advanced prompt

- **Prompt Structuring Frameworks**
  Prompt Structuring Frameworks Understanding the role of CO STAR in structured prompting   How CRISPE enhances clarity in AI generated outputs   SPEC as a guiding model for consistent prompts   Using SCQA framing to align prompts with user intent   Adapting BRIEF for instructional content design   When to combine CO STAR and CRISPE for complex tasks   Framework selection for multi step reasoning prompts   Practical uses of SPEC in technical documentation   How SCQA improves logical flow in AI conversations   Evaluating framework fit for different content goals   Framework based prompting for collaborative writing   Mapping prompt frameworks to industry applications
  - **Reasoning and Problem-Solving Techniques**
    Reasoning and Problem-Solving Techniques Exploring chain of thought for stepwise reasoning   Tree of thought as a method for decision exploration   Applying ReAct to combine reasoning with actions   How self ask prompts support Socratic style inquiry   Critic and editor prompting for iterative refinement   Plan and solve prompting for structured solutions   Self consistency sampling to stabilize reasoning outputs   Using scratchpad memory to extend logical processes   Multi pass reasoning for deeper content generation   Combining few shot examples with reasoning prompts   Exploring debate style multi agent reasoning   Adaptive reasoning strategies for complex AI tasks
    - **About Us**

Practical uses of SPEC in technical documentation

Multi-Stage Prompt Design

Okay, lets talk about SPEC. Not the CPU benchmark kind, but the SPEC that stands for Simplified Procedural English. RAG pipelines demonstrate how retrieval can anchor generative systems in factual data **controlled output formatting with AI** Website. Sounds a bit robotic, doesnt it? But trust me, when it comes to making user guides that actually *help* people, its a real game-changer.

Think about those times youve wrestled with a manual. You know, the ones filled with jargon, passive voice, and sentences that go on longer than a Tolkien novel. Frustrating, right? Thats where SPEC comes in. Its all about clarity and conciseness. Imagine a technical writer, armed with the SPEC guidelines, ruthlessly cutting out unnecessary words, using active voice like a ninja, and crafting sentences that are short, sweet, and to the point.

The practical payoff is huge. Suddenly, instructions become easier to follow. Users spend less time scratching their heads and more time actually using the product. This translates to fewer support calls, happier customers, and a smoother overall experience.

SPEC also promotes consistency. If everyone on the technical writing team is using the same guidelines, the documentation will have a unified voice and style. This makes it easier for users to navigate different sections and find the information they need.

Beyond just clarity, SPEC can also help with translation. Because it relies on simple language and consistent phrasing, it makes the documentation easier and more cost-effective to translate into other languages.

So, while the name "Simplified Procedural English" might not sound particularly exciting, the benefits are undeniable. By leveraging SPEC, we can transform clunky, confusing user guides into clear, concise, and user-friendly resources that actually empower people to use the products they buy. And that, my friends, is a win for everyone.

Integrating SPEC in API Documentation

In the realm of technical documentation, particularly for APIs, the practical application of SPEC (Specifications for Enhanced Clarity) can significantly enhance the utility and user-friendliness of the documentation. SPEC, a framework designed to standardize and clarify the presentation of technical specifications, becomes particularly valuable when embedded within API documentation.

Firstly, consider the primary audience of API documentation: developers and technical teams who require precise, unambiguous information to integrate and utilize an API effectively. By incorporating SPEC, documentation can be structured in a way that aligns with the cognitive processes of these professionals. For instance, SPEC encourages the use of a consistent schema for describing API endpoints, methods, parameters, and expected responses. This consistency reduces cognitive load, allowing developers to quickly grasp the necessary details without sifting through varied formats or styles.

Moreover, SPECs emphasis on clarity plays a crucial role in reducing errors during implementation. API documentation often includes complex interactions and data structures. SPEC provides guidelines on how to present this complexity in a digestible manner, using diagrams, flowcharts, or structured text that visually and textually map out the APIs operations. This visual aid not only aids in comprehension but also in troubleshooting, as developers can trace back through the documentation to identify where an integration might have gone awry.

Another practical aspect of integrating SPEC is in the area of versioning and updates. APIs are dynamic; they evolve with new features, bug fixes, and deprecations. SPEC recommends a clear versioning strategy within documentation, ensuring that users are always aware of which version they are working with and what changes have occurred. This practice minimizes confusion and maintains compatibility, especially in environments where multiple versions of an API might be in use.

Additionally, SPECs approach to documentation includes considerations for accessibility and internationalization, which are often overlooked in API documentation. By standardizing how documentation is presented, SPEC ensures that the information can be easily translated or adapted for different languages or accessibility needs, broadening the APIs usability across diverse developer communities.

In conclusion, integrating SPEC into API documentation isnt just about following a set of rules; its about enhancing the practical utility of the documentation. It ensures that the documentation serves its purpose efficiently, aiding developers in their work by providing clear, structured, and accessible information. This approach not only improves the developer experience but also contributes to the overall success of the API by fostering better integrations, fewer errors, and a more inclusive user base.

Dynamic Prompt Adaptation Strategies

Okay, so youre staring at this behemoth of a complex system, right? Think MRI machines, industrial robots, or even a super intricate software platform. And someones tasked you with writing the manual. Yikes. Where do you even start? Thats where SPEC comes in, like a friendly sherpa guiding you up a technical Everest.

SPEC, in this context, isnt about those detailed specifications you see on datasheets (though those are important too!). Instead, think of it as a structured approach to documentation. Its about being deliberate and systematic in how you plan, write, and organize your content. Why is this so practical? Well, imagine trying to explain how a jet engine works if you just started rambling about random parts. Chaos, right?

SPEC helps you avoid that chaos. It encourages you to define your scope *before* you start writing. What exactly are you documenting? Who is your audience? Are they experienced engineers, or are they new users? Knowing this upfront shapes everything. It stops you from going down rabbit holes and ensures youre focusing on whats *actually* important to the people who will be using your manual.

Then, SPEC pushes you to think about the structure. How will you organize the information? Will you use a task-based approach ("How to calibrate the sensor") or a component-based approach ("Understanding the X-Y axis motor")? Having a clear, consistent structure makes the manual navigable and searchable. Users can quickly find what they need, instead of wading through pages of irrelevant text.

And finally, SPEC promotes consistency. It encourages you to define terms, use consistent language, and follow a standardized format for procedures and warnings. This might seem like a small thing, but it makes a huge difference in readability and comprehension. It prevents confusion and reduces the risk of users misinterpreting instructions, especially when dealing with complex or potentially dangerous systems.

So, SPEC isnt some abstract theoretical concept. Its a practical tool that helps you wrangle the complexity of technical documentation. Its about making your manuals more useful, more accessible, and ultimately, more effective in helping users understand and operate those complex systems. Its about turning that daunting mountain of information into a clear, well-marked trail. And thats a pretty powerful thing.

Evaluation Metrics for Prompt Effectiveness

Okay, so were talking about SPEC, right? And how it fits into technical training materials, specifically when were trying to show people the *practical* side of things. Lets ditch the jargon for a minute and imagine youre trying to teach someone how to fix a leaky faucet. You wouldnt just throw a plumbing textbook at them, would you? Youd walk them through it, step-by-step, showing them exactly what to do. Thats where SPEC comes in.

SPEC, at its heart, is about being specific, precise, and clear. Think of it as the secret sauce for making technical documentation actually useful. Instead of saying, "Tighten the nut," which leaves room for interpretation and potential over-tightening, youd say, "Tighten the nut with a wrench until its snug, but do not overtighten." See the difference? Its about removing ambiguity.

Now, when youre building training materials, applying SPEC means considering your audience. What level of knowledge do they already have? Are they complete beginners? Then you need to break down even the simplest steps into smaller, more manageable chunks. Use concrete examples, not abstract concepts. Show, dont just tell. Include diagrams, illustrations, or even short videos that demonstrate the process.

For example, if youre teaching someone how to use a complex software program, dont just list the functions. Instead, create a realistic scenario – "Imagine you need to generate a report showing sales figures for the last quarter." Then, walk them through the exact steps, using SPEC to guide them: "Click the Reports tab. Select Sales Analysis from the dropdown menu. Enter the date range: October 1st to December 31st. Click Generate Report."

The key is to make it relatable and actionable. Use real-world examples that resonate with your audience. And always, always, test your materials. Get feedback from people who are representative of your target audience. Do they understand the instructions? Can they follow them successfully? If not, revise and refine until you achieve the desired level of clarity and understanding.

Ultimately, applying SPEC in technical training materials is about empowering people to learn and do. Its about making complex information accessible and understandable, so they can confidently apply their new skills in the real world. Its not just about writing instructions; its about enabling success.

About Natural language processing

All-natural language processing (NLP) is the handling of natural language info by a computer. The research study of NLP, a subfield of computer science, is typically connected with artificial intelligence. NLP is associated with information access, understanding representation, computational linguistics, and much more extensively with grammars. Major handling jobs in an NLP system consist of: speech acknowledgment, text category, natural language understanding, and natural language generation.
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About Training, validation, and test data sets

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Part of a series on

Machine learning and data mining

Paradigms

- Supervised learning
- Unsupervised learning
- Semi-supervised learning
- Self-supervised learning
- Reinforcement learning
- Meta-learning
- Online learning
- Batch learning
- Curriculum learning
- Rule-based learning
- Neuro-symbolic AI
- Neuromorphic engineering
- Quantum machine learning

Problems

- Classification
- Generative modeling
- Regression
- Clustering
- Dimensionality reduction
- Density estimation
- Anomaly detection
- Data cleaning
- AutoML
- Association rules
- Semantic analysis
- Structured prediction
- Feature engineering
- Feature learning
- Learning to rank
- Grammar induction
- Ontology learning
- Multimodal learning

Supervised learning
(**classification • regression**)

- Apprenticeship learning
- Decision trees
- Ensembles
  - Bagging
  - Boosting
  - Random forest
- *k*-NN
- Linear regression
- Naive Bayes
- Artificial neural networks
- Logistic regression
- Perceptron
- Relevance vector machine (RVM)
- Support vector machine (SVM)

Clustering

- BIRCH
- CURE
- Hierarchical
- *k*-means
- Fuzzy
- Expectation–maximization (EM)
- DBSCAN
- OPTICS
- Mean shift

Dimensionality reduction

- Factor analysis
- CCA
- ICA
- LDA
- NMF
- PCA
- PGD
- t-SNE
- SDL

Structured prediction

- Graphical models
  - Bayes net
  - Conditional random field
  - Hidden Markov

Anomaly detection

- RANSAC
- *k*-NN
- Local outlier factor
- Isolation forest

Neural networks

- Autoencoder
- Deep learning
- Feedforward neural network
- Recurrent neural network
  - LSTM
  - GRU
  - ESN
  - reservoir computing
- Boltzmann machine
  - Restricted
- GAN
- Diffusion model
- SOM
- Convolutional neural network
  - U-Net
  - LeNet
  - AlexNet
  - DeepDream
- Neural field
  - Neural radiance field
  - Physics-informed neural networks
- Transformer
  - Vision
- Mamba
- Spiking neural network
- Memtransistor
- Electrochemical RAM (ECRAM)

Reinforcement learning

- Q-learning
- Policy gradient
- SARSA
- Temporal difference (TD)
- Multi-agent
  - Self-play

Learning with humans

- Active learning
- Crowdsourcing
- Human-in-the-loop
- Mechanistic interpretability
- RLHF

Model diagnostics

- Coefficient of determination
- Confusion matrix
- Learning curve
- ROC curve

Mathematical foundations

- Kernel machines
- Bias–variance tradeoff
- Computational learning theory
- Empirical risk minimization
- Occam learning
- PAC learning
- Statistical learning
- VC theory
- Topological deep learning

Journals and conferences

- AAAI
- ECML PKDD
- NeurIPS
- ICML
- ICLR
- IJCAI
- ML
- JMLR

Related articles

- Glossary of artificial intelligence
- List of datasets for machine-learning research
    - List of datasets in computer vision and image processing
- Outline of machine learning

In machine learning, a common task is the study and construction of algorithms that can learn from and make predictions on data.[1] Such algorithms function by making data-driven predictions or decisions,[2] through building a mathematical model from input data. These input data used to build the model are usually divided into multiple data sets. In particular, three data sets are commonly used in different stages of the creation of the model: training, validation, and test sets.

The model is initially fit on a **training data set**,[3] which is a set of examples used to fit the parameters (e.g. weights of connections between neurons in artificial neural networks) of the model.[4] The model (e.g. a naive Bayes classifier) is trained on the training data set using a supervised learning method, for example using optimization methods such as gradient descent or stochastic gradient descent. In practice, the training data set often consists of pairs of an input vector (or scalar) and the corresponding output vector (or scalar), where the answer key is commonly denoted as the *target* (or *label*). The current model is run with the training data set and produces a result, which is then compared with the *target*, for each input vector in the training data set. Based on the result of the comparison and the specific learning algorithm being used, the parameters of the model are adjusted. The model fitting can include both variable selection and parameter estimation.

Successively, the fitted model is used to predict the responses for the observations in a second data set called the **validation data set**.[3] The validation data set provides an unbiased evaluation of a model fit on the training data set while tuning the model's hyperparameters[5] (e.g. the number of hidden units—layers and layer widths—in a neural network[4]). Validation data sets can be used for regularization by early stopping (stopping training when the error on the validation data set increases, as this is a sign of over-fitting to the training data set).[6] This simple procedure is complicated in practice by the fact that the validation data set's error may fluctuate during training, producing multiple local minima. This complication has led to the creation of many ad-hoc rules for deciding when over-fitting has truly begun.[6]

Finally, the **test data set** is a data set used to provide an unbiased evaluation of a *final* model fit on the training data set.[5] If the data in the test data set has never been used in training (for example in cross-validation), the test data set is also called a **holdout data set**. The term "validation set" is sometimes used instead of "test set" in some literature (e.g., if the original data set was partitioned into only two subsets, the test set might be referred to as the validation set).[5]

Deciding the sizes and strategies for data set division in training, test and validation sets is very dependent on the problem and data available.[7]

Training data set

[edit]

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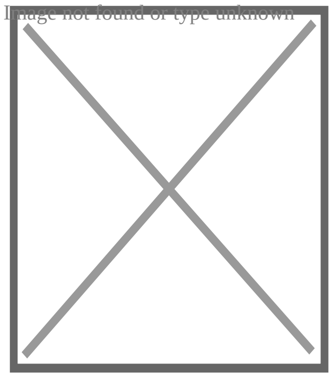
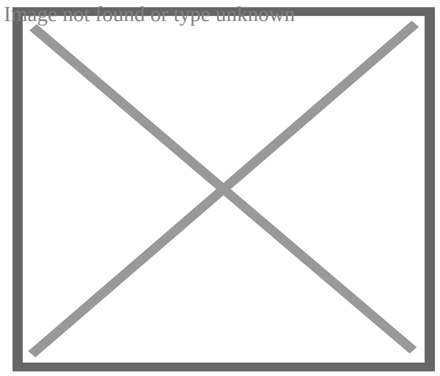


Simplified example of training a neural network in object detection: The network is trained by multiple images that are known to depict starfish and sea urchins, which are correlated with "nodes" that represent visual features. The starfish match with a ringed texture and a star outline, whereas most sea urchins match with a striped texture and oval shape. However, the instance of a ring textured sea urchin creates a weakly weighted association between them.



Subsequent run of the network on an input image (left):[8] The network correctly detects the starfish. However, the weakly weighted association between ringed texture and sea urchin also confers a weak signal to the latter from

one of two intermediate nodes. In addition, a shell that was not included in the training gives a weak signal for the oval shape, also resulting in a weak signal for the sea urchin output. These weak signals may result in a false positive result for sea urchin.
In reality, textures and outlines would not be represented by single nodes, but rather by associated weight patterns of multiple nodes.

A training data set is a data set of examples used during the learning process and is used to fit the parameters (e.g., weights) of, for example, a classifier.[9][10]

For classification tasks, a supervised learning algorithm looks at the training data set to determine, or learn, the optimal combinations of variables that will generate a good predictive model.[11] The goal is to produce a trained (fitted) model that generalizes well to new, unknown data.[12] The fitted model is evaluated using “new” examples from the held-out data sets (validation and test data sets) to estimate the model’s accuracy in classifying new data.[5] To reduce the risk of issues such as over-fitting, the examples in the validation and test data sets should not be used to train the model.[5]

Most approaches that search through training data for empirical relationships tend to overfit the data, meaning that they can identify and exploit apparent relationships in the training data that do not hold in general.

When a training set is continuously expanded with new data, then this is incremental learning.

Validation data set

[edit]

A validation data set is a data set of examples used to tune the hyperparameters (i.e. the architecture) of a model. It is sometimes also called the development set or the "dev set".[13] An example of a hyperparameter for artificial neural networks includes the number of hidden units in each layer.[9][10] It, as well as the testing set (as mentioned below), should follow the same probability distribution as the training data set.

In order to avoid overfitting, when any classification parameter needs to be adjusted, it is necessary to have a validation data set in addition to the training and test data sets. For example, if the most suitable classifier for the problem is sought, the training data set is used to train the different candidate classifiers, the validation data set is used to compare their performances and decide which one to take and, finally, the test data set is used to obtain the performance characteristics such as accuracy, sensitivity, specificity, F-measure, and so on. The validation data set functions as a hybrid: it is training data used for testing, but neither as part of the low-level training nor as part of the final testing.

The basic process of using a validation data set for model selection (as part of training data set, validation data set, and test data set) is:[10][14]

> Since our goal is to find the network having the best performance on new data, the simplest approach to the comparison of different networks is to evaluate the error function using data which is independent of that used for training. Various networks are trained by minimization of an appropriate error function defined with respect to a training data set. The performance of the networks is then compared by evaluating the error function using an independent validation set, and the network having the smallest error with respect to the validation set is selected. This approach is called the *hold out* method. Since this procedure can itself lead to some overfitting to the validation set, the performance of the selected network should be confirmed by measuring its performance on a third independent set of data called a test set.

An application of this process is in early stopping, where the candidate models are successive iterations of the same network, and training stops when the error on the validation set grows, choosing the previous model (the one with minimum error).

Test data set

[edit]

A test data set is a data set that is independent of the training data set, but that follows the same probability distribution as the training data set. If a model fit to the training data set also fits the test data set well, minimal overfitting has taken place (see figure below). A better fitting of the training data set as opposed to the test data set usually points to over-fitting.

A test set is therefore a set of examples used only to assess the performance (i.e. generalization) of a fully specified classifier.[9][10] To do this, the final model is used to predict classifications of examples in the test set. Those predictions are compared to the examples' true classifications to assess the model's accuracy.[11]

In a scenario where both validation and test data sets are used, the test data set is typically used to assess the final model that is selected during the validation process. In the case where the original data set is partitioned into two subsets (training and test data sets), the test data set might assess the model only once (e.g., in the holdout method).[15] Note that some sources advise against such a method.[12] However, when using a method such as cross-validation, two partitions can be sufficient and effective since results are averaged after repeated rounds of model training and testing to help reduce bias and variability.[5][12]

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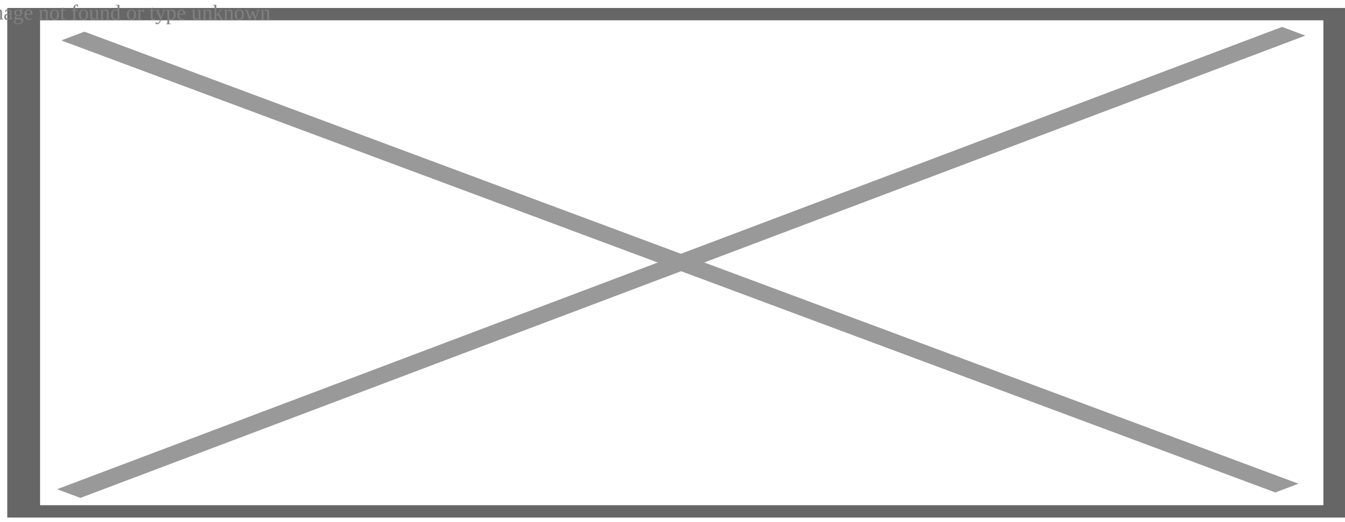


A training set (left) and a test set (right) from the same statistical population are shown as blue points. Two predictive models are fit to the training data. Both fitted models are plotted with both the training and test sets. In the training set, the MSE of the fit shown in orange is 4 whereas the MSE for the fit shown in green is 9. In the test set, the MSE for the fit shown in orange is 15 and the MSE for the fit shown in green is 13. The orange curve severely overfits the training data, since its MSE increases by almost a factor of four when comparing the test set to the training set. The green curve overfits the training data much less, as its MSE increases by less than a factor of 2.

Confusion in terminology

[edit]

Testing is trying something to find out about it ("To put to the proof; to prove the truth, genuineness, or quality of by experiment" according to the Collaborative International Dictionary of English) and to validate is to prove that something is valid ("To confirm; to render valid" Collaborative International Dictionary of English). With this perspective, the most common use of the terms **test set** and **validation set** is the one here described. However, in both industry and academia, they are sometimes used interchanged, by considering that the internal process is testing different models to improve (test set as a development set) and the final model is the one that needs to be validated before real use with an unseen data (validation set). "The literature on machine learning often reverses the meaning of 'validation' and 'test' sets. This is the most blatant example of the terminological confusion that pervades artificial intelligence research."[16] Nevertheless, the important concept that must be kept is that the final set, whether called test or validation, should only be used in the final experiment.

Cross-validation

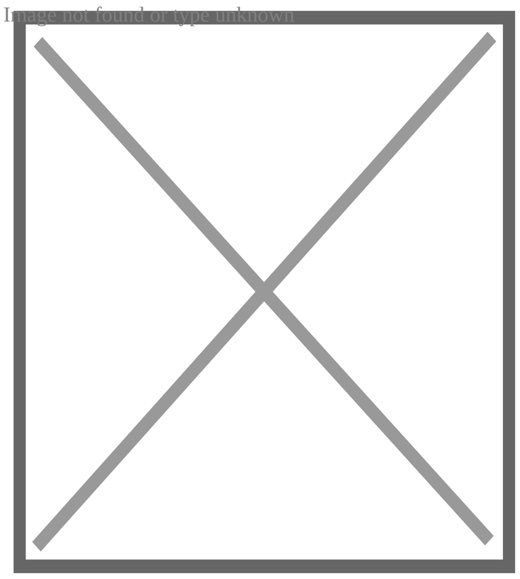
[edit]

In order to get more stable results and use all valuable data for training, a data set can be repeatedly split into several training and a validation data sets. This is known as cross-validation. To confirm the model's performance, an additional test data set held out from cross-validation is normally used.

It is possible to use cross-validation on training and validation sets, and *within* each training set have further cross-validation for a test set for hyperparameter tuning. This is known as nested cross-validation.

Causes of error

[edit]



Comic strip demonstrating a fictional erroneous computer output (making a coffee 5 million degrees, from a previous definition of "extra hot"). This can be classified as both a failure in logic and a failure to include various relevant environmental conditions.[17]

Omissions in the training of algorithms are a major cause of erroneous outputs.[17] Types of such omissions include:[17]

- Particular circumstances or variations were not included.
- Obsolete data
- Ambiguous input information
- Inability to change to new environments
- Inability to request help from a human or another AI system when needed

An example of an omission of particular circumstances is a case where a boy was able to unlock the phone because his mother registered her face under indoor, nighttime lighting, a condition which was not appropriately included in the training of the system.[17][18]

Usage of relatively irrelevant input can include situations where algorithms use the background rather than the object of interest for object detection, such as being trained by pictures of sheep on grasslands, leading to a risk that a different object will be interpreted as a sheep if located on a grassland.[17]

See also

[edit]

- Statistical classification
- List of datasets for machine learning research
- Hierarchical classification

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[edit]

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Artificial intelligence (AI)

- History
    - timeline
- Companies
- Projects

Concepts	◦ Parameter ◦ Hyperparameter ◦ Loss functions ◦ Regression ◦ Bias–variance tradeoff ◦ Double descent ◦ Overfitting ◦ Clustering ◦ Gradient descent ◦ SGD ◦ Quasi-Newton method ◦ Conjugate gradient method ◦ Backpropagation ◦ Attention ◦ Convolution ◦ Normalization ◦ Batchnorm ◦ Activation ◦ Softmax ◦ Sigmoid ◦ Rectifier ◦ Gating ◦ Weight initialization ◦ Regularization ◦ Datasets ◦ Augmentation ◦ Prompt engineering ◦ Reinforcement learning ◦ Q-learning ◦ SARSA ◦ Imitation ◦ Policy gradient ◦ Diffusion ◦ Latent diffusion model ◦ Autoregression ◦ Adversary ◦ RAG ◦ Uncanny valley ◦ RLHF ◦ Self-supervised learning ◦ Reflection ◦ Recursive self-improvement ◦ Hallucination ◦ Word embedding ◦ Vibe coding

Applications	○ Machine learning ○ In-context learning ○ Artificial neural network ○ Deep learning ○ Language model ○ Large language model ○ NMT ○ Reasoning language model ○ Model Context Protocol ○ Intelligent agent ○ Artificial human companion ○ Humanity's Last Exam ○ Artificial general intelligence (AGI)

Implementations

Audio–visual

- AlexNet
- WaveNet
- Human image synthesis
- HWR
- OCR
- Computer vision
- Speech synthesis
  - 15.ai
  - ElevenLabs
- Speech recognition
  - Whisper
- Facial recognition
- AlphaFold
- Text-to-image models
  - Aurora
  - DALL-E
  - Firefly
  - Flux
  - Ideogram
  - Imagen
  - Midjourney
  - Recraft
  - Stable Diffusion
- Text-to-video models
  - Dream Machine
  - Runway Gen
  - Hailuo AI
  - Kling
  - Sora
  - Veo
- Music generation
  - Riffusion
  - Suno AI
  - Udio

- Word2vec
- Seq2seq
- GloVe
- BERT
- T5
- Llama
- Chinchilla AI
- PaLM
- GPT
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  - 2
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People

- Alan Turing
- Warren Sturgis McCulloch
- Walter Pitts
- John von Neumann
- Claude Shannon
- Shun'ichi Amari
- Kunihiko Fukushima
- Takeo Kanade
- Marvin Minsky
- John McCarthy
- Nathaniel Rochester
- Allen Newell
- Cliff Shaw
- Herbert A. Simon
- Oliver Selfridge
- Frank Rosenblatt
- Bernard Widrow
- Joseph Weizenbaum
- Seymour Papert
- Seppo Linnainmaa
- Paul Werbos
- Geoffrey Hinton
- John Hopfield
- Jürgen Schmidhuber
- Yann LeCun
- Yoshua Bengio
- Lotfi A. Zadeh
- Stephen Grossberg
- Alex Graves
- James Goodnight
- Andrew Ng
- Fei-Fei Li
- Alex Krizhevsky
- Ilya Sutskever
- Oriol Vinyals
- Quoc V. Le
- Ian Goodfellow
- Demis Hassabis
- David Silver
- Andrej Karpathy
- Ashish Vaswani
- Noam Shazeer
- Aidan Gomez
- John Schulman
- Mustafa Suleyman
- Jan Leike
- Daniel Kokotajlo
- François Chollet

Architectures

- Neural Turing machine
- Differentiable neural computer
- Transformer
  - Vision transformer (ViT)
- Recurrent neural network (RNN)
- Long short-term memory (LSTM)
- Gated recurrent unit (GRU)
- Echo state network
- Multilayer perceptron (MLP)
- Convolutional neural network (CNN)
- Residual neural network (RNN)
- Highway network
- Mamba
- Autoencoder
- Variational autoencoder (VAE)
- Generative adversarial network (GAN)
- Graph neural network (GNN)

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Check our other pages :

- **Critic and editor prompting for iterative refinement**
- **Combining few shot examples with reasoning prompts**
- **Self consistency sampling to stabilize reasoning outputs**
- **Reasoning and Problem-Solving Techniques**