A Short Survey of Systematic Generalization

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Abstract
This survey includes systematic generalization and a history of how machine learning addresses it. We aim to summarize and organize the related information of both conventional and recent improvements. We first look at the definition of systematic generalization, then introduce Classicist and Connectionist. We then discuss different types of Connectionists and how they approach the generalization. Two crucial problems of variable binding and causality are discussed. We look into systematic generalization in language, vision, and VQA fields. Recent improvements from different aspects are discussed. Systematic generalization has a long history in artificial intelligence. We could cover only a small portion of many contributions. We hope this paper provides a background and is beneficial for discoveries in future work.

1 Introduction
Artificial intelligence with deep learning has rapid improvement in recent years. As it addresses many problems, an old question of systematic generalization (Fodor and Pylyshyn 1988; Lake and Baroni 2018) returns to receive focus. Systematic generalization requires correctly addressing unseen samples by recombining seen ones. For example, a model trained with blue rectangles and green triangles predicts blue triangles. Though it is straightforward for humans, it is still challenging for deep learning models. It has a long history and many recent related works. This survey summarizes and organizes the information into a series of subtopics. The initial ones mainly focus on historical perspectives, and the latter discuss recent works. We will go through them in this introduction and look at their details in the following sections.

The fast growth of deep learning has addressed many i.i.d. problems in artificial intelligence. On the other hand, systematic generalization is an out-of-distribution (o.o.d.) generalization with disjoint training and test domains. It provides the ability for fast learning and creation. They are essential for more human-like intelligence, which current machine learning does not achieve (Section2).

Artificial intelligence has Classicist and Connectionist approaches, and they have complementary advantages. Connectionist (Feldman and Ballard 1982) is good at i.i.d. generalization but not at systematic generalization (Fodor and Pylyshyn 1988; Marcus 1998). Classicist with symbol processing is the opposite. A neural network originates from the Connectionist model and is still weak at such generalization (Section3).

Three types of Connectionist are explored to facilitate the advantages of Classicist and Connectionist. Eliminative Connectionist does not use symbolic processing. Hybrid Connectionist involves both Connectionist and symbolic processing. Implementational Connectionist uses Connectionism to implement symbolic processing (Section5).

Variable binding is a Connectionist topic closely related to systematic generalization. A variable is a placeholder, and it can be replaced with values. It decouples the manipulation of a variable and its value, so it generalizes to their combinations (Section5).

Causality is also a related topic. It uses do-calculus with intervention and enables studying probabilities of counterfactual events. Systematic generalization is such a counterfactual event (Section6).

Systematic generalization problems are widely encountered in different fields. We mainly focus on language, vision, and visual question answering (VQA). Many datasets are designed in these fields. Language has historically been more studied since sentences are more straightforward to process than images. The recent refocus on systematic generalization also started from language tasks (Lake and Baroni 2018) (Section7).

Many deep learning approaches have been recently proposed for systematic generalization, such as disentangled representation learning, meta-learning, attention mechanism, modular architecture, specialized architectures, and data augmentation (Section8).

We cover the history of systematic generalization in
artificial intelligence and summarize the recent development after the wide use of deep learning. We hope this survey is helpful as background information for potential future research. The following sections have more detailed discussions for each subtopic mentioned above.

2 Systematic Generalization

A fundamental property of artificial intelligence is generalization, where a trained model appropriately addresses unseen test samples. Many problems adopt the i.i.d. assumption, where training and test samples are independently drawn from the identical distribution (i.i.d. generalization). On the other hand, test distribution can be different from training distribution, and they may have disjoint input domains or support. It means that the test samples have zero probability in training distribution (o.o.d. generalization).

Systematic generalization is an o.o.d. generalization. Systematicity is a property where the ability to produce or understand some sentences (or objects in general) is intrinsically connected to that ability for others (Fodor and Pylyshyn 1988). It usually uses factors of variation (Bengio et al. 2013) for recombination. For example, a model trained with blue rectangles and green triangles predicts blue triangles. A systematic generalization is often called a compositional generalization, mainly in language domains.

Systematic generalization is considered the "Great Move" of evolution, developed to process an increasing amount and diversity of information from the environment; for example, humans can recognize new spatial relationships of seen objects (Newell 1990). It is also related to the evolution of the prefrontal cortex (Robin and Holyoak 1995). Cognitive scientists see such generalizations as central for an organism to view the world (Gallistel and King 2009). A book (Calvo and Symons 2014) contains works mainly from cognitive science perspectives.

It has been discussed that commonsense is critical (Mccarthy 1959; Lenat et al. 1986) for systematic generalization. The discussions also seek general prior knowledge for systematic generalization, e.g., Consciousness Prior (Bengio 2017). Recently, different types of inductive bias (Goyal and Bengio 2020) were summarized. There are different ways to categorize systematicity. Three levels of systematicity, from weak to strong, are defined (Hadley 1992). More precisely, six levels of systematicity are defined (Niklasson and van Gelder 1994). Recently, five types of tests are summarized (Hupkes et al. 2020).

The development of deep learning reliably addresses many i.i.d. problems, so it is also encouraged to address systematic generalization. It relates to many areas, including reasoning (Talmor et al. 2020), continual learning (Li et al. 2020), zero-shot learning (Sylvain et al. 2020), and language inference (Geiger et al. 2019). GFlowNets (Bengio et al. 2021) generate informative samples to address systematic generalization for active learning and exploration in reinforcement learning.

3 Classicist and Connectionist

Artificial Intelligence has been developed in two approaches: Classicists and Connectionists. They are discussed for human cognition and refer to approaches in artificial intelligence.

Classicist (Fodor 1975; Pylyshyn 1980) refers to the computing operations on symbols (e.g., tokens) derived from Turing and Von Neumann machines. It typically means fixed serial rules with variables, e.g., computer programs. The Physical Symbol System (PSS) hypothesis (Newell and Simon 1976) was developed to study the systematic mental representations of humans, and it says that human cognition is physically the product of a symbol system. Connectionist (Feldman and Ballard 1982; Rumelhart et al. 1986b) uses many simple neuron-like units which are richly interconnected and processed in parallel (Hinton 1991). It implies learning from data without explicit symbol information, e.g., neural networks.

While Connectionist is good at i.i.d. generalization, it does not address o.o.d. generalization in general (Fodor and Pylyshyn 1988). On the other hand, Classicist is good at o.o.d. generalization, while not at i.i.d. generalization (sometimes referred to as the "graceful degradation" issue). For example, computer programs can be reliable for new data that strictly fit input requirements, but it is brittle to process noisy images or speech. There is a spectrum between Classicist and Connectionist, which is a trade-off between the advantages of both approaches (Section 4).

Distributed representation Connectionist has distributed and localist representations (Feldman 1986; Sejnowski and Rosenberg 1987). We mainly discuss distributed representation, which is widely used and more efficient when many items are present (Touretzky and Hinton 1988). It refers to Parallel Distributed Processing (PDP) models (Rumelhart et al. 1986b). Distributed representations of symbols (Rumelhart et al. 1986a) were introduced to capture relationships between family members. A distributed representation can describe an object in terms of primitive descriptors; it has a significant advantage because it can describe a novel object using the same primitive descriptors to create novel combinations as representations (Hinton 1990). During training, primitive descriptors or hidden nodes in distributed representation continually change their meanings;
though they might be stable in the short term, they shift around in the longer term (Hinton et al. 1986a).

Localist representation often refers to a one-hot representation when used in deep learning. It is efficient in the following cases (Hinton 1990). A significant portion of samples activates a node, e.g., the end-of-sentence symbol in sentences. Entries are mutually exclusive, e.g., classification outputs and input words.

**Disentangled representation** Distributed representation can be disentangled (Bengio et al. 2013). With fewer requirements, e.g., linearity, it is also referred to as factorized representation (Ke et al. 2021) or micro-features (Hinton et al. 1986b). Many early works for systematic generalization studies disentangled representation. Also, disentangled representation learning is mainly studied in unsupervised manners (Higgins et al. 2017), and it can be used as a feature extractor for systematic generalization models. These previous works usually do not discuss disentangled representation learning and systematic generalization together. However, it is necessary in some cases because humans systematically generalize many entangled data, such as images and sentences.

Disentangled representation is also related to Invariant Risk Minimization (IRM) (Arjovsky et al. 2019; Peters et al. 2016), a learning paradigm that estimates invariant predictors from multiple training environments. IRM focuses on learning individual features. However, disentangled representations require decomposing an input to features, and the features together should keep the original input information (Bengio et al. 2013). IRM is used in domain generalization, and there is a recent related survey (Wang et al. 2022).

**Connectionist and systematic generalization** It is argued that Connectionism lacks systematicity, which also indicates that the mind is not a Connectionist network (Fodor and Pylyshyn 1988). Current machine learning methods also seem weak at generalization beyond the training distribution (Goyal et al. 2021a; Hendrycks and Dietterich 2019), though it is often necessary in many cases. Also, state-of-the-art models often learn spurious statistical patterns while humans avoid them (Nie et al. 2020).

There has been the exploration of compositionality in neural networks for systematic behavior (Wong and Wang 2007; Brakel and Frank 2019). Counting ability (Rodriguez and Wiles 1998; Weiss et al. 2018), and sensitivity to the hierarchical structure (Linzen et al. 2016). Systematicity has been partially achieved in previous work (Niklasson and van Gelder 1994; Hadley and Hayward 1997; Bodén and Niklasson 2000). More recent related efforts are summarized (Jansen and Watter 2012). There are also recent improvements in systematic generalization with structure design (Andreas et al. 2016; Gaunt et al. 2017) and structure prediction (Johnson et al. 2017; Hu et al. 2017). More recently, neural production systems (Goyal et al. 2021a), shared global workspace (Goyal et al. 2022), and reinforcement learning (Ke et al. 2021) are also investigated to address this problem. We will discuss more in Section 8.

**System 1 and System 2 in human thinking** Human thinking has two systems. System 1 refers to fast and less reliable thinking. People always make unconscious decisions, and the process is mundane reasoning. System 2 refers to slow and more reliable thinking. It is a conscious process including logical thinking, e.g., solving a math problem. System 2 is a more precious resource. People switch between the two systems to best use the resources. We mainly use system 1 in daily life and system 2 for complicated problems that system 1 cannot address. An introductory book (Kahneman 2011) contains many examples, experiments, and discussions of how humans think on different occasions.

Systematic generalization is more related to system 2, where a decision in a new environment is inferred with logical reasoning with familiar knowledge. Human thinking is also discussed from other perspectives. Dynamic memory is considered a fundamental ingredient of intelligence (Schank 1982). Consciousness prior (Bengio 2017) is also proposed in deep learning. It leads to sparseness prior and attention-based modular networks.

### 4 Types of Connectionist

Classicists and Connectionists have complementary advantages. Implementational Connectionist merely implements a Classicist symbol manipulation system. On the contrary, eliminative or radical Connectionist is not designed with knowledge of the symbol system, so it eliminates the PSS hypothesis. Also, there are hybrid methods that combine both of them. Eliminative, hybrid, and implementational Connectionists have weak to intense use of symbol systems.

#### 4.1 Eliminative Connectionist

Eliminative Connectionist eliminates the symbol system by purely using distributed representation (Pinker and Prince 1988; Marcus 1998). It is attractive because it avoids knowledge of symbol systems. For example, a model without symbolic rules or lexicon can learn past tense grammar rules and exceptions in English verbs (Rumelhart and McClelland 1986).
Eliminative Connectionist also uses prior knowledge, not including symbol systems, e.g., layered architecture. Also, some architecture designs, such as convolutional layers and attention mechanisms, are less mentioned as symbol systems. Regularization algorithms like noise insertion and optimization algorithms like Adam are not much related to symbol systems. Modular architecture design a module for a factor, but the prior knowledge is not specific to each symbol.

Pure eliminative Connectionist has many challenges. One long-standing problem is that a model has a fixed-length vector of units for representations of recursive symbol structure (Pollack 1990), which vary in size and complexity (Hollyoak and Hummel 2000), e.g., context-free languages. Tree-structured composition (Bowman et al. 2015) is developed to address such cases.

4.2 Implementational Connectionist

Implementational Connectionist (Ballard 1986; Pinker and Prince 1988; Hinton and Anderson 1981; Hinton et al. 1986b; Touretzky 1986) directly designs symbol-processing architectures in PDP models (Chalmers 1993). It was argued that the only Connectionist approach to achieve systematic generalization is implementational Connectionist (Fodor and Pylyshyn 1988). Such approaches share the explanatory capability and the empirical results of Classicist models.

For example, PDP networks can implement parts of LISP and production systems (Touretzky and Hinton 1985). BoltzCONS (Touretzky 1986) is another example. Also, µKLONE (Derthick 1990) uses microfeatures to implement functionality similar to the knowledge representation system KL-ONE.

4.3 Hybrid Neural Systems

It is proposed to integrate symbolic processing into neural networks (Hinton 1990; Sun 1996; Wermter and Sun 1998) to take advantage of both. The majority of early hybrid systems have a neural network and rule-based modules (McGarry et al. 1999).

Like classicists, the neural net was designed to separate modules for storing values and operations (Miikkulainen 1993). It has been shown that some logic can be translated into neural networks (Shavlik 1994). Methods are proposed for variable binding (Section 5) with tensor products (Smolensky 1990) and semantic pointers (Eliasmith 2013). There is also a local tensor product representation, such as the semantic net model (Hinton and Anderson 1981). Neural-symbolic methods are proposed for logical operations (Niklasson and van Gelder 1994) and reasoning (D’Avila Garcez et al. 2009; d’Avila Garcez et al. 2019).

Recently, the Neuro-Symbolic concept learner (Mao et al. 2019) has been proposed for VQA. Tensor-Product Transformer combines BERT and tensor products to represent symbolic variables and their bindings (Schlag et al. 2020). Neural-symbol stack machines (Chen et al. 2020) are used for instruction learning problems. Recent work also includes Edge Transformers (Bergen et al. 2021), which combines Transformers and rule-based symbolic systems. Inspired by logical programming, it proposes triangular attention to manipulate pairs of input nodes. It is proposed to use symbolic modules to examine the logical reasoning of neural sequence modules (Nye et al. 2021). A book (Hinton 1991) contains works for connectionist symbol processing.

5 Variable binding

Variable binding assigns a value to a variable. It is a difficult and important problem in Connectionist models (Babcock 1984), and it is required for complex reasoning tasks (Browne and Sun 2000) and more efficient computation (Sun 1992). Systematic generalization requires learning true rules containing variables, so it must do something equivalent to the variable binding (Touretzky and Hinton 1988). Manipulation of variables is essential for animal cognition (Gallistel and King 2009). For example, honeybees extend the solar azimuth function to the lighting of unseen conditions (Dyer and Dickinson 1994). Variable binding may be one of the reasons to force people to be sequential processors (Newell 1980a).

We look at an example. Variable binding enables one general rule: dog(X), barks(X). It means “X barks if X is a dog.” Without variable binding, we need a specific rule for each possible value, such as dog(rei) and dog(bue) (Browne and Sun 2000). Similarly, the binding problem occurs when we encode feature conjunctions in a representation, e.g., a red triangle and a blue square (Treisman 1998). Production systems (Touretzky and Hinton 1988; Goyal et al. 2021) have rule and placeholder variables, and variable binding is required for both of them.

It is argued that eliminative Connectionists cannot explicitly address the variable binding problem (Hollyoak and Hummel 2000). Many Connectionist researchers have considered embedding symbol systems in a neural network for variable binding (Feldman and Ballard 1982; Pollack 1990). Holographic Reduced Representations (Plate 1991) use convolution. Temporal Synchrony (Shastri and Ajjanagadda 1993) is proposed for reasoning. Analogical Access and Mapping (Hummel and Holyoak 1997) mainly regards tree-structure grammar in language. Please also refer to recent surveys (Gosmann and Eliasmith 2019; Frady et al. 2021).
6 Causality

Causal learning has a long history, rooted in the eighteenth century (Hume 2003) and the classical field of AI (Pearl 2003). The primary exploration has been from statistical perspectives (Pearl 2009; Peters et al. 2016; Greenland et al. 1999; Pearl 2018). Much causal reasoning literature is built upon do-calculus (Pearl 1995, 2009) and interventions (Peters et al. 2016), though some early work does not consider interventions (Heckerman et al. 1995). The question of how to separate correlation and causation is raised (Welling 2015).

The causation forms Independent Causal Mechanisms (Peters et al. 2017; Schölkopf et al. 2021), or ICMs, which avoid spurious connections. ICM is robust across different domains (Schölkopf et al. 2016) to support systematic generalization (Parascandolo et al. 2018; Goyal et al. 2021c).

Causality and variable binding have been discussed in different fields while closely related. For example, an ICM states that an output variable depends only on the values of a factor in a disentangled input variable. Causality also indicates that the binding is robust in different domains.

Systematic generalization is the counterfactual when the joint input distribution is intervened to have new values with zero probability in training (covariate shift). With ICMs, models can be trained with data distributions induced by causal models to achieve systematic generalization (Tsirtsis et al. 2020). For example, causal mechanisms are augmented into generative models for constructing images and planning (Kocaoglu et al. 2018; Kurutach et al. 2018).

As mentioned in the book (Peters et al. 2017), causality research is still in an early stage, and the assumptions are not general. The theory has more results on linear models. Some main approaches include the following.

- Independence-based methods
- Restricted structural models, such as additive noise
- Invariant causal prediction

The current approaches mainly study disentangled input representations. Research for entangled representations has been recently conducted (Bengio et al. 2020), and it uses adaptation speed to learn causality with meta-learning. However, extending such a representation-learning algorithm to multiple variables is still challenging. Some work includes multiple variables but disentangled data (Ke et al. 2019).

One possibility is to use the causality module as an intermediate part of a neural network model (Schölkopf et al. 2021). A model can be divided into an encoder, an intermediate network, and a decoder. The encoder converts an entangled input to a disentangled input representation. The intermediate network models the causality between input and output disentangled representations. The decoder converts a disentangled output representation to an entangled output. Graph networks (Battaglia et al. 2018) can be used as intermediate networks (Ke et al. 2021).

7 Language, Vision, and VQA

Systematic generalization has been studied in different fields, and we look into language, vision, and VQA.

7.1 Language

Systematicity is often referred to as compositionality in the language domain. They may be different aspects of the same phenomenon (Fodor and Pylyshyn 1988). Compositionality is the algebraic capacity to understand and produce novel combinations from known components (Chomsky 1957; Montague 1970). For example, a person who knows how to “step,” “step twice,” and “jump” naturally knows how to “jump twice” (Lake and Baroni 2018). This generalization ability is critical in human cognition (Minsky 1986; Lake et al. 2017). It helps humans to learn languages flexibly and efficiently from limited data and extend to unseen sentences.

Human-level compositional learning has been an open challenge (Yang et al. 2019). With the breakthroughs in sequence-to-sequence neural networks for NLP, such as RNN (Sutskever et al. 2014), Attention (Xu et al. 2015), Pointer Network (Vinyals et al. 2015), and Transformer (Vaswani et al. 2017), there are more contemporary attempts to encode compositionality in sequence-to-sequence neural networks. Words are natural symbols in language and are extended to word embeddings (Deerwester et al. 1990). Further, neural language models (Bengio et al. 2003) introduce interpretable word embeddings.

SCAN dataset (Lake and Baroni 2018) is an early compositional generalization dataset in recent years. It is a sequence-to-sequence task that translates natural language into a sequence of robot actions. It considers several aspects of compositional generalization. One of them is primitive substitutions, where a word is replaced with another, and the combination of the word and the context is new. Please see the “jump” example above. Many related tasks (Loula et al. 2018; Liška et al. 2018; Bastings et al. 2018; Lake et al. 2019) are also proposed.

Multiple methods (Bastings et al. 2018; Loula et al. 2018; Kliegl and Xd 2018; Chang et al. 2019) have been proposed using various RNN models and attention mechanisms. These methods successfully generalize when the difference between training and test
data is slight. Requirements for systematic generalization are discussed (Bahdanau et al. 2019), concluding that additional regularization or prior is necessary for modular designs. SCAN dataset inspired multiple approaches (Russin et al. 2019; Lake 2019; Li et al. 2019; Andreas 2020; Gordon et al. 2020; Liu et al. 2020; Chen et al. 2020) discussed in the next section.

The CFQ dataset considers syntactic compositionality in real data (Kevers et al. 2020). It generally requires recombining syntactic structures beyond primitive substitution. The methods on the SCAN dataset do not work well on CFQ, while pretraining provides improvements (Furrer et al. 2020). The Semantic Parsing approach also addresses part of the problem (Shaw et al. 2021). There are analyses for training data size (Tsankov et al. 2021) and model size (Qiu et al. 2022) for compositional generalization.

There are other recent semantic parsing datasets. COGS (Kim and Linzen 2020) is a synthetic dataset with pairs of sentences and logical forms, and the generalization test set evaluates novel linguistic structures. PCFG (Hupkes et al. 2020) manipulates executable operations. GeoQuery (Shaw et al. 2021) is a non-synthetic dataset with pairs of questions and meaning representations annotated by humans. It has three systematic generalization splits. Template split has disjoint abstract output templates for training and test data. TMCD split has training and test compound distributions as divergent as possible. Length split has different lengths for training and test data. SMCalFlow-CS (Yin et al. 2021) is a split of SMCalFlow for compositional skills. Machine translation dataset is also recently proposed (Dankers et al. 2022). Math expressions can be treated as language, and a mathematical reasoning dataset is proposed (Saxton et al. 2019).

7.2 Vision

Systematic generalization is often referred to as zero-shot learning in vision (Rohrbach et al. 2011; Larochelle et al. 2008; Yu and Aloimonos 2010; Xu et al. 2017; Ding et al. 2017). The difference is that vision tasks are additionally given attributes (factors) for classes or samples. Common datasets include AWA (Lampert et al. 2014; Xian et al. 2019), CUB (Wah et al. 2011), SUN (Patterson and Hays 2012), and aPY (Farhadi et al. 2009). There are also recent vision benchmarks (Hendrycks and Dietterich 2019; Hendrycks et al. 2020; Tang et al. 2021) for systematic generalization.

Many approaches have been proposed with linear (Frome et al. 2013; Romera-Paredes and Tori 2015; Akata et al. 2015, 2017) and nonlinear (Socher et al. 2013; Norouzi et al. 2014) compatibility models. Other algorithms learn independent attributes (Lampert et al. 2014). There are also hybrid models between them (Changpinyo et al. 2016; Zhang and Saligrama 2015; Xian et al. 2016). There are related surveys (Wang and Deng 2018; Zhou et al. 2022).

Using attributes or other side information makes the problem easier than systematic generalization. Many works have been done to avoid attribute annotation, e.g., one-shot image novel class (Mensink et al. 2012), external lexical information for class embeddings (Rohrbach et al. 2011; Akata et al. 2015), and visual descriptions (Reed et al. 2016). Other work has been done to understand the systematicity of images (Goyal et al. 2022). It has also been argued that zero-shot learning is related to the attention mechanism (Sylvain et al. 2020).

A related topic is domain generalization with multiple vision datasets, such as PACS (Li et al. 2017), VLCS (Torralba and Efros 2011), MNIST-M (Ganin and Lempitsky 2015), and NICO (He et al. 2021; Zhang et al. 2022). NICO labels both concept and context and the context can be attributes or backgrounds.

7.3 VQA

Both language and vision are essential for human recognition, and VQA (Antol et al. 2015) combines them. VQA naturally includes grounding, which finds the mapping between words and objects or their properties. Systematicity is also applicable and critical in other multimodal problems, including Image Captioning (Karpathy and Li 2015), Image Generation (Klinger et al. 2020), and Embodied Question Answering (Das et al. 2018).

In early VQA, it was found that the trained models are likely to learn superficial and spurious relations between input and output. For example, when a question asks what is on the ground, the answer is likely to be snow. It is because the snow on the ground is worth to be asked. They are systematic generalization problems. VQA datasets are designed for systematic generalization. CLEVR (Johnson et al. 2017) contains Compositional Generalization Test (CoGenT) for novel attribute combinations in the test. CLOSURE (Bahdanau et al. 2019) measures systematic generalization in the CLEVR dataset. Another VQA dataset is SQOOP (Bahdanau et al. 2019), which is more realistic (Hudson and Manning 2019).

Algorithms for visual question answering include architecture design of Neural Module Networks (Andreas et al. 2016), Film (Perez et al. 2018), Relation Networks (Santoro et al. 2017), and MAC networks (Hudson and Manning 2018). Latent Compositional Representation (Bogin et al. 2021) also helps.

Also, following the SCAN dataset for one-shot learning in language, the gSCAN dataset was proposed for one-shot learning problems in grounding and visual question answering (Ruis et al. 2020). The input is a human language instruction and an environment, and...
the output is a sequence of robot actions. A study on gSCAN shows that it is crucial to think before acting (Heinze-Deml and Bouchacourt 2020). The object relations are modeled in the contexts (Gao et al. 2020). It is important to fit the network structure to the compositional structure of the problem (Kuo et al. 2021). A general transformer with cross-modal attention achieves nearly perfect results for majority splits, and the remaining problems correspond to the fundamental challenges of compositional generalization for language (Qiu et al. 2021).

There are also various simulated settings for grounded language acquisition with reinforcement learning, such as X World (Yu et al. 2018), BabyAI (Chevalier-Boisvert et al. 2019), and others (Hermann et al. 2017, Wu et al. 2018).

8 Recent Improvements

Different systematic generalization approaches have been investigated. However, the generalization is still difficult for deep learning in general (Hendrycks and Dietterich 2019, Goyal et al. 2021c). The main directions include disentangled representation learning, meta-learning, attention mechanism, modular architectures, specialized architectures, and data augmentation.

8.1 Disentangled Representation Learning

It was argued that good representations should help express the regularities (Hinton 1990). Disentangled representation (Bengio et al. 2013) learning is developing quickly. Early work learns the representation from statistical marginal independence (Higgins et al. 2017, Burgess et al. 2018, Locatello et al. 2019).

The definition of disentangled representation has recently been proposed with symmetry transformation in Physics (Higgins et al. 2018). It leads to Symmetry-based Disentangled Representation Learning (Caselles-Dupré et al. 2019, Quessard et al. 2020, Painter et al. 2020, Piffl et al. 2020). Such approaches explain disentangled representation using group theory and Physics.

It is mentioned that disentangled representation is an example of ICM learning (Schölkopf et al. 2021). There are also methods to measure compositionality in representations (Andreas 2019). Disentangled representation tends to be discussed without simultaneous systematic generalization. It can be a feature extractor to obtain disentangled representations, and in other systematic generalization tasks, the representations are used as inputs for downstream modules.

8.2 Meta-learning

Meta-learning is an approach for systematic generalization (Lake 2019). It usually designs a series of training tasks for learning a meta-learner, which is used to address the problem in the target task. There is training and test data in each training task, where test data requires systematic generalization from training data. The training tasks need to have similar structures as the target task so that the meta-learner can learn how to generalize from the training data in the target task.

When ICMs are available, they can be used to generate meta-learning tasks (Schölkopf et al. 2021). It is discussed to employ meta-reinforcement learning for causal reasoning (Dasgupta et al. 2015). Meta-learning can also capture the adaptation speed to discover causal relations (Bengio et al. 2020, Ke et al. 2019). However, it is hard to disentangle the factors when multiple variables exist.

There are other works with meta-learning. Pairs of meta-learning tasks are constructed from sub-sampling training data (Conklin et al. 2021). Representation and task-specific layers of models are trained differently to generalize mismatched splits on pre-finetuning tasks, so transfer learning between compositional generalization tasks is enabled (Zhu et al. 2021).

8.3 Attention Mechanism

Attention mechanisms, especially key-value attention mechanisms, are widely used in neural networks (Bahdanau et al. 2015). The key-value mechanisms are composed of a query, keys, and values. The query and the keys generate an attention map, which extracts a value from the values. An attention map is similar to a pointer, often used in symbol processing. It is also a type of distal access (Newell 1980b), which uses an abbreviated tag for referring to a structure. A symbol is informally regarded as a small representation of an object, which provides “remote access” for the fuller representation of an object (Hinton 1990).

Transformers (Vaswani et al. 2017) are modern neural network architectures with self-attention. Recurrent Independent Mechanisms (Goyal et al. 2021c) use attention mechanisms and the names of the incoming nodes for variable binding. Global workspace (Goyal et al. 2022) improves them by using limited-capacity global communication to enable the exchangeability of knowledge for systematic generalization. Discrete-valued communication bottleneck (Liu et al. 2021) further enhances the generalization.

Different extensions to attention modules are discussed (Oren et al. 2020). Auxiliary objectives to bias attention in encoder-decoder models are proposed (Yin et al. 2021, Jiang and Bansal 2021). There are also sparse variants (Shazeer et al. 2017) of attention. Compositional Attention (Mittal et al. 2022a) disentangles search and retrieval in Transformer architecture. It addresses redundancies in multi-head attention with different numbers of searches and retrievals and
dynamic selection.

We like to discuss the relationship between the attention mechanism and ICMs. The sparse connection prior knowledge (Bengio 2017) has two types. The first is the sparseness on a dynamic graph or the routes for each sample. It corresponds to attention mechanisms. The second is the sparseness on a static graph or the connections between variables. It corresponds to ICMs. ICMs enable systematic generalization. The dynamic sparseness may not infer the static one, so attention may not establish ICMs to enable the generalization. However, attention reduces the size of a module input, so test inputs are more likely to remain in the training domain, which helps systematic generalization. For example, a word is a part of an input sentence, so an attended word can be correctly processed, even if the sentence is unseen. Also, the attention mechanism is usually an operator and does not contain parameters, so the mechanism suffers less from the change of distribution.

8.4 Modular architectures

Modular architecture has a long history, such as the mixture of experts (Jacobs et al. 1991) (Jordan and Jacobs 1994). Early related ideas apply micro-inference, which uses some of the features of some of the role-fillers to infer some of the features of the other role-fillers (Hinton 1990). There are also recent results (Graves et al. 2014; Andreas et al. 2016; Hu et al. 2017; Vaswani et al. 2017; Goyal et al. 2021; Mittal et al. 2020; Ke et al. 2021).

Modular architectures are natural for combinatorial generalization (Battaglia et al. 2018). There are task-specific modular networks (Jacobs et al. 1991). Though modules can be designed for different factors, the input to each module may still have spurious influence from other factors when the model input is entangled. It can be helpful to regularize entropy to bottleneck modules in such cases (Li et al. 2019).

Attention mechanisms can be used with modular architecture (Rieger et al. 2016; Peters et al. 2017; Mittal et al. 2022a). Object-centric slot attention (Locatello et al. 2020) finds objects for downstream networks. Neural Interpreters (Rahaman et al. 2021) factorize inferences to modules in a self-attention network. It can be trained end-to-end by routing through modules.

Modular and compositional computation (Rosenbaum et al. 2019) in routing networks were analyzed. A differentiable weight mask is used to examine the modularity of neural networks. It finds that neural networks are not trained to be modular. Common modular architectures are assessed (Mittal et al. 2022a) with collapse and specialization problems, finding end-to-end learned modular systems are not optimal.

8.5 Specialized architectures

Another common approach is specialized architecture design (Russin et al. 2019; Gordon et al. 2020; Liu et al. 2020; Chen et al. 2020). The importance of design decisions is reported (Ontanon et al. 2022).

Transformers significantly improve semantic parsing when model configurations are carefully adjusted, and Universal Transformer variants also work well (Csordás et al. 2021). Reordering and aligning the structure (Wang et al. 2021a) can model segment-to-segment alignments with a neural reordering module for separable permutations. The span-based parser (Herzig and Berant 2021) treats a tree as a hidden variable.

Large pre-trained language models convert inputs to intermediate language representations for semantic parsing (Shin et al. 2021). Intermediate representation helps compositional generalization for pre-trained seq2seq models (Herzig et al. 2021). Program synthesis (Nve et al. 2020) learns explicit programs from training data. Semantic tagging (Zheng and Lapata 2021) trains an alignment tagger by entity linking with λ-calculus and SQL expressions. It uses tags to supervise hidden variables. Iterative decoding (Ruiz et al. 2021) breaks training examples down into a sequence of intermediate steps.

8.6 Data augmentation

Data augmentation is primarily for language tasks, as words and phrases in a sentence are more straightforward to modify than the pixels in images. Multiple approaches are proposed for adding data (Guo et al. 2021; Wang et al. 2021b; Guo et al. 2020) and training from labeled data (Yu et al. 2021; Zhong et al. 2020).

GECA (good-enough compositional augmentation) (Andreas 2020) is a rule-based protocol for sequence modeling. It provides inductive bias for compositionality. It can replace discontinuous sentence fragments, e.g., “Tom picks apples up.” R&R (recombine and resample) (Akşu et al. 2021) learns schemes for data augmentation. It replaces the symbolic generative process with neural models and obtains the inductive bias as explicit rules.

Data recombination (Jia and Liang 2016) injects task-specific prior knowledge for modeling logical regularities in semantic parsing. It induces synchronous context-free grammar from training data. It is also studied that the diverse sampling structure of synthetic examples helps systematic generalization (Oren et al. 2021). CSL (Compositional Structure Learning) (Qi et al. 2022a) is a generative model with context-free grammar induced from training data. The examples from CSL are recombined and used to fine-tune a pre-trained model. It is studied to use subtree substitution (Yang et al. 2022) for data augmentation.
There is also data augmentation for images, e.g., interpolating both image input and label output (Yao et al. 2022). Stable learning (Zhang et al. 2021) learns weights for training samples to remove dependencies between features.

9 Conclusion

Systematic generalization is a critical capability for artificial intelligence. While it is straightforward for classic symbol processing approaches, it is difficult for Connectionist approaches. It has been discussed with crucial problems of variable binding and causal learning. Our discussion covers different AI fields, such as language, vision, and VQA, and there are recent improvements in different aspects. Though some specific problems are addressed, there are still many things unknown about systematic generalization in deep learning. We hope this survey helps in understanding the background and inspiring future work.

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