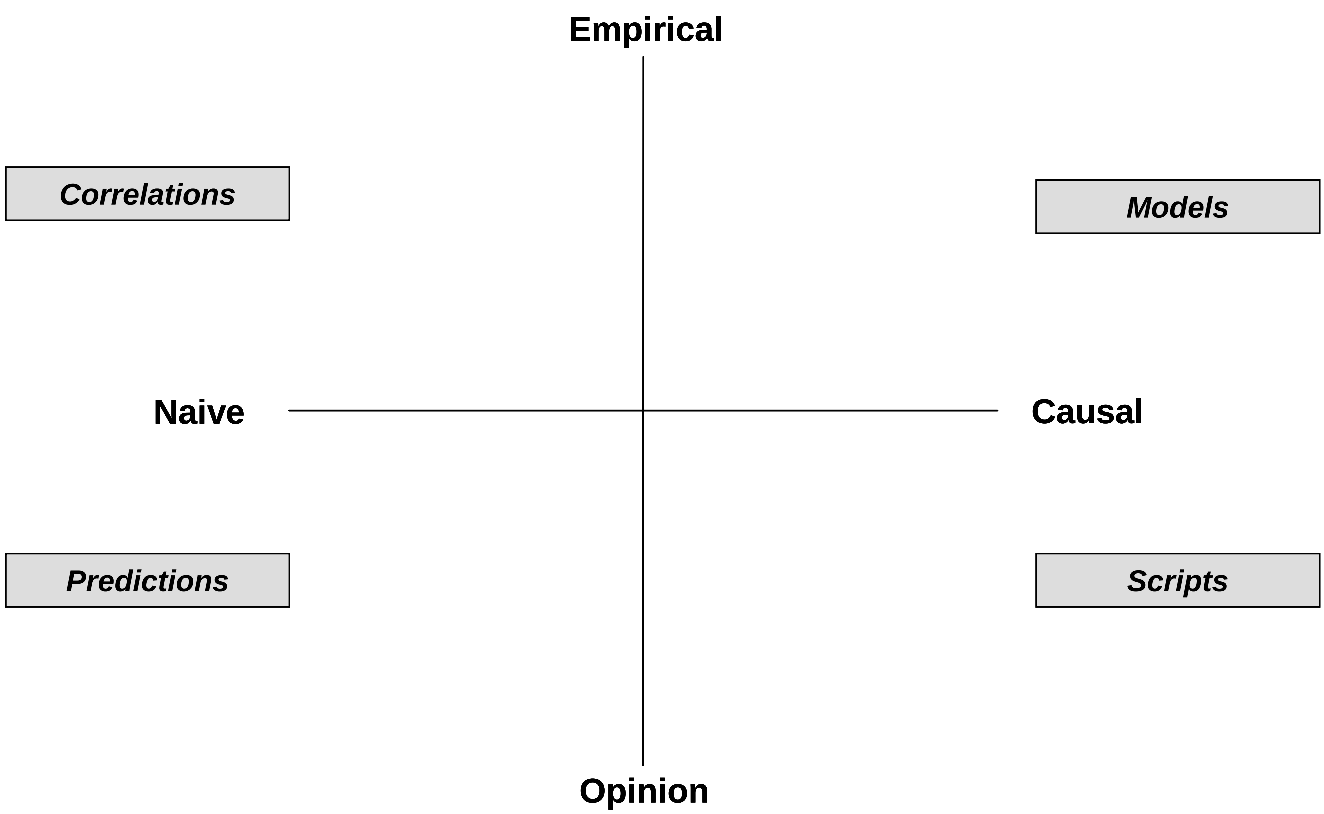
Table 1: Summary of Forecasting Classification Schemes

Source	Classifications		Strength(s)	Weakness(es)
Cetron and Ralph, 1971	5	intuitive methods, trend extrapolation, trend correlation, analogy, and dynamic predictive models	concise	neither exhaustive nor exclusive
Martino, 1972	5	intuitive, consensus, analogy, trend extrapolation, and structural models	concise and exclusive	not exhaustive
Bright, 1978	8	intuitive forecasting, trend extrapolation, dynamic modeling, morphological analysis, normative forecasting, monitoring, cross-impact analysis, and scenarios	added concept of scenarios, could be considered exhaustive with a liberal interpretation	neither exclusive nor concise; also included some categories that were inappropriate
Armstrong, 1985	5	judgmental, bootstrapping, extrapolation, econometric, and segmentation	concise, added naive/causal continuum, provided guidance to which forecast should be used	neither exclusive nor exhaustive
Armstrong, 2001	11	role playing, intentions, conjoint analysis, expert opinions, judgmental bootstrapping, analogies, extrapolation methods, rule-based forecasting, expert systems, econometric models, and multivariate models	provides guidance to which forecast should be used	flawed classification system (neither exclusive, exhaustive, nor concise).

THE PROPOSED FORECASTING CLASSIFICATION GRID

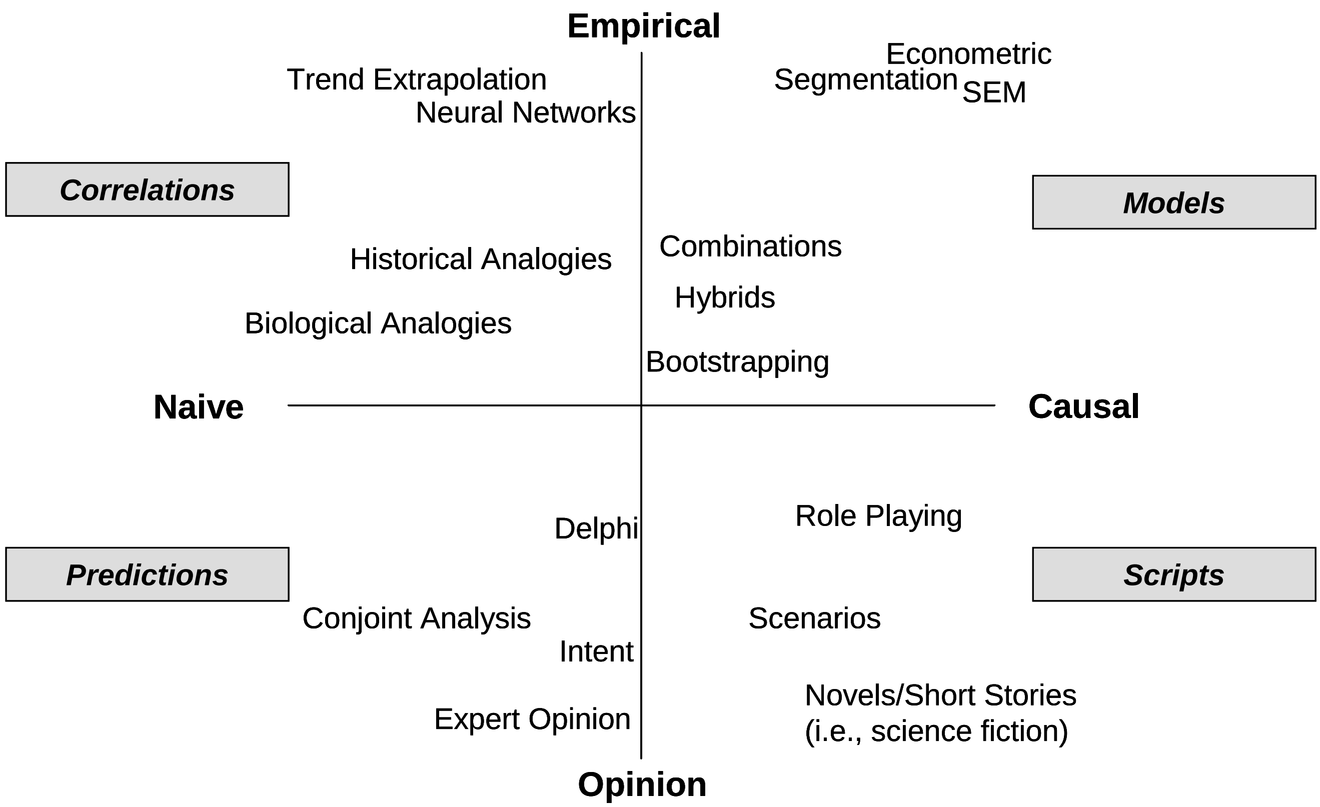
Based on previous work, a new classification of forecasting methods is proposed. Figure 3 shows the Forecasting Classification Grid (hereafter, simply the “Grid”). The classification is based on two dimensions: the continuum of opinion and empirical, and the continuum of causal and naïve. Like all the other classification schemes, it recognizes the importance of distinguishing between opinion and ideas that can be empirically evaluated. It also includes Armstrong's distinction between naive and causal. This typology assumes that these two continuums are independent. Given this assumption, four exclusive categories logically follow: predictions, scripts, correlations, and models. Predictions are defined as explicit forecasts that are based upon opinions whose assumptions have not been made explicit. Scripts are defined as constructed scenarios in which a potential future is described and causal assumptions are made. Correlations are defined as forecasts based upon the performance of another factor without any causal assumptions. Models are defined as any forecast with explicit causal assumptions (i.e., assumptions that may be mathematically stated).

Figure 3: Forecasting Classification Grid



One of the attractions of the Forecasting Classification Grid is its simplicity relative to the other ways of classifying forecasts. As it only has four classifications, it is definitely the most concise scheme yet discussed. Founded upon two independent dimensions, the four categories are exclusive and exhaustive. Also, the grid covers and fits well with the existing forecasting techniques. Figure 4 shows how the existing techniques fit within the proposed classification scheme. The various techniques and their applicability to forecasting as noted in the literature are discussed using the Grid classifications (predictions, scripts, correlations, and models).

Figure 4: Existing Forecasting Techniques and the Grid



PREDICTIONS

By definition, predictions are opinion-based speculation with no explicit causal assumptions. Techniques in this classification include methods such as intentions, conjoint analysis, and expert opinion practices (e.g., Delphi). Since intentions have been shown to influence behavior (Fishbein and Ajzen, 1975; Ajzen, 1991), polling purchase intentions of potential consumers is used by many firms to develop market forecasts. Jamieson and Bass (1989) found that 70% to 90% of market-research clients use purchase intentions data on a regular basis. Wittink and Bergestuen (2001) suggested that conjoint analysis should not be used for discontinuous innovations. If a forecaster strongly desires to use conjoint analysis to make a forecast about "new-to-the-world types of products", Wittink and Bergestuen recommended first educating respondents about the category. Even then, they had limited hope for the accuracy of such a forecast. The authors' own experience with professional market-research firms' attempts to forecast consumer demand for radical and really new products in the consumer electronic, telephony, and PC industries support their recommendation and conclusion. For expert opinion practices, Harvey (2001) recommended that experts use a checklist when making their forecast in order to minimize the problems with judgments (i.e., experts not using information that they should use, while employing information that they should not). Given the evidence that expert forecasters are overconfident, Harvey found it reasonable to allow for an overconfidence bias of approximately 10 to 14 percent.

SCRIPTS

Scripts are opinion-based speculation with detailed causal assumptions described in writing. Techniques in this classification include role-playing, scenarios, and the traditional writings of many hard science fiction[3] authors and futurists. In role playing, subjects are asked to take on roles and act accordingly. Researchers use their decisions as forecasts. Armstrong (2001) concluded, "Experts are probably better at identifying what *should* happen than what *will* happen. Role playing should be more accurate as to what will happen." Herman Kahn popularized the scenario technique in the 1950s when he worked at the Rand Corporation. Bright (1978) advocated the use of scenarios, but sometimes referred to them as an anti-forecast. In his thinking, scenarios were important tools for contingency planning; but the probabilities of each scenario were of little import. Bright's focus was on the benefits of planning for all reasonable outcomes.

CORRELATIONS

Correlations are defined as forecasts based upon the performance of another factor without any causal assumptions. Techniques in this classification include methods such as extrapolation, analogies, and neural networks. Armstrong (2001) suggested five conditions that favored the use of extrapolation:

1) when a large number of forecasts is needed;
2) when the forecaster is ignorant about the situation;
3) when the situation is stable;
4) when other methods would be subject to forecaster bias; and/or
5) as a benchmark in assessing the effects of policy changes.

Analogies were originally simply used as patterns or parameterization templates for growth models. No causal reasoning was desired; forecasters simply selected a pattern that they thought – or hoped – would be appropriate (Cetron and Ralph, 1971; Martino, 1972). Forecasters sometimes used biological analogies for growth models – Cetron and Ralph even discussed how one firm created forecasts based upon the growth rate of a rat's cell. The main problem with forecasting by analogy is that the proper analogy is usually not known until after the new opportunity unfolds – at which point the researcher is using hindsight (Martino, 1971). Naive analogies are rarely seen in the current literature. This may be due to the academic bias toward theory-based solutions. This is not to say analogies are no longer used. However, researchers now pick an analogy and use the parameters in explicit growth curve models. These hybrids are explicit models, not analogies or correlations, and give the appearance of being more scientific. However, the historical problems related to analogies still apply to these models. For example, the author of the most widely used forecasting model, the Bass Model, still struggles with the same problems the perplexed users of analogies: "Choosing the appropriate analogy of previously introduced new products is important for the Bass model. However, little is known about the best way to guess by analogy other to say that it depends on judgment" (Bass et al, 2001). Armstrong (2001) also found it "surprising that little research has been done on such topics as how to select analogies…and how much gain one might achieve by pooling data from analogies."

Forecasts produced by neural networks are commonly perceived as a "black box" production – examining the model parameters does not indicate why the model makes good predictions (Remus and O'Conner, 2001). Given this lack of explicit causal assumption, neural network forecasting is classified as a correlation method. However, any neural network forecasts that explicitly documents its causal assumption should be considered a model, not a correlation. If causal assumptions are someday routinely included in neural network forecasts, then the method should be reclassified as a model at that time.

MODELS

Models are defined as forecasts with explicit causal assumptions that may be mathematically stated. These models could also be known as rule-based forecasting, but at least one forecasting expert (Armstrong, 2001) reserved this term for forecasts of time series data. Techniques in the "model" classification include expert systems, econometric models, and structural models (e.g., the Bass 1969 model). Armstrong (2001) sometimes distinguished between judgmental bootstrapping and expert systems, but was inconsistent in his descriptions (e.g., on page 188 he stated bootstrapping is a "type of expert system," but on page 283 he introduced an article on expert systems by contrasting bootstrapping methods with expert systems). In this document, expert systems are systems that use a model of how an expert would act in making a forecast. Judgmental bootstrapping is a subset of expert systems that infers the rules an expert uses by reverse engineering these rules from the results. Forecasters who desire to create expert systems that directly ask experts how they make their forecasts should ensure the availability of experts with a lot of time (Collopy, Adya, and Armstrong, 2001). The distinction between econometric models and structural models is vague. This vagueness is one of the reasons the Grid classifies both techniques as models. Technically, it is difficult to create a definition that would differentiate the two techniques – which is one of the reasons against using the term econometrics as one of the four proposed forecasting classifications. In practice, econometrics usually refers to the use of regression analysis. As such, econometrics is a forecasting technique within the proposed model classification.

CONCLUSION

The proposed forecasting classification grid provides a systematic way to organize various forecasting methods in the literature. The classification recognizes both the distinction between judgmental opinions and empirically evaluated ideas and the distinction between naive and causal forecasting. Compared to the previous classifications, this classification is simpler, logical, and meets the requirement of a good typology (i.e., concise, exclusive, and exhaustive). The new classification also provides guidance for choosing forecasting methods in various contexts. Given the large variety of forecasting methods, the choice of forecasting methods is critical for improving forecasting accuracy. This paper discussed the distinction of different forecasting methods and the proper context of applying them.

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[1] An exception to this expectation would be in the theoretical case where the demand was to slow down progress (e.g., Luddites making policy decisions).

[2] As discussed earlier, Armstrong saw little point in non-linear econometric models and his nomenclature reinforced his bias.

[3] Hard science fiction is the subset of the genre that limits itself to known facts and possibilities.