Long-term Forecasting for Policymaking with Structured Analogies and Interaction Groups

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Joint work

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Arab Open University
Salford University

Time Horizon in economic forecasting

Today	Short Term	Mid Term	Long Term
	(3months - 5years)	(up to 10years)	(more than 10years)

Long Term Forecasting (LTF)

- The long-term forecast (LTF) is a complex task.
- LTF is affected by **several factors** and **special events**.
- The past is less important for long-term forecasts.
- There are two types of factors.
  - **Hard Factors**
  - **Soft Factors**

Factors

Hard (Tangible)	Soft (Intangible)
Numerical data (Variables)	Contextual Information
Short term impact	Long term impact
Fast change	Slow change
Measurable	Non measurable
Ex: Prices, Inflation, Unemployment rate	Ex: Strategies, Policies, Culture

Impact

Hard (Tangible)	Soft (Intangible)
Numerical data (Variables) Short term impact Fast change Measurable	Contextual Information long term impact Slow change Non measurable
Ex: Prices, Inflation, Unemployment rate	Ex: Strategies, Policies, Culture

Long Term Impact		Short Term Impact	
Causes	**Effects**	**Causes**	**Effects**
Soft Factors	Hard Factors	Hard Factors	Soft Factors

Case Study: Saudi Arabia

- Saudi GDP growth relies on the Oil sector.
- 90% of Saudi income from oil revenue.
- Government spending, consumption and net export fluctuate with changing oil prices.
- Recently launched a new vision called **Saudi vision 2030**.
- We are interested in the potential of Diversification strategies and the GDP composition in 10/20 years from now….

The Forecast

Research Design & Methodology

- **Performing Experiments where experts are forecasting with Judgmental methods**

- **Unaided Judgment:** Benchmark.
- **Structured Analogies (SA and sSA):** Evidence of working better. (Armstrong and Green 2007, Savio and Nikolopoulos 2013, Nikolopoulos et al. 2015, Litsiou et al 2019)
- **Interaction Groups with sSA:** Seeking consensus and allowing interaction with anonymity not protected… (Nikolopoulos et al. 2015, Litsiou et al 2019)

Structured Analogies

2007

Structured analogies for forecasting

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vs Semi Structured Analogies

ELSEVIER

International Journal of Forecasting
Volume 29, Issue 2, April–June 2013, Pages 311-321

A strategic forecasting framework for governmental decision-making and planning

Nicolas D. Savio [a], Konstantinos Nikolopoulos [b]

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https://doi.org/10.1016/j.ijforecast.2011.08.002 Get rights and content

Abstract

An important stage in the policy-making process involves deciding on the strategy to be adopted for implementation, so that the objectives of the policy are met in the best possible way. A Policy Implementation Strategy (PIS) adopts a broad view of implementation, which is argued to transcend formulation and decision-making, thereby offering a more realistic view of the policy process. Governmental decision-makers are often faced with having to choose one PIS from among several possible alternatives, at varying cost levels. In order to aid such a decision-making process, PIS effectiveness forecasts are proposed as a strategic decision-support tool. The methods currently available for such a purpose are found to include resource-intensive evaluative techniques such as Impact Assessment and Cost-Benefit Analysis. In this study, a Structured Analogies forecasting approach is proposed, and the empirical evidence suggests that it could be seen as a strategic tool in the hands of governmental officers.

vs RCF

Reference class forecasting

From Wikipedia, the free encyclopedia

Reference class forecasting or **comparison class forecasting** is a method of predicting the future by looking at similar past situations and their outcomes. The theories behind reference class forecasting were developed by Daniel Kahneman and Amos Tversky. The theoretical work helped Kahneman win the Nobel Prize in Economics.

Reference class forecasting is so named as it predicts the outcome of a planned action based on actual outcomes in a reference class of similar actions to that being forecast.

Discussion of which reference class to use when forecasting a given situation is known as the reference class problem.

Contents [hide]

Overview [edit]

Kahneman and Tversky[1][2] found that human judgment is generally optimistic due to overconfidence and insufficient consideration of distributional information about outcomes.

People tend to underestimate the costs, completion times, and risks of planned actions, whereas they tend to overestimate the benefits of those same actions. Such error is caused by actors taking an "**inside view**", where focus is on the constituents of the specific planned action instead of on the actual outcomes of similar ventures that have already been completed.

Kahneman and Tversky concluded that disregard of distributional information, i.e. risk, is perhaps the major source of error in forecasting. On that basis they recommended that forecasters "should therefore make every effort to frame the forecasting problem so as to facilitate utilizing all the distributional information that is available".[2]:416 Using distributional information from previous ventures similar to the one being forecast is called taking an "**outside view**". Reference class forecasting is a method for taking an outside view on planned actions.

Reference class forecasting for a specific project involves the following three steps:

1. Identify a reference class of past, similar projects.
2. Establish a probability distribution for the selected reference class for the parameter that is being forecast.
3. Compare the specific project with the reference class distribution, in order to establish the most likely outcome for the specific project.

Reference class tennis [edit]

The reference class problem, also known as reference class tennis, is the discussion of which reference class to use when forecasting a given situation.

Suppose someone were trying to predict how long it would take to write a psychology textbook. Reference class tennis would involve debating whether we should take the average of all books (closest to an outside view), just all textbooks, or just all psychology textbooks (closest to an inside view).[3][4]

Practical use in policy and planning [edit]

Whereas Kahneman and Tversky developed the theories of reference class forecasting, Flyvbjerg and COWI (2004) developed the method for its practical use in policy and planning, which was published as an official Guidance Document in June 2004 by the UK Department for Transport.[5]

The first instance of reference class forecasting in practice is described in Flyvbjerg (2006).[6] This forecast was part of a review of the Edinburgh Tram Line 2 business case, which was carried out in October 2004 by Ove Arup and Partners Scotland. At the time, the project was forecast to cost a total of £320 million, of which £64 million – or 25% – was allocated for contingency. Using the newly implemented reference class forecasting guidelines, Ove Arup and Partners Scotland calculated the 80th percentile value (i.e., 80% likelihood of staying within budget) for total capital costs to be £400 million, which equaled 57% contingency. Similarly, they calculated the 50th percentile value (i.e., 50% likelihood of staying within budget) to be £357 million, which equaled 40% contingency. The review further acknowledged that the reference class forecasts were likely to be too low because the guidelines recommended that the uplifts should be applied at the time of decision to build, which the project had not yet reached, and that the risks therefore would be substantially higher at this early business case stage. On this basis, the review concluded that the forecasted costs could have been underestimated. The Edinburgh Tram Line 2 opened three years late in May 2014 with a final outturn cost of £776 million, which equals £628 million in 2004-prices.[7]

Since the Edinburgh forecast, reference class forecasting has been applied to numerous other projects in the UK, including the £15 (US$29) billion Crossrail project in London. After 2004, The Netherlands, Denmark, and Switzerland have also implemented various types of reference class forecasting.

Before this, in 2001 (updated in 2011), AACE International (the Association for the Advancement of Cost Engineering) included Estimate Validation as a distinct step in the recommended practice of Cost Estimating (Estimate Validation is equivalent to Reference class forecasting in that it calls for separate empirical-based evaluations to benchmark the base estimate):

vs kNN

k-nearest neighbors algorithm

From Wikipedia, the free encyclopedia

Not to be confused with k-means clustering.

In statistics, the ***k*-nearest neighbors algorithm** (***k*-NN**) is a non-parametric classification method first developed by Evelyn Fix and Joseph Hodges in 1951,[1] and later expanded by Thomas Cover.[2] It is used for classification and regression. In both cases, the input consists of the *k* closest training examples in a data set. The output depends on whether *k*-NN is used for classification or regression:

- In *k-NN classification*, the output is a class membership. An object is classified by a plurality vote of its neighbors, with the object being assigned to the class most common among its *k* nearest neighbors (*k* is a positive integer, typically small). If $k = 1$, then the object is simply assigned to the class of that single nearest neighbor.
- In *k-NN regression*, the output is the property value for the object. This value is the average of the values of *k* nearest neighbors.

k-NN is a type of classification where the function is only approximated locally and all computation is deferred until function evaluation. Since this algorithm relies on distance for classification, if the features represent different physical units or come in vastly different scales then normalizing the training data can improve its accuracy dramatically.[3][4]

Both for classification and regression, a useful technique can be to assign weights to the contributions of the neighbors, so that the nearer neighbors contribute more to the average than the more distant ones. For example, a common weighting scheme consists in giving each neighbor a weight of $1/d$, where d is the distance to the neighbor.[5]

The neighbors are taken from a set of objects for which the class (for *k*-NN classification) or the object property value (for *k*-NN regression) is known. This can be thought of as the training set for the algorithm, though no explicit training step is required.

A peculiarity of the *k*-NN algorithm is that it is sensitive to the local structure of the data.

Real Case: Saudi Arabia

Interaction Groups with Structured Analogies (Saudi Arabia) (sSA&IG)	
Country Name	Saudi Arabia
Participation Type	Groups
Participants	Three levels of expertise, three experiments in Bangor, UK and KSA Novice, Semi experts and Experts
Sample Size (n)	110
Domain Knowledge	Business

Results: which Analogies the experts identified

Sectors	Analogies
Energy & Mining	Norway
FDI (Foreign Direct Investment)	India
Tourism	UAE
Industry	South Korea
Services (Shipping and Aviation)	Singapore

Further results

Investment in Energy & Mining Sector		
Participants' Insights	Expected Return % of Saudi Income	Rate of Analogy Saudi Arabia & Norway
Novices	30%	0.30
Semi Experts	40%	0.25
Experts	40%	0.10

Investment in FDI Sector		
Participants' Insights	Expected Return % of Saudi Income	Rate of Analogy Saudi Arabia & India
Novices	15%	0.35
Semi Experts	10%	0.20
Experts	10%	0.20

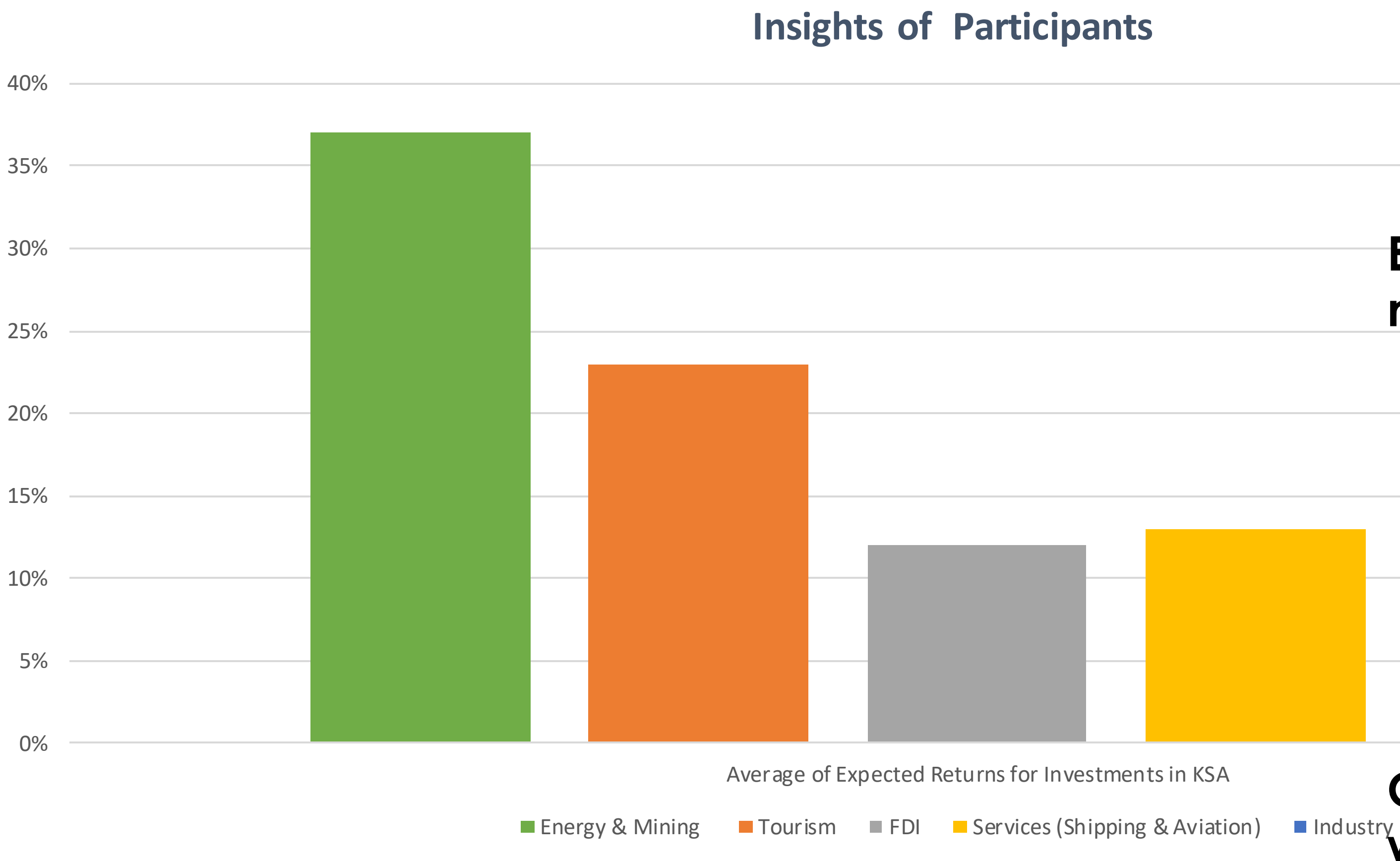
Investment in Tourism Sector		
Participants' Insights	Expected Return	Rate of Analogy
	% of Saudi Income	Saudi Arabia & UAE
Novices	25%	0.80
Semi Experts	20%	0.80
Experts	25%	0.60

Investment in Industry Sector		
Participants' Insights	Expected Return	Rate of Analogy
	% of Saudi Income	Saudi Arabia & South Korea
Novices	20%	0.25
Semi Experts	15%	0.30
Experts	10%	0.10

Investment in Shipping and Aviation		
Participants Insights	Expected Return	Rate of Analogy
	% of Saudi Income	Saudi Arabia & Singapore
Novices	10%	0.20
Semi Experts	15%	0.25
Experts	15%	0.10

The first giant leap…

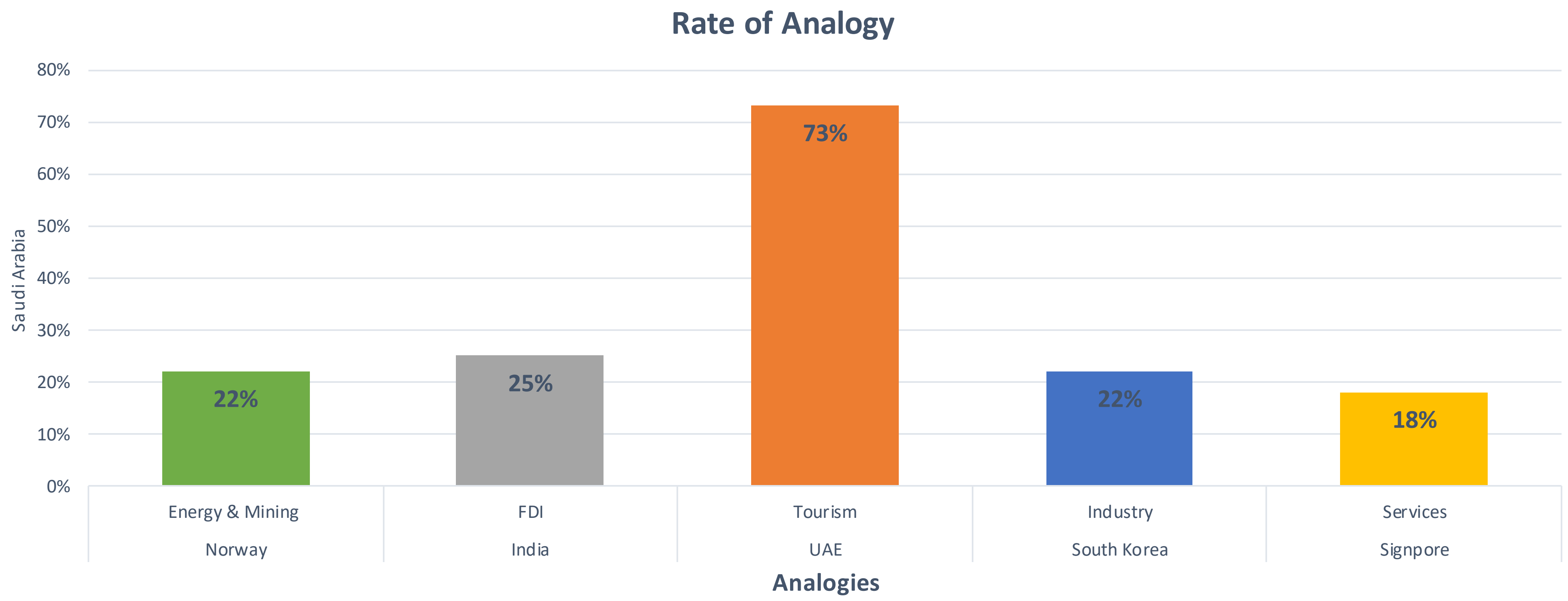
The (Average + standardized) 20-years ahead Expected composition of Saudi GDP…



Equal weights for levels of expertise normalized only for sample sizes…

Could have given proportionate weights to the level of expertise or empirical ones …

Comparison Saudi Arabia and Cited Countries



Findings and Recommendations

Participants' Insights and Analogies of Investments in Saudi Arabia						Rate of Success
Sectors	Sub Sectors	Expected Return	Analogies	Variance	Rate of Analogy	
Public Sector	Energy & Mining	37%	Norway	High	0.22	8%
Private Sector	FDI	12%	India	High	0.25	3%
	Tourism	23%	UAE	Low	0.73	17%
	Industry	15%	South Korea	High	0.22	3%
	Services (Shipping & Aviation)	13%	Singapore	High	0.18	2%
Total		?	???			?

The real giaaaaant leap…

Findings and Recommendations

Participants' Insights and Analogies of Investments in Saudi Arabia						Rate of Success
Sectors	**Sub Sectors**	**Expected Return**	**Analogies**	**Variance**	**Rate of Analogy**	
Public Sector	Energy & Mining	37%	Norway	High	0.22	8%
Private Sector	FDI	12%	India	High	0.25	3%
	Tourism	23%	UAE	Low	0.73	17%
	Industry	15%	South Korea	High	0.22	3%
	Services (Shipping & Aviation)	13%	Singapore	High	0.18	2%
Total		**100%**	**Chances of 'scenario' happening?**			**34%**

Or 34% of GDP Explained ?

A forecast with 34% confidence?

Estimating Participants Ability to Derive Accurate Forecasts

- Estimating the accuracy of forecasts for each group is through giving the participants a specific case as a mock case. This case is a real case, and is occurred in the past, as well as, its outcomes is known in advance…Brexit!

Participants	Novices	Semi experts	Experts
Mean Absolute Error (MAE)	0.316	0.370	0.167

The Elephant in the room….

How similar is this forecasting task to the one at hand?

The white Elephant in the room….

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Carry-Over Effect (Carryover Effect)

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In research a carry-over or carryover effect refers to any lingering effects of a previous experimental condition that are affecting a current experimental condition.

Essentially it is an effect that "carries over" from one experimental condition to another. This effect is seen when a subject performs in more than one condition making this is a common concern in within-subjects design.

For instance, a researcher wants to know the effects of a medication on memory. The subject is given a list of words to memorize in two different conditions: with a placebo and with the real medication. The researcher doesn't consider the possibility of carryover effects and uses the same list of words for both experimental conditions.

Any significant results of improved memory may not be a result of the medication - the improved memorization could have been carryover effects from the first condition. By using the same list from the first condition the subject is more likely to recall the words the second time. The carryover effects from the first condition are influencing the second condition making it seem as if there is significance when there is not.

- The story of this paper…
- 2+ years in IJF and multiple ISFs
- Foresight…
- So TFSC now

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