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Incorporating physics into data-driven computer vision

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Achuta Kadambi[1], Celso de Melo[2], Cho-Jui Hsieh[1], Mani Srivastava[1] & Stefano Soatto[1]

Many computer vision techniques infer properties of our physical world from images. Although images are formed through the physics of light and mechanics, computer vision techniques are typically data driven. This trend is mostly performance related: classical techniques from physics-based vision often score lower on metrics compared with modern deep learning. However, recent research, covered in this Perspective, has shown that physical models can be included as a constraint into data-driven pipelines. In doing so, one can combine the performance benefits of a data-driven method with advantages offered from a physics-based method, such as intepretability, falsifiability and generalizability. The aim of this Perspective is to provide an overview into specific approaches for integrating physical models into artificial intelligence pipelines, referred to as physics-based machine learning. We discuss technical approaches that range from modifications to the dataset, network design, loss functions, optimization and regularization schemes.

Modern approaches in computer vision are starting to combine insights from machine learning techniques and physical models. This hybrid approach is referred to as physics-based learning (Fig. 1). Computer vision has a special, inherent link to physics, compared with other forms of artificial intelligence (AI), like language, that draw primarily from symbolic entities. In particular, many vision techniques infer properties of the physical world from images; and image formation is a process that can be formalized by physical laws. For example, 3D vision involves inference of scene geometry by leveraging physical models that describe how real-world points project to virtual camera planes[1,2]. Video-based computer vision, such as ego-motion control[3–5], leverages the physics of motion to predict states of dynamic agents. The physics of motion takes many forms in computer vision, from a rigid body described by a trajectory (a group of rigid transformations in 3D space), to complex deformations described by partial differential equations[6–8]. Even semantic tasks like object recognition involve physics. Our semantic notion of an object can be seen as a physical surface surrounded by a medium[9], capable of independent physical motion from a surrounding scene, with geometric (for example, proximity and shape similarity)[10,11], photometric (for example, material similarity) or dynamic (for example, relative motion)[12] features.

Having described this close link between physics and the foundations of computer vision, one would expect vision algorithms to heavily incorporate physical knowledge. Though physics and vision algorithms are tightly coupled in recent literature, this is a relatively new development. It is fair to say that physics has not been the focus of the past decade of computer vision, machine learning has. Even longstanding problems in vision that have close ties to physical equations are now being addressed with a data-driven approach. Consider the problem of shape reconstruction. This was previously addressed with traditional techniques of light transport[13], and now researchers have demonstrated better results when using a neural network[14]. However, although data-driven performance can be superior to a physical model alone, there are problems with a data-driven approach. A neural network is not guaranteed to avoid predictions of shapes or objects that are physically implausible. For example, a neural network for 3D reconstruction will hallucinate detail that is below the resolvable limit of a stereo sensor. Since we know this is not resolvable by a camera, physics would inform us a priori that this prediction could

[1]University of California, Los Angeles, Los Angeles, CA, USA. [2]DEVCOM United States Army Research Laboratory, Los Angeles, CA, USA. e-mail: achuta@ee.ucla.edu

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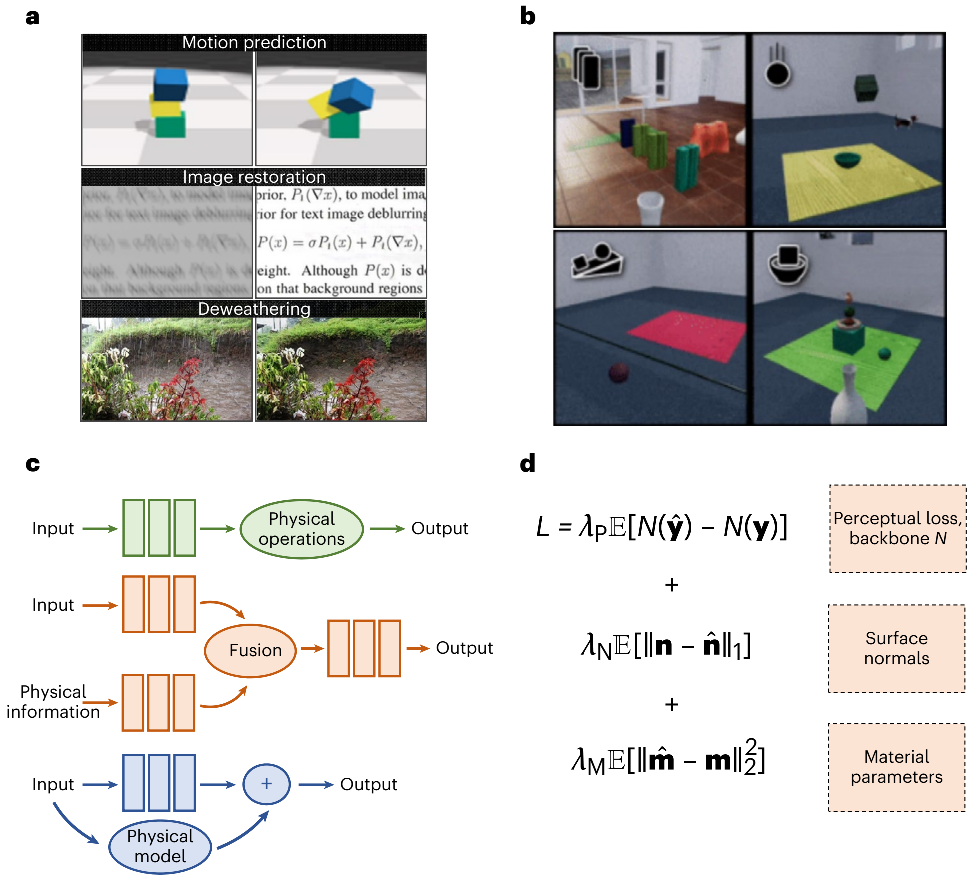

Fig. 1 | Incorporating physics in neural pipelines in modern computer vision. **a**, Physics-based learning enables a multitude of applications including motion prediction (top)[85], image restoration (middle)[96] and deweathering (bottom)[97]. **b**, Deep learning networks can become physics-based if trained on synthetic datasets with strong links to physical rules. Images show scenes from a dataset with physical behaviours[98]. **c**, Neural network architectures can incorporate physics as a constraint to the network topology[99]. **d**, Differentiable loss functions that incorporate a physical model can be used to regularize neural networks, where m describes material parameters, n describes surface normals, and N(y) describes a perceptual loss function. Panels reproduced with permission from: **a** (top row), ref. 85, PMLR; **a** (middle row), ref. 96, IEEE; **a** (bottom row), ref. 97, Springer Nature Ltd; **b**, ref. 98. Panel **c** adapted with permission from ref. 99.

be a hallucination. Quantifying the worst case error of a data-driven approach is intrinsically hard due to the inductive hypothesis implicit in data-driven methods. Although theoretical machine learning research aims to guarantee neural network performance by bounding error (referred to as generalization bounds[15]), such bounds are only valid under assumptions that cannot be validated in reality, for instance that the finite training data and yet-unseen test data be drawn from the same unknown distribution.

For such reasons, a key question that is being asked is how do we incorporate physics into data-driven pipelines. The motivation is clear: physics and data-driven techniques have complementary strengths and weaknesses, so perhaps the combination will obtain the best of both worlds. Physics can offer interpretable steps and the potential to generalize with limited data, but can be too idealized to describe real-world scenarios. Data-driven methods can return viable predictions when physical models have model mismatch error, but are not interpretable and require large amounts of data. While combining physics and data might be well motivated, the tactical question of how to combine these entities does not have a single answer. A neural network has many components (weights, losses, inputs, outputs and so on) and there are multiple ways to incorporate physics into neural networks, with differing tradeoffs.

In this Perspective, we discuss modern methods in vision that have successfully incorporated physics into data-driven pipelines. Many of these methods succeed because they take a holistic approach to methods in visual reasoning. Reasoning in computer vision is usually of an inductive form, and these methods incorporate data and physics into the inductive process. Induction is the process of inferring general conclusions from specific information. Any inference process requires biases of some form. Biases can come from design[16] (for example, choice of an inference or optimization criterion, for instance, a segmentation functional or grouping criterion), from physical laws[17,18] (empirically validated known constraints) or, as in modern techniques, from data-driven induction (for example, the assumption that properties of a finite dataset are shared by the entire distribution of possible data to be measured in the future). Critically, the inductive process does not need to be purely based on physics or data alone. Given where we are as a species, we do not need to learn everything from scratch, so the question arises of how to best make use of verified physical laws in visual inference. As the 'why' has been discussed in these introductory paragraphs, the remainder of this piece focuses on 'when' and 'how' to incorporate physics into data-driven vision pipelines. In particular, the section 'Incorporating physics into AI datasets' discusses when a problem might merit a physics-based learning approach. The final three sections of this Perspective focus on the how and discuss specific physics-based AI tactics that pertain to datasets, architectures and loss functions.

When to use physics-based learning

A first question that this piece addresses is when to incorporate a combined approach of physics and learning (Fig. 2). Learning here specifically refers to inductive learning: the process by which a learner

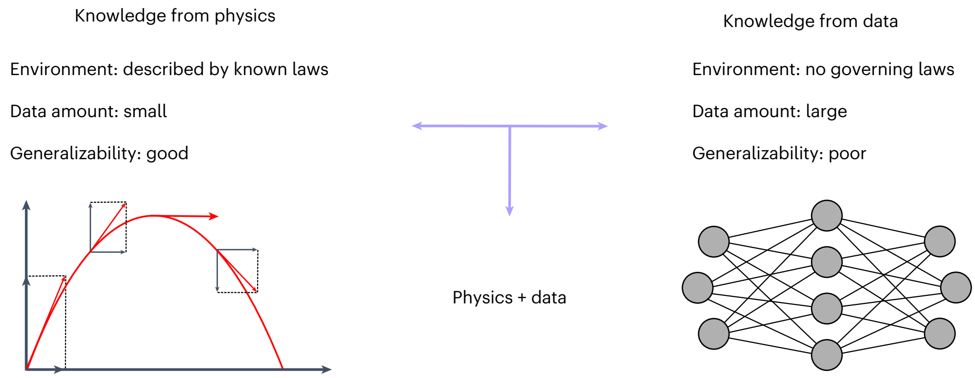

Fig. 2 | When to approach a problem from a physics, data-driven or physics-based learning approach. Left, if datasets are small and environments match physics, then a physics-alone approach makes sense. Right, by contrast, if the dataset is large and the environments are 'real' (deviating from all but the most ideal cases), then a data-driven approach is a better candidate. As we discuss in this Perspective, many interesting problems benefit from combining the approaches.

or learning algorithm elucidates generalizable rules or functions from a specific set of examples or data. In vision, the data collected by sensors like cameras are inherently lower dimensional than the real-world processes they attempt to observe. As such, the data-driven inductive possibilities are assumed to be very large. By contrast, physics-based induction uses a first-order, idealized model that returns a smaller set of inductive possibilities. Therefore, physical laws may be used as an additional inductive bias to reduce the set of generalizable functions provided by a learning algorithm operating on data-driven bias only, for example, by pruning or regularizing any clearly unreasonable solutions. Inductive bias refers to a set of assumptions or rules that the learner uses to predict outputs of given inputs that it has not encountered (that is, at test time). Such a hybrid approach is known as physics-based machine learning.

Let us return to the question of when to adopt a physics-based learning approach. Consider two extreme cases. In the first case, an inference problem is posed that can just be solved with physics alone, for example, solving for video tracking of particle motion in an idealized setting. If the accuracy demands of the problem are met with physics alone, the problem should be solved with physics alone. In a second case, a problem can have a negligible relationship to physics, unquantifiable by any form of physical model – such a problem should be solved with data alone. Neither of these two cases are therefore suitable for physics-based learning. However, tasks with partially predictive forward and inverse problems, for example, including object recognition in degraded visual conditions[19], super-resolution of satellite imagery[20] and system failure prediction[21], are of a third case. These problems lie in a space where physical models are inexact or physical parameters for the models are unknown. In this case, we are better positioned to incorporate this model as an inductive bias, rather than trusting the network to relearn an alternate version of the physical model. A summary of these paradigms is illustrated in Fig. 2.

Therefore, a scenario where physics-based learning should be considered is one where the physics alone is meaningful but, by itself, does not optimally address the inference problem. In particular, there are at least three key considerations one must make in deciding to use physics-based learning: (1) the 'goodness of data'; (2) the 'goodness of physics'; and (3) the ease of integrating data and physics together. The next paragraph outlines technical approaches to assess the 'goodness' of data and physics.

There are a few ways to assess the goodness of data with respect to physics. Consider in a first case where the physical model alone can predict the desired task output: then we recommend the use of task performance as an assessment metric. Concretely, the goodness of data can be assessed through metrics of task performance using a data-driven approach and compared with the goodness of physics by assessing the same metrics of task performance on the physical model alone. While performance metrics are important, one should also consider that the types of errors from data-driven and physical approaches could be different. For example, in deep-learning-based stereo, one may observe that a physics-based stereo method does not recover fine detail, while a data-driven method is able to super-resolve and hallucinate details. Since the data-driven and physics-based methods may behave differently on task performance, the fusion of deep-learning-based stereo with physics-based stereo could be attractive. However, what about a second case where the physics cannot predict the entire task output: is it still possible to assess the relative quality of physics and data? While end-to-end task output might not be as straightforward to use, one can appeal to representation probing where the latent space in a data-driven model is regressed to see if it can predict physics. A third option is to appeal to intermediate task behaviour, where the performance of a data-driven method is evaluated versus physical models on an intermediate output that physics can predict, which may not be the final task.

Having discussed two conditions (the goodness of data and of physics), we turn to a third condition – the ease of integrating a given physical model with data. A first remark is that integrating physics is easier if the physical model is itself tractable. A tractable model is useful not only for intepretability, but it also enables one to convert machine learning problems from supervised learning to self-supervised learning, as in the case of deep learning from monocular depth estimation[22–25]. In such examples, a stereo pair is used for data collection, but only one camera is used in the machine learning inference since it is monocular depth estimation. For this case, the problem does not require annotation of data and is self-supervised. Another example of incorporating physics and learning together is when a physical model does not directly predict the inference output, but can prune unreasonable solutions. For example, an object-tracking task of dynamic agents like moving vehicles is not described exactly by a physical model: behavioural intent of the driver plays a large role in the possible dynamics. However, even in this situation, physics can be used to prune unreasonable solutions. For example, if an object tracker estimates that the vehicle moves from two locations that are further apart than a vehicle's achievable speed would allow, then it can be flagged as a model violation. Yet another type of relationship between physics and data pertains to the representation space of an AI pipeline, for example, in probing a neural representation to see if the physics can be decoded from the latent space. In summary, the section takeaways are: (1) the choice to use a physics-based learning method depends on the quality of physics and data in the problem; and (2) there are specific tactical considerations to assess the value of physics and data in a problem setting.

Incorporating physics into AI datasets

A first tier of incorporating physics into AI pipelines is to modify the dataset. Even an ordinary neural network can become 'physics based' if the training data used has a strong link to physics. This could be done through synthetic and/or real data. In particular, synthetically generated datasets, where the synthesis is constrained by physical laws (for example, physics-based engines) help focus the data distribution more efficiently around the feasible set of data, although they may not cover the tails of the distribution due to oversimplification of synthetic engines. This points to a complementary statement, where coarse behaviours can be captured by synthetic datasets, and fine nuances by raw data.

Consider training an object tracker on two different dataset scenarios. The first scenario consists of simulated data of moving pedestrians and cars whose motion is dependent on laws of physics and traffic laws. While this is not a real-world scenario, the concocted, simulated example is dependent on the rules of physics, and neural networks have been shown to implicitly learn approximations of these rules. Now, consider a second scenario of real data of moving pedestrians and cars in a chaotic city. The laws of physics no longer directly predict the motion of pedestrians and cars, as the motion trajectory is not one of a billiard ball, but an autonomous agent that can decide its motion path, based on human behaviour and psychology.

However, even in the second scenario, there are some base rules of physics that do carry over (for example, biophysics dictates that the speed of pedestrians cannot be more than 25 miles per hour). It would be useful to force a network to learn these laws, because many prediction errors we see on real-world object detectors are easily flagged post facto, because of their physical plausibility (for example, a pedestrian suddenly disappears from the face of the Earth, or re-appears further away in a scene than the maximum mobility of a pedestrian would permit).

Flagging prediction errors post facto is suboptimal: in a deployed model it would be akin to noting the occurrence of an accident after it happens. For this reason it is useful to concoct physics-driven datasets that can be blended with real data to improve AI tasks. For example, physical models of object collision and intersection have been used to create Stilleben[26], a framework for generating realistic cluttered scenes for the task of semantic segmentation. Similarly, UETorch, a version of the popular Unreal game engine with PyTorch incorporated into the game loop, has been used[27] to train a model to predict whether a tower of blocks would fall over and yet other work[28] incorporates a physics engine into a generative model to be able to accurately predict object velocities based on the objects' physical parameters. Other approaches include[29,30]. These approaches rely on highly effective pipelines for synthetic data augmentation[31].

A future frontier of the field is in increasing the (optical) realism of physically-rendered datasets[32]. The field of physics-based rendering aims to represent the physical properties of light as it travels through a scene. Fortunately, raytracers and other forms of renderers are able to render scenes in accordance with physical laws. Recent approaches known as differentiable rendering, covered in[33], discuss how the forward raytracers are now differentiable, enabling one to optimize scene parameters with respect to visual outputs. This has been extended to more advanced scene physics, for example, beyond photometry research like[34,35] enable scene understanding in context of polarized light. There are specific approaches that use differentiable rendering like[36] that enable robust estimation of material properties of objects in a scene given a sparse set of views as input. While many of these works developed their own rendering methods, others have used Unity[37,38], Unreal Engine[39,40] or other game engines[41], which employ physics-based rendering techniques. Using game-engine-rendered synthetic data has allowed many of these works to excel in vision tasks, such as object detection[39], object tracking[37,40] or semantic segmentation[38,41]. In another study, a physics-based model was used[42] to generate highly realistic faces with blood-flow characteristics, which provide robust synthetic data. The use of physical engines can be used beyond the creation of data alone as a way to infer invisible quantities in an image. The inference of forces and pressures – quantities not visible in an image – has been demonstrated[43] during human object interactions through physically based simulation. In addition, physically based simulation can be used for other domains, such as learning whether acoustic sensing in a 3D environment can help navigation[44] or learning policies for object tracking with unseen objects, nuisance objects and so on[45].

Despite these advances, there remains a domain gap in how synthetic data map to real data, underscoring the need for generative models that are even more attuned to real-world physics. Fortunately, there is progress in reducing the domain gap between the simulation and real world, through techniques like domain randomization[46] or a related term, environment augmentation[45,47]. The basic idea of these techniques is to perturb the generation process of synthetic data, such that the perturbations assist with generalizing to real data. Despite the challenges that need to be overcome to use synthetic data, the use of physically realistic generative models is poised to be an impactful area of research that draws from vision, graphics and machine learning communities. In summary, the section takeaways are that: (1) datasets can be simulated using known physical lows; (2) AI models trained on these data will be inductively biased toward these laws; and (3) simulation engines exhibit a domain gap (between the real and synthetic worlds) that must be minimized.

Incorporating physics into network architectures

A second tier of incorporating physics into AI is through the inference function. Modern inference functions are deep learning models, and hence this section will focus on incorporating physics into deep learning architectures.

Coupled with recent advances in improving interpretability of deep learning models, various techniques have emerged to combine physics and learning. One technique is known as residual physics, which (as the name suggests) aims to use deep learning to elucidate the null space of what physics cannot predict. A trivial, data-driven solution is to input video frames into a convolutional neural network to predict trajectories. However, this would be susceptible to the inaccuracies of a data-driven-only approach (for example, requiring large amounts of data, predictions that can grossly violate laws of physics and so on). In the residual physics school of thought (Fig. 3), one may note that simple physics (for example, a parabola equation) can predict the coarse motion arc of the ball. One can then create a skip connection between the parabola prediction and the neural network output. Now the neural network only needs to predict the residual caused by model mismatch in the real data and the simple physical prior of a parabola fit, for example, air resistance, spin and so on. Many techniques leverage residual physics. For example, residual physics has been used[48] to teach a robot named TossingBot to grasp arbitrary objects from unstructured bins and to throw them into target boxes. Residual learning is employed to predict throw release velocity. TossingBot achieves 85% throwing accuracy. In addition[49], model uncertainty has been used as residuals for the task of simulating planar pushing and ball bouncing. Furthermore[50], residual physics has been combined with neural networks for the task of predicting an action's effect from sensory data.

Residual physics is not the only way to incorporate physics into deep learning architectures. Indeed, for many problems, residual physics is perhaps not even the best architecture. For example, it requires a fairly accurate physical model to begin with, so that the residual can be bounded to a small norm. In cases where the physics is a weaker predictor of the output, it might be useful to study a second approach,

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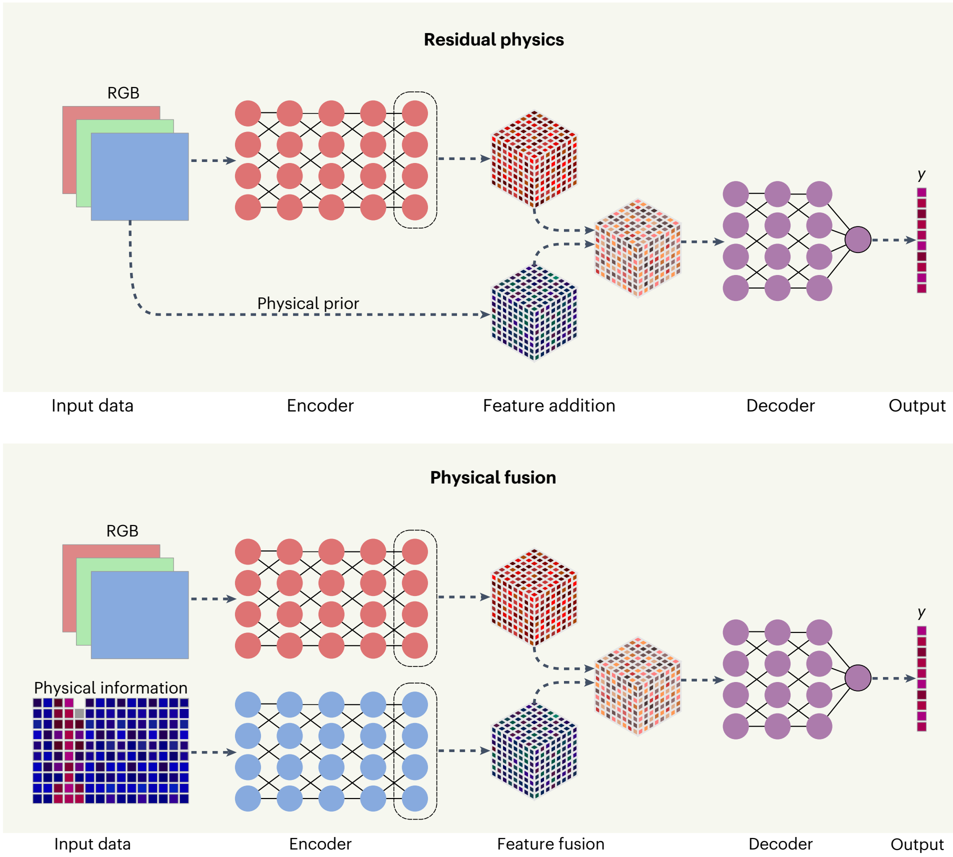

Fig. 3 | Two techniques to incorporate physics into machine learning pipelines. Top, residual physics is an architectural choice where the neural network is geared to predict the residual from the physical model. Bottom, physical fusion is where physics is treated as a multimodal input to a deep learning model. Late or early fusion can be used to combine features from data and physics. The output vector of both neural models is denoted by y.

known as physical fusion, shown in Fig. 3. In this technique, the physical prediction is provided as an input feature (in contrast to residual learning where it was skip connected directly to the output). One can think of the physical prediction as multimodal data, and the network branches into multiple streams that eventually merge to predict the output. This enables physical fusion to be useful in cases where the physics itself is inaccurate and needs to be transformed in a non-linear way before it can be merged into a meaningful representation. As a concrete example, consider the 'shape from polarization'[51,52] problem in computer vision. The goal is to estimate the surface normals of an object given photographs of the scene through different polarizer angles. The relationship between polarization data and shape is a very complex physical model with many unknown constants (like the refractive index and surface specularity). Therefore, the state-of-the-art methods that use deep learning for shape from polarization incorporate some form of physical fusion by concatenating approximate physical predictions with a dataset[14,53]. Other work has used physical laws in the form of rule representations as a second encoder branch, where the first encoder branch is a pure data-driven encoder. These are then stochastically concatenated via a control parameter, alpha, that regulates the strength of the rule on the output. Yet when alpha is fixed prior to training, the trained model cannot operate flexibly based on how much the data satisfy the rule, and therefore rule strength is not adaptable to target data at inference if there is any mismatch with the training setup. Recent work has shown by removing this predetermined constraint on alpha, a higher rule verification ratio, and thus more reliable predictions, can be achieved[54]. Here the rule verification ratio is the fraction of output samples that satisfy the rules. Operating at a better verification ratio could be beneficial, especially if the rules are known to be always valid, as in physics.

While pure deep learning methods are currently used to attempt answers to scene-related questions such as where and what an object is, scene understanding of shape, reflectance and lighting can be improved by incorporating physical priors[55]. The process of achieving these components through intrinsic image decomposition can yield solutions to intricate problems where the "ground truth" is not always available and unsupervised learning with physics-based constraints dominates[56–59] used the superposition of light to decompose an image with multiple illuminants into separate light-source-specific scenes. Learning how light affects an image leads to applications in relighting, where the detected lighting can be replaced with a new source in a different location and colour spectrum[60]. Other applications include finding haemoglobin and melanin concentrations on the face through the combination of intrinsic image decomposition and molecule reflectance spectrum modelling[61]. While the reconstruction problem is commonly applied to natural images, the reverse problem of rendering is also inherently physics based[33,62–65]. In summary, the section takeaways are that: (1) neural architectures have emerged that incorporate physics as a constraint or inductive bias; (2) two common example architectures are physical fusion and residual physics; and (3) the choice of architecture is based on factors that include the relevance of the physical model.

Incorporating physics into network loss functions

Related to the previous tier of modifying the neural network topology, a third tier of incorporating physics into deep learning is to incorporate physics into the loss function. When the physical model is known, it can be incorporated into the loss function as a form of regularization. An example is shown in Fig. 4, which involves a data-driven

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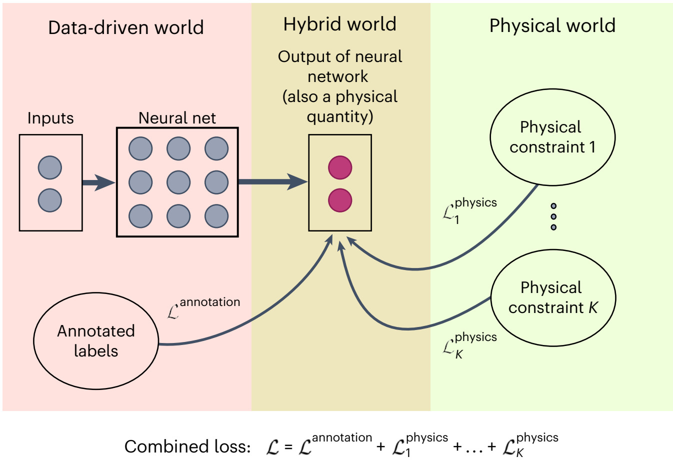

Fig. 4 | Combined loss functions that use both data-driven annotations and physical constraints. When outputs of a traditional deep learning model are physical quantities, this last output layer lives in a hybrid world. A compelling case for physics-based learning is made: it is easy to place a loss on the output layer that is based on annotated labels and physical models, as shown in the figure.

annotation loss and additional loss terms from physical constraints. A few general trends are observed: (1) the loss functions are inspired by well-defined physical priors; (2) these physical priors are often highly domain specific; and (3) the loss functions are differentiable to enable gradient based learning. If the ground-truth physics is not in a differentiable form, a relaxation to a differentiable function can be used. We will now illustrate a few examples, drawing from diverse tasks in computer vision.

For example, consider the task of vision in bad weather[66]. In this subfield, one goal is to recover a sharp image (for example, of an outdoor scene) given an input image (which may be corrupted by haze). Since such adverse weather is characterized by the physics of light transport and scattering, we often see differentiable expressions incorporating the physics of light transport and scattering making their way into neural loss functions. For example[67], proposes a new edge-preserving loss function to enable accurate estimation of the transmission map for dehazing. Loss functions evolve over time, as ref. 68 uses different physics-based priors in the loss formulation to enable synthetic to real transfer of dehazing models. Incorporating physics into the loss function is not limited to weather problems. The task of shadow detection and removal also sees tangible benefits from physics-based loss function design. For example, an adversarial shadow attenuation model has been used to improve shadow detection[69]; the shadow-attenuation model relies on physics-inspired loss-incorporating shadow-domain knowledge. Another method in the same area[70] uses physics-based chromaticity, boundary smoothness and perceptual features for single-image shadow removal. Human body pose estimation is another area in computer vision that leverages physical priors. Various works incorporate the physics of the human body into the supervision for a network, via loss functions on reprojection[71] or joint pose optimization that are combined with data-driven losses[72].

Physics-based loss functions also find significant use in computational imaging tasks. For the purpose of positron attenuation correction in computed tomography imaging, a novel line integral projection loss has been proposed[73], consistent with attenuation physics, that leads to improved reconstruction. Other studies have proposed[74] using translation-invariant loss functions for the task of 'non-line-of-sight' correlography. And in lensless microscopy[75], reconstruct phase by fitting the network weights to the captured intensity measurements. Instead of optimizing phase directly, the network optimizes the angular spectrum representation of the measurement in the object plane, allowing an unsupervised training setup. The use of similar physical constraints to remove hallucinations has also been successfully used to advance virtual staining microscopy[76,77]. Finally, methods for equitable imaging and medical devices use physics-based loss constraints to ensure that light-based medical devices perform equally well on the human population[78,79,80]. These diverse imaging setups each have their own ad-hoc loss function setups, but the common theme of having a closed-form, differentiable expression that encapsulates domain knowledge is a cross-cutting theme in this area. Looking ahead, much of the future work lies in finding expressions that are both physics based and yet also differentiable. In cases where this is not always possible, we expect that future work will find relaxations, or use learning to set the parameters of a simpler, differentiable model. In summary, the section takeaways are that: (1) loss functions can incorporate a physical model to regularize a neural network; (2) physics-based loss terms should ideally be differentiable; and (3) if the physics is in a form that does not admit a differentiable loss, then a physically approximate loss that is differentiable can be developed.

Future outlook and conclusions

The integration of deep learning methods with physics introduces an opportunity to better understand and predict noisy complex natural physical systems. As discussed here, the integration in these hybrid systems can occur at various levels, from the training data to novel network architectures and loss objectives. As reviewed here, these methods have already shown much promise in enhancing performance in a multitude of forward prediction tasks (object tracking, motion prediction, physical consequences of robot actions and so on) and inverse problems (scene de-weathering, super-resolution reconstruction of remote imagery, inverse 3D rendering and more).

An additional direction that is perhaps a few years out lies in unsupervised discovery of physics from visual scenes. We have discussed many studies that have used known physical relationships to recover parameters or directly infer a desired output. However, in some problems one might not have sufficient knowledge of either the underlying physical law or its parameters. This unknown–unknown problem is known as distilling physical laws from data. Physical laws are a human construct, expressed in human language, while recent work with large-scale neural networks hypothesizes the emergence of an 'inner language', separate from the human language in which they are trained[81]. A network may then encode physical laws implicitly already, in a language that may not be interpretable by humans. It can be shown that abstract concepts, such as laws of physics, can be finitely represented by a neural network, and are, in principle, learnable, but external observers cannot know if and when such a concept has been positively encoded[18], although the hypothesis can be falsified. Work in this area is nascent[82–86] and mostly confined to limited settings with relatively simple physical laws for the moment.

The methods described in this Perspective will also play a central role in enabling a next generation of deep neural networks that learn more like biological systems[31,87–89]. Humans are able to acquire rich internal representations of the physical compositionality of the world by interacting, multimodally and continuously, with objects[90,91]. By having the ability to reason about the physical properties of the world, as described here, it may become possible to develop novel neural network architectures that are able to interpret scenes by decomposing objects into their physical properties (for example, shape, surface normals and colour)[92], and enabling robust generalization of the learnt knowledge to novel tasks[93].

As this article is being written, modern large language models (LLMs) are exhibiting a remarkable ability to 'reason' about many topics, and this includes physics. For example, a recent LLM has shown an ability to outperform the average human test-taker on the Advanced Placement Physics test, used in the United States[94]. This exciting result should be tempered with the caveat that LLMs cannot learn completely new concepts that are not in their training data[95], and suffer from hallucinations when trying to extrapolate beyond the training data. However, since an LLM is inherently a learning-based method, the ideas in this piece of physics-based learning can be used in a similar fashion as has been discussed to incorporate physics into LLMs. This includes specific ways to incorporate physics into datasets, architectures or loss functions.

The field of physics-based deep learning provides a path to integrating critical physics knowledge for many visual domains, and also opens the door to novel learning paradigms that will enable a new generation of applications.

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Author contributions

All authors contributed to the ideas in the manuscript. A.K. took the lead in coordinating the figures and writing the manuscript. S.S. and C.d.M. had a supporting role in writing the manuscript. All authors proofread the manuscript.

Competing interests

A.K. is an employee, receives salary and owns stock in Intrinsic (an Alphabet company); and is a co-founder and owns stock in Vayu Robotics. C.d.M. declares no competing interests. C.-J.H., M.S. and S.S. hold employment, draw salary from and hold stock in Amazon.

Additional information

Correspondence should be addressed to Achuta Kadambi.

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