Interpolation techniques: A possible way to bypass offshore resource assessment limitations?

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ABSTRACT: Over time, the offshore energy sector, focusing on wave and offshore wind energies, is gaining more and more attention, due to their enormous energy potential. Yet, these technologies are still not commercially viable due to many technical challenges. One of these challenges is the limited understanding of resource behavior in specific areas. Traditionally, resource assessment involves deploying measuring devices to monitor site-specific conditions over time, a method not feasible on a global scale due to the ocean's vastness. Alternatively, numerical simulations can estimate site conditions but face a trade-off between accuracy and computational time, limiting their use. A promising solution lies in data-driven interpolation techniques, which can expand in space and time the limited available measurements and/or be assimilated into numerical simulations. This approach, similar to Kriging in mining engineering and Data Assimilation in weather forecasting, could significantly enhance the offshore energy resource assessment. This article describes the essential parameters for wave and wind energy assessment, then it discusses the interpolation techniques most commonly applied in the offshore sector and finally it presents case studies using these techniques in this sector. Ultimately, the article demonstrates the potential of these techniques to address offshore energy assessment challenges, leveraging methods already proven in other fields.

1 INTRODUCTION

As global energy needs continue to rise, so does the interest in harnessing renewable energy sources to meet this growing demand. Among the various options for renewable energy, the offshore energy sector, which mainly consists in wave energy and offshore wind energy production, results to be particularly interesting. The wave renewable sector stands out as a particularly promising yet underexploited source with vast potential (González 2021). Unlike other renewables such as solar and wind, wave energy has still not reached commercial success. This is due to several challenges, like the lack of agreement on an optimal design that functions effectively across all sea conditions (Bingyong Guo 2021).
Another significant challenge for the offshore renewable energy industry lies in accurately assessing suitable locations for deploying devices: in order to determine the optimal deployment site for a device or plant, it is crucial to evaluate the potential energy output across various locations, ensuring it is situated where it can generate the highest amount of energy (Rusu 2014). Another critical information that has to be evaluated when choosing a proper location is the variability of the energy production in that location, for example for considering the interactions with the electric grid (Giglio et al. 2023).
For traditional sectors, two main routes are possible for tackling the location assessment problems: using measuring devices that actually measure and record the real parameter values in the location of interest or resorting to numerical physical simulation of the system (Guillou et al. 2020), (Yang et al. 2022). Both these routes are used for the offshore sector, but both end up showing off their limits: the ocean is too vast and complex to be characterized in its entirety by a restricted number of expensive measuring devices, and the dynamics regulating its evolution is given by the Navier-Stokes equations, which are notoriously hard to solve, translating in a non-negligible computational time versus accuracy trade-off in the numerical simulations.
An hidden third route may be given by resorting to mathematical interpolation techniques. These tools can offer a way for spatially and temporally extending the restricted amount of measurements available, so generating more useful data for a proper location assessment.
The following of this article is structured as follows:

- An accurate description of the actual state of the art, regarding the wave and wind parameters of interest, the devices used for measuring them and the numerical tools available for simulating their evolution.

- A presentation of the most used mathematical interpolation techniques, highlighting the points of strength and of weakness of each one, along with a possible classification for them.
- A collection of case studies employing an interpolation technique in the offshore sector for a specific parameter of interest, with some tables resuming all these case studies.
- A final conclusion, underlying the main findings of this article and depicting the possible future steps.

2 STATE OF THE ART

For performing a location assessment of a specific site, the time evolution in that location of some parameters of interest is needed. This implies that the first thing that has to be defined is which is the parameter to be measured. After that a measuring devices that can properly measure that parameter has to be identified. For the numerical simulation approach instead, a model for the system has to be chosen, possibly considering already in this stage the needed accuracy of the simulation, in order to choose a model whose complexity is enough to give the wanted accuracy, but no more complex since it would unnecessarily increase the computational time required for performing the simulation.

2.1 *Parameters of interest*

For wave energy, a sea state is totally characterized by its wave spectrum. The wave spectrum provides a complete characterization of the sea state by describing the distribution of wave energy across different frequencies. Anyway characterizing the entirety of a wave spectrum may be too difficult. Moreover the whole spectrum could contain unnecessary or redundant information. For most energy related applications, some synthetic parameters related to the wave spectrum are enough. Typically two parameters are considered: the significant wave height H_s and the energy period T_e. Both these parameters can be obtained from the wave spectrum by considering its spectral moments:

$$H_s = \sqrt{4m_0} \tag{1}$$

$$T_e = \frac{m_{-1}}{m_0} \tag{2}$$

where with m_i it is indicated the i^{th} spectral moment of the wave spectrum.

For offshore wind energy instead, typically the parameter of interest is the horizontal wind speed at a $10m$ height, which is a 2d vector and can be represented either as a modulus $|V|$ and a direction $\angle V$ or by its Cartesian components u, v.

$$u = |V| * cos(\angle V) \tag{3}$$

$$v = |V| * sin(\angle V) \tag{4}$$

This $10m$ height wind speed can then be extrapolated to another height of interest (like the height of the rotor hub of a wind turbine) using the typical vertical exponential wind speed profile or more sophisticated techniques (Optis et al. 2021).

2.2 *Offshore measuring devices*

Considering the offshore sector, the most common measuring devices are in situ buoys (Urquhart et al. 2013),(Gambarelli et al. 2023) that have measuring devices attached to them, for example recording the wave elevation over time.
These measures are what is actually considered as the 'ground truth' being direct in situ measurement, with a degree of trust way higher than that of numerical simulations. The main problems related to these devices are their cost and their maintenance expenses: the ocean environment is notoriously hard towards mechanical devices due to its corrosive property and the presence of extreme events that can damage the devices irreversibly. Moreover, a periodic maintenance is needed for keeping the buoys operative, which translates in the need of reaching the buoy offshore, with all the expenses associated.
These economic downsides are one of the main reasons why also numerical simulation have to be used for making location assessments in the offshore sector.
Almost all of these measuring devices are deployed by large monitoring networks operated by national and international programs such as NOAA (Meindl and Hamilton 1992), Puertos del Estado (Pérez 2017), Ifremer (Petrenko 2017) and POSEIDON-HCMR (Papathanassiou 2005).
There are different types of offshore in situ measuring devices, like moored instruments (K. W. Doherty and Toole 1999), drifting instruments, autonomous vehicle instruments (Sánchez et al. 2020) and coastal structure instruments (B. Mutlu Sumer 2001). Each one of these types is more suited for different specific parameters and applicaitons.

2.3 *Numerical models*

For simulating these complex environments such as the ocean and the atmosphere, different numerical models exist, with different physical domains, used equations, achieved accuracy and required computational time.

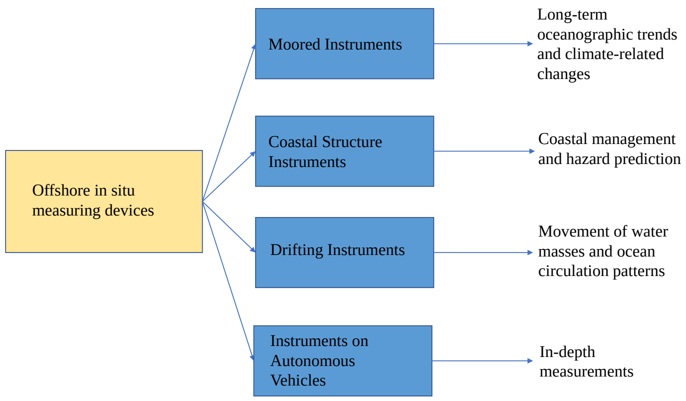

Figure 1: Classification of the in situ measuring devices and their main applications

Considering the offshore energy sector, it is possible to divide these models into three categories, with respect to the physical domain considered:

- Ocean models: These models are essential for predicting the physical state of the sea, including wave height, period, direction, and ocean currents. They directly influence the performance of wave energy converters and offshore wind turbines. Commonly used models include the Simulating WAves Nearshore (SWAN) (Booij et al. 1999), which utilizes the action balance equation and is suitable for nearshore areas where wave transformations are complex, and the WAVEWATCH III (WW3) (Tolman et al. 2019), which solves the spectral action density balance equation, covering vast oceanic domains but requiring substantial computational resources.

- Atmospheric models: These models simulate the Earth's atmosphere to predict wind speeds, directions, and other meteorological parameters, which are crucial for assessing offshore wind energy sites. The two most commonly used atmospheric models are the WRF (Powers et al. 2017), which utilizes fully compressible nonhydrostatic Euler equations with options for hydrostatic approximation, and the Global Forecast System (GFS) (National Centers for Environmental Prediction 2004), which is based on the primitive equations governing fluid motion on a rotating sphere and includes comprehensive physics for atmospheric processes, such as radiation, convection, cloud formation, and land-surface interactions, but it runs at a coarser resolution compared to mesoscale models like WRF.

- Integrated models: these multiphysical models represent the pinnacle of complexity and comprehensiveness in environmental modeling by synthesizing atmospheric, oceanic, wave, and sometimes also biogeochemical processes into a single framework. Two prominent integrated models are the Coupled Ocean-Atmosphere-Wave-Sediment Transport (COAWST) (Warner et al. 2010), which integrates several models, each governed by its own set of equations, and can significantly increase its computational complexity, depending on the desired resolution and extent of the simulated domain, and the Earth System Models (ESMs) (Cox et al. 2000), which are governed by a comprehensive set of equations covering atmospheric dynamics, oceanography, cryospheric science, land surface processes, and biogeochemistry, and are among the most computationally intensive models in environmental science, requiring vast computing power to simulate Earth's components over decadal to centennial timescales.

3 MATHEMATICAL INTERPOLATION TECHNIQUES

Interpolation techniques are the mathematical tools used for extending spatially and temporally a finite set of measurements over a domain of interest. Here it is reported a list of the most commonly used interpolation techniques, along with a brief description of their mathematical principle.

- Inverse Distance Weighting (IDW): A deterministic interpolation whose key idea is that points closer to the location of interest have more influence on the predicted value than those farther away (Luo et al. 2008). Indeed the predicted value is given as a linear combination of the known values, with a coefficient that decreases with the distance between them. Calling x_i, the positions of the n measured points, the prediction at the generic point x_0 will be given as in Equation 5, where d_i is the distance between x_0 and x_i and $p \geq 1$ is a design parameter .

$$\hat{f}(x_0) = \frac{\sum_{i=1}^{n} w_i \cdot f(x_i)}{\sum_{i=1}^{n} w_i} = \frac{\sum_{i=1}^{n} \frac{1}{d_i^p} \cdot f(x_i)}{\sum_{i=1}^{n} \frac{1}{d_i^p}}, \tag{5}$$

- Thin Plate Spline (TPS): Another deterministic interpolation named for its analogy to bending a thin sheet of metal into the shape defined by a set of points. The foundation of TPS interpolation is based on minimizing a functional $E_{\text{tps,smooth}}(f)$ (Tahir et al. 2023), shown in Equation 6, that represents a bending energy measure subject to fitting the data points. This mathematical formulation involves solving a system of linear equations derived from this minimization problem, resulting in a smooth surface that can interpolate the data points. In Equation 6, x_1 and x_2 represent 2 spatial dimensions, the x_i are the K points to be interpolated with y_i the value measured at those points and λ is a trade off parameter.

$$E_{\text{tps,smooth}}(f) = \sum_{i=1}^{K} |y_i - f(x_i)|^2 + \lambda \iint \left[\left(\frac{\partial^2 f}{\partial x_1^2}\right)^2 + 2\left(\frac{\partial^2 f}{\partial x_1 \partial x_2}\right)^2 + \left(\frac{\partial^2 f}{\partial x_2^2}\right)^2 \right] dx_1 dx_2. \tag{6}$$

- Radial Basis Function (RBF): Also a deterministic interpolation particularly used for multidimensional problem. Similar to Thin Plate Splines (TPS), the interpolation problem in RBF is framed as an optimization problem. As the name suggests, the method is based on radial basis functions ϕ, which are a class of functions whose value at any point depends solely on the distance from that point to a certain center point. These functions get added one at a time over the domain of interest so generating an approximation of the function to be reconstructed. The whole process stops once a convergence criteria is met and the final predicted value will be given as in Equation 7, where l is a design parameter.

$$\hat{f}(x_0) = \sum_{i=1}^{n} w_i \cdot \phi(\frac{\|x_0 - x_i\|}{l}), \tag{7}$$

- Optimal interpolation (OI): One of the most used geostatistical interpolation techniques for Data Assimilation, specially in the meteorology sector. The core idea (Janjić et al. 2018) is that the state of the system x and the measurements y can be described as a vectors, with a linear mapping H relating them. Usually the background state vector x^b is given by numerical simulation, while the measurement vector y^o from actual measurements. Due to errors, the actual measurements differ from the measurement vector obtained by the mapping of the true (and unknown) state vector x^t (Equation 8). The state vector is then consequently updated in order to match more with the actual measurements, trying not to diverge too much from the original state vector, so obtaining the final state vector, called analysis state x^a (Equation 10). It is a geostatistical technique since, using the Kalman gain matrix K, it addresses also the statistical properties of the measurement vector and of the state vector and can even provide an uncertainty range for the estimates, by modelling the covariance matrices of the measurement error ϵ and of the background error η^b, which are respectively R and P^b

$$y^o = Hx^t + \epsilon \tag{8}$$

$$x^b = x^t + \eta^b \tag{9}$$

$$x^a = x^b + K(y^o - Hx^b) \tag{10}$$

$$K = P^b H^T (H P^b H^T + R)^{-1}, \tag{11}$$

- 3-Dimensional Variational Data Assimilation and 4-Dimensional Variational Data Assimilation (3D-Var and 4D-Var): These are more advanced DA techniques where the assimilation problem is cast into an optimization one (Hunt et al. 2007). The variable to be tuned is called the analysis state, representing the state obtained by the assimilation of the real data into the numerical simulation. The functional J to be optimized is given as the sum of two terms, one quantifying the mismatch between the analysis state the the simulation state J^b, and the other quantifying the mismatch between the analysis state and the real measurements J^o. The 3D-Var solves the optimization problem only considering the three spatial dimensions, while the 4D-Var considers also the time, thus being more accurate but also more computationally expensive. Also variational techniques can provide an uncertainty range.

$$J(x^a) = J^b(x^a) + J^o(x^a), \tag{12}$$

$$J^b(x^a) = (x^a - x^b)^T (P^b)^{-1} (x^a - x^b), \tag{13}$$

$$J^o(x^a) = (H(x^a) - y^o)^T R^{-1} (H(x^a) - y^o), \tag{14}$$

- Local Ensemble Transform Kalman Filter (LETKF): Unlike the previously mentioned DA techniques, which were weakly coupled and so considered the errors as uncorrelated (the covariance matrices R and P^b were considered diagonal matrices), the LETKF is a strongly coupled DA technique (Sluka et al. 2016), which can directly address the correlation between the errors. Since this can drastically increase the computational time of the algorithm, a ensemble range has to be defined and only inside each ensemble the errors are allowed to be correlated. This technique provides more accurate results with respect to the other DA technique since it can account for the spatial autocorrelation of the errors. Like the previously mentioned DA techniques, LETKF can also provide a measure of uncertainty.

- Kriging techniques: a family of techniques originally developed for studying the distribution of underground minerals (Degré et al. 2015). The measurements of the parameter of interest are considered as realizations of a stochastic process, specified by a mean function and a covariance function, modelled through a variogram. Different choices for the type of those functions give rise to different Kriging techniques. The variogram is the instrument used for modelling the spatial autocorrelation of the variable of interest. The shape of the mean function and of the variogram are specified a priori while their parameters are tuned in order to fit the empirical measurements. These functions and the measured values are then used for obtaining an estimate of the parameter of interest where it is not being measured through statistical inference. Treating the variable of interest as a random variable, also Kriging techniques can naturally provide an uncertainty range for their estimates. Considering a constant zero mean, the prediction at the generic point x_0 will be given as in Equation 15, where the weights w_i are obtaining using the variogram, modelling both the proximity and the reduncancy of the stochastic process.

$$\hat{f}(x_0) = \sum_{i=1}^{n} w_i f(x_i) \tag{15}$$

4 CASE STUDIES DESCRIPTION

In this section, the considered case studies are described along with tables highlighting their main features. The case studies are divided into two categories with respect to the type of interpolation technique used: deterministic interpolation case studies and statistical/geostatistical interpolation case studies.

4.1 *Deterministic interpolation case studies*

Four articles focusing on the usage of deterministic interpolation in the offshore sector have been considered in this work. Essentially, deterministic techniques involve applying predefined functions to fit a set number of training points across an entire domain. Due to their straightforward nature, these methods generally do not integrate any model-based physical process information, relying solely on data for interpolation.

(Jahanmard et al. 2022) employs several interpolators—linear, IDW, and TPS—not primarily to model sea level but to merge diverse data sources (tide gauge, hydrodynamic models, and satellite altimetry) and interpolate errors relative to a numerical simulation. The study highlights that the IDW interpolator yields the most accurate and realistic outcomes. Another analysis of deterministic interpolators is detailed in (Knysh et al. 2022), which compares three methods for assessing the vertical movement of current velocity: averaging, linear interpolation, and RBF interpolation. This research is crucial for accurately feeding data into a numerical simulation. It demonstrates that the simplifications inherent in the linear and mean methods result in less realistic simulation outputs than those achieved with the RBF interpolation.

More complex deterministic interpolation techniques are explored in (Liu et al. 2014) and (Støle-Hentschel et al. 2021). (Liu et al. 2014) introduces two innovative methods: the wavelet refined cubic technique and the fractal method, specifically for addressing time gaps in in situ measurements. These were tested against a standard spline method at two different sites, demonstrating superior performance, with the wavelet method excelling at one site and the fractal method at the other. On the other hand, (Støle-Hentschel et al. 2021) delves into the use of a deconvolution operator to reconstruct temporal gaps in wave measurement data collected in situ. This reconstruction was initially performed on a simulated numerical dataset (JONSWAP) and subsequently on actual in situ measurements. The study also evaluates the robustness of this technique by introducing noise into the data, showing that the method can handle noise up to 10% of the signal's amplitude effectively.

4.2 *Statistical and Geostatistical interpolation case studies*

Nine articles employing statistical/geostatistical interpolation techniques have been considered in this work, including (Wei and Davison 2022) even if it focused on comparing deterministic and statistical/geostatistical techniques. Statistical/geostatistical techniques are more complex and superior techniques that can directly incorporate physical information from a numerical model and often can also give an estimate of the uncertainty in the predictions. In (Wei and Davison 2022), in order to assess the potential for wind-generated power in Jiangsu Province, the study first required the interpolation of wind speed data. The research compared several interpolation methods: Spline, Nearest Neighbor, IDW, and Oridnary Kriging. After evaluating the accuracy of these methods through cross-validation, the Ordinary Kriging method was selected for the assessment because it produced the lowest error rates. This result underscores its suitability for providing the most reliable data for further analysis of wind power potential, compared to traditional deterministic techniques. Ordinary Kriging is used also in (Yin et al. 2022) for extending spatially the measurements of fish population density. The spatially extended data are then analyzed using a Generalized Additive Model (GAM) to explore the correlation between fish population density and the presence of biomass. This methodological approach highlights the effectiveness of combining OK

Table 1: Deterministic interpolation case studies table. ♦: Only data and no model information used.♦: Information from a numerical model used.

Ref.	Domain	Model	Specific technique	Interpolated parameter
(Liu et al. 2014)	Time	♦	Wavelet refined method and fractal method	H_s
(Støle-Hentschel et al. 2021)	Time	♦	Deconvolution	Wave Elevation
(Jahanmard et al. 2022)	Space	♦	Linear Interpolator, IDW, TPS	Sea level
(Knysh et al. 2022)	Space	♦	Mean,Linear Interpolator, RBF	Current Velocity

with GAM for detailed ecological assessments.

(Emmanouil et al. 2012) uses OI for interpolating H_s measurements from in situ devices and satellites where no measurement are available, after having processed the input data with a statistical Kalman filter. Another practical application of OI is given by (Houghton et al. 2022): the study utilizes measurements from over 600 Sofar Spotter buoys to perform a global DA on wave model spectra derived from the WW3 (WaveWatch III) model. This assimilation, conducted through OI, aligns the model with observed data. Following the DA process, there was a notable enhancement in the forecasts of all wave parameters. Specifically, the improvements were approximately 38% for H_s and about 45% for the other wave parameters, demonstrating the effectiveness of OI in refining model accuracy.

A variation of standard OI, known as Ensemble OI (EnOI), is explored in (Liu et al. 2023). Unlike traditional OI, which uses a single simulation for background data, EnOI employs multiple simulations or forecasts (ensemble members) to capture uncertainty in the system. This approach involves considering all these ensemble members during the data assimilation process to improve the accuracy and robustness of system state estimates. In this article the enhancements in forecasting the significant wave height H_s are quantified following the integration of satellite and in situ measurements using EnOI. The study demonstrates that this DA technique reduces the systematic errors in the predictions. It also highlights that the numerical simulations, when used alone, are more accurate offshore than nearshore, underscoring the value of EnOI in improving coastal forecasting accuracy. (Smit et al. 2021) identifies a significant limitation of OI when applied over long time periods, specifically in the context of assimilating H_s. The study finds that the improvements in the background data provided by OI are less durable in scenarios where H_s is heavily influenced by wind speed. This is because, in such cases, the system behaves more like one driven by an external force (the wind), making the updates less stable. Conversely, in situations where wind plays a less dominant role, the problem resembles more one of initial conditions, resulting in more lasting updates from the OI process.

(Sluka et al. 2016) and (Houghton et al. 2023) are the only two studies that apply strongly coupled DA and both perform the DA using the LETKF. (Sluka et al. 2016) focuses on updating sea surface salinity (SSS) and sea surface temperature (SST), while (Houghton et al. 2023) performs DA on the H_s results from the WAVEWATCH III (WW3) wave model. Both studies demonstrate that strongly coupled DA with LETKF provides more accurate and realistic results compared to weakly coupled DA, such as standard Optimal Interpolation (OI), despite requiring higher computational resources.

A final DA example is found in (Mao et al. 2023), where the 4-dimensional variational technique is used to incorporate in situ measurements and satellite images data in a numerical model, updating the background forecasts for sea surface height (SSH), sea surface temperature (SST), subsurface temperature, and subsurface salinity. Following the DA process, the validation results indicate a reduction in the errors across all parameters and the resulting distributions appear more realistic compared to the initial forecasts.

5 CONCLUSIONS

This article introduces the problem of obtaining an exhaustive set of measurements for an hostile environment like the ocean. The main parameters of interest for the offshore energy sector are described along with the types of in situ measuring devices used to measuring them and with the numerical models used for simulating those systems. Then, a solution to the problem of limited amounts of data is seen in the mathematical interpolation techniques, and an overview of these techniques is given.

After the theoretical introduction, 13 case studies employing interpolation techniques in the offshore sector have been analyzed. Two main families of techniques have been considered and used for classifying these case studies. Statistical/geostatistical techniques seem a more attractive alternative for many reasons, as suggested by the number of articles in this category being more than the double of the deterministic case studies. Indeed, statistical techniques are tools with an higher degree of complexity which are able to directly address the uncertainty in the measurements and most of them can even provide an estimate of the uncertainty in the predictions. Moreover, different sources of measures can be easily merged together with statistical techniques, and also a numerical model can be integrated in the algorithm for improving the predictions.

Due to their higher degree of complexity, statistical techniques can also tackle more easily problems in the Spacetime domain, unlike their deterministic counterpart which mainly focus on either Space or Time.

Table 2: Statistical/geostatistical interpolation case studies table. ◆: Only data and no model information used.◆: Information from a numerical model used.

Ref.	Domain	Model	Specific technique	Interpolated parameter
(Houghton et al. 2023)	Spacetime	◆	LETKF	H_s
(Smit et al. 2021)	Spacetime	◆	OI	H_s
(Sluka et al. 2016)	Spacetime	◆	LETKF	SSS, SST
(Emmanouil et al. 2012)	Spacetime	◆	Statistical Kalman Filter with OI	H_s
(Houghton et al. 2022)	Spacetime	◆	OI	Wave Directional Spectra
(Mao et al. 2023)	Spacetime	◆	4d-Var	SSH, SST, SSS
(Liu et al. 2023)	Spacetime	◆	Ensemble based OI	H_s
(Yin et al. 2022)	Space	◆	OK	Fish Populations
(Wei et al. 2019)	Space	◆	Spline, Natural Neighbor, IDW, OK	Wind Speed

Anyway, due to their higher degree of complexity, these techniques are more computationally demanding with respect to their deterministic counterparts, implying that when there is a huge quantity of available data, deterministic techniques may work better due to their simplicity.
Future advancements in this field might include the other sources of measurements. This, however, would favor even more the usage of statistical techniques and also more advanced data-driven technique, like technqiues from the Machine Learning field.

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