Feature Interactions on Steroids: On the Composition of ML Models

Christian Kästner, Eunsuk Kang, Sven Apel

Much has been written about how machine learning changes software engineering practices in big and small ways [e.g., Sculley et al., 2015, Amershi et al., 2019, Ozkaya, 2020, Kästner and Kang, 2020]. Among all differences, the lack of specifications comes up again and again and has rippling effects on all kinds of other practices. Here, we discuss how it drastically impacts how we think about divide-and-conquer approaches to system design, and how it impacts reuse, testing and debugging activities.

Traditionally, specifications provide a cornerstone for compositional reasoning and for the divide-and-conquer strategy of how we build large and complex systems from components, but those are hard to come by for machine-learned components. While the lack of specification seems like a fundamental new problem at first sight, in fact software engineers routinely deal with iffy specifications in practice: we face weak specifications, wrong specifications, and *unanticipated interactions* among components and their specifications. Machine learning may push us further, but the problems are not fundamentally new. Rethinking machine-learning model composition from the perspective of the *feature interaction problem*, we may even teach us a thing or two on how to move forward.

1 Challenges in Composing ML Models

Let's jump right into the problem with an example from the excellent AAAI'17 paper *"On human intellect and machine failures: Troubleshooting integrative machine learning systems"* [Nushi et al., 2017]. The paper discusses a system with the goal to generate captions for images, which was part of a machine learning competition (see Fig. 1).

Notice that *the problem and what makes a good solution is somewhat fuzzy*, which will become a key point in a second: Given an image, provide a description for that image. A number of examples of good descriptions are provided (for training and evaluation), but there is no clear, formal specification of what makes a caption *"correct"* or *"good."* It is important to note that we use machine learning (in this case) exactly because we do not have a specification in the first place! The goal is to automatically find heuristics that best imitate human (or any other) behavior without explicitly specifying it—this is *inductive reasoning*: learning rules from observations. In fact, in said research competition, the quality of a solution is eventually judged by humans, who rate the

Figure 1: Example images and corresponding captions from the COCO competition [Cui et al., 2015]

quality of captions generated for example images, not by checking results against fixed rules. Needless to say, different judges may come to different conclusions.

Building such a captioning system with a single model is a huge step. Instead, the state-of-the-art approach discussed (which comes from another paper [Fang et al., 2015]) *decomposes the problem* into three steps, each with a separate ML model, as shown in Figure 2:

- **Visual detector:** First, a convolutional neural network is trained as a visual detector with a vocabulary of 1000 objects, which attempts to identify what kinds of objects are present in the image and produces corresponding confidence scores. This component takes an image and produces scores for different objects: `Image -> List[(Objectname, ConfidenceScore)]`.

- **Language model:** Second, a maximum-entropy language model is trained on many image captions and used to generate plausible sentences with the words from the detected objects. This component will generate 500 sentences with different subsets of the detected objects. The key here is to generate sentences that contain some of the words for the detected objects and that are likely and plausible based on typical grammatical patterns and word frequencies appearing generally in image captions—but without any actual information about the image beyond what objects are (possibly) in it. For example, the model would hopefully generate "a mountain covered in snow" as a more likely phrase than "a mountain skiing downhill". For each sentence, the model also produces a likelihood score that indicates how well this sentence mirrors typical image captions: `List[(Objectname, ConfidenceScore)] -> List[(Sentence, Likelihood)]`.

- **Caption ranker:** Finally, a deep multimodal similarity model, consisting of two

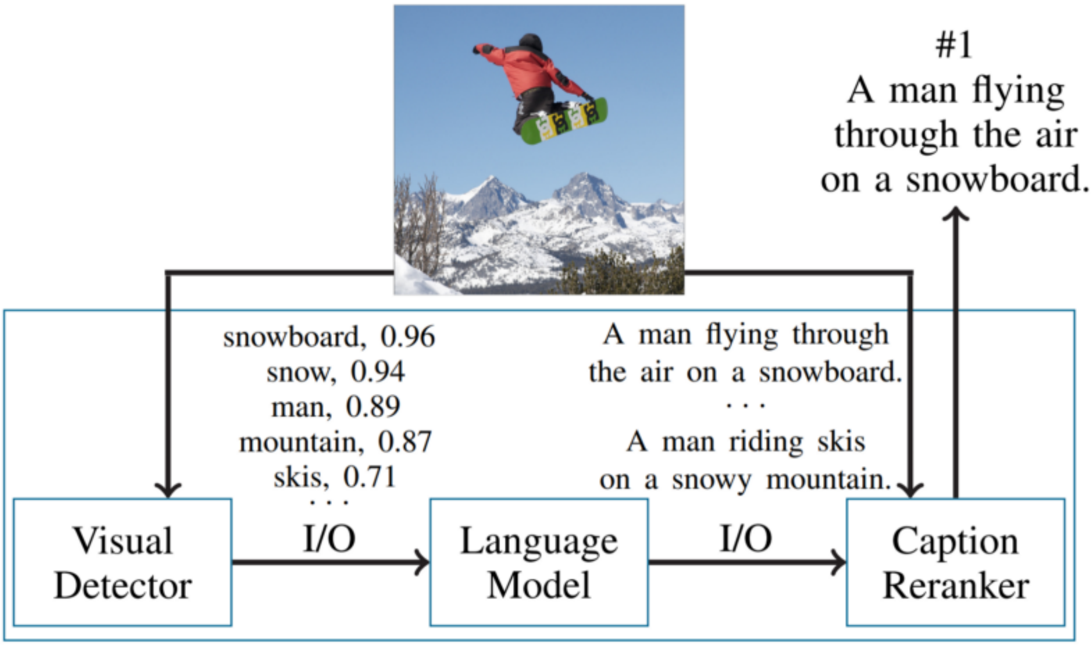

Figure 2: Three-step architecture of the image captioning system [Nushi et al., 2017]

neural networks, takes both the original image and the generated sentences, extracts features from both, and scores the combination (don't ask for details, please). The component then picks the sentence with the best score. Internally, the ranker uses multiple features, including objects detected in the image (similar to the visual detector) and the similarity between the vector representations of images and captions. This component has the signature: `Image -> List[(Sentence, Likelihood)] -> Sentence`.

At a first glance, this looks like a great divide-and-conquer story: We can think about how a human would break down the task and then let the solution (partially) mirror some of those steps, such as recognizing objects and formulating short plausible sentences about those objects. Each component can be developed, tested, and even deployed independently, using different modeling and implementation techniques. We can describe the interface (signature, types, invariants, etc.), deploy them as microservices, and roughly describe the intended behavior of each component. These components (especially, the detector and the language model) may be general-purpose and reused in other contexts. Moreover, independent teams can work on improving each of the components. At a technical level, it is fairly straightforward to compose a system with these three components.

1.1 Problem #1: Assigning blame

At a second glance, various problems emerge: If something goes wrong somewhere, and we get a poor caption for an image, what caused the problem? How can we improve the system? How do changes to one component affect the rest of the system? For example, in the AAAI paper, the system is reported to create the caption *"A blender sitting on top of a cake"* for the image in Figure 3, but why?

When looking at the individual steps in Figure 3, the authors see that potentially all components can be blamed:

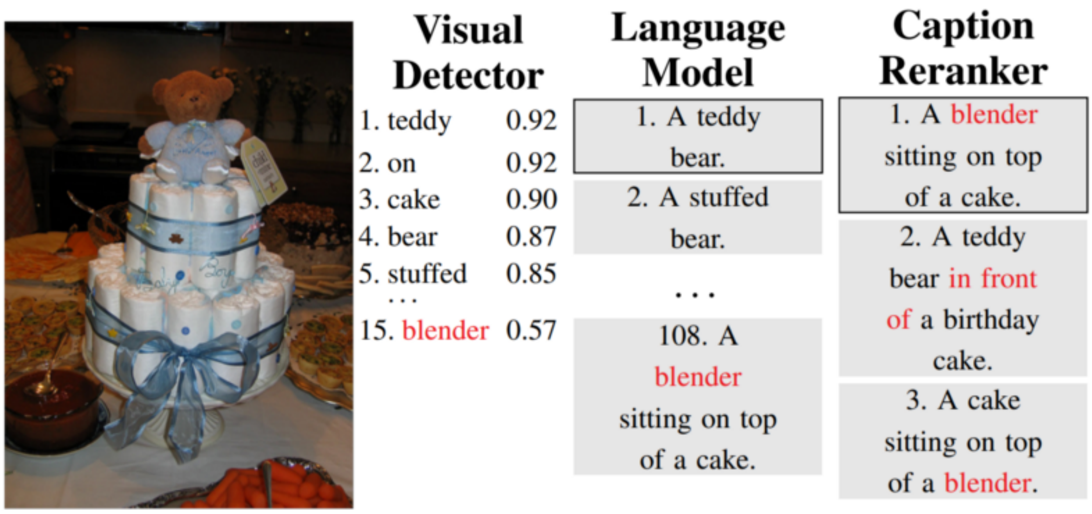

Figure 3: Problems in each component leading the to the poor caption *"A blender sitting on top of a cake"* (from Nushi et al. [2017])

- First, the visual detector detects a blender where there is none. To its credit, the confidence score is fairly low, but we can clearly consider this a mistake.
- Second, the language model takes these words and suggests "a blender sitting on top of a cake" as a plausible sentence containing the detected words "blender", "on", and "cake". We might argue to give this component some slack, because "blender" probably should not be part of its input, but even for the given input words, the produced sentence does not seem quite right, given that a "sitting blender" is not a very plausible expression, i.e., the model shows low common-sense awareness. It's ranked 108 out of 500 generated sentences.
- Finally, the ranking algorithm picks that sentence, even though it includes a word with a low object detection score. Actually, none of the top-scored sentences seems particularly great.

So, no component is behaving perfectly or compensating enough for problems in other components. It seems hard to blame a single component. There are no clear responsibilities or boundaries between the components. If we had only a limited budget for improving the system, which component should we start with?

1.2 Problem #2: Nonmonotonic errors

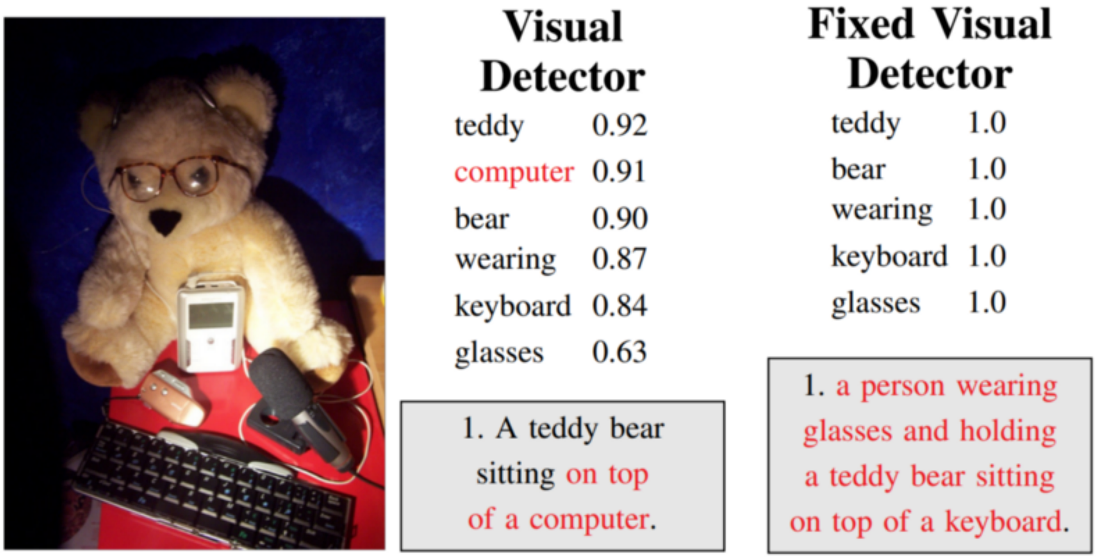

Figure 4: Results get worse if output of first component is fixed (from Nushi et al. [2017])

It gets worse though. One would hope that by improving any one component of the system, overall results would improve. Unfortunately, this is not always the case. In Figure 4, we show another example from the paper: The initially generated caption *"A teddy bear sitting on top of a computer"* is not great, given that there is no computer in the picture. However, if we fixed the object detector for this example (i.e., removing "computer" and setting confidence of all objects actually present to 1.0), the caption get's clearly worse: *"a person wearing glasses holding a teddy bear sitting on top of a keyboard."* It's hard to give a causal explanation for what happens here, but it seems that, with larger emphasis on "glasses", a sentence that includes glasses is picked, but the language model probably rates a "teddy wearing glasses" as less plausible than "a person wearing glasses" and thus makes up an object not originally detected.

Note that the language model was somewhat robust to imperfect inputs: The component and the overall system usually works even with mistakes in the object detector. The language model does not expect or require perfectly accurate inputs and making up new objects for more plausible captions is perfectly okay. Generally, some models may even learn to compensate for common mistakes in their inputs.

The key problem is that it is not always the case that improving one component improves the overall system's quality. So, if we already have a problem with composing three models, how are we expecting to build reliable systems with many more ML and non-ML components, say the 18 models in Baidu's self-driving car system Apollo shown in Figure 5.

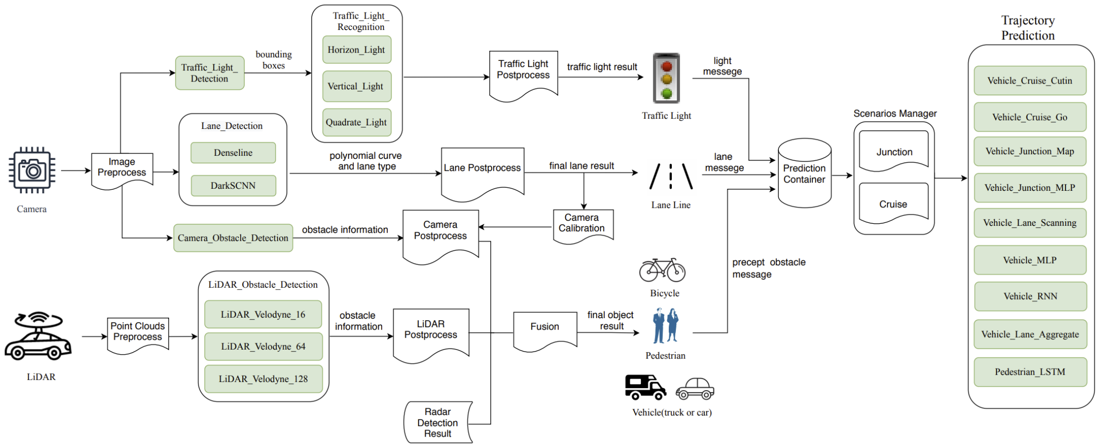

Figure 5: High-level architecture of Apollo and the 18 ML models composed in a system to autonomously drive a car—graphic from Peng et al. [2020]; see the paper for details on the models and their inputs and outputs.

2 The Root of the Problem: Lack of Specifications

The problem with reasoning about and composing ML models is that we do not have clear specifications for what they are supposed to do. A traditional specification would tell us for a given input whether a produced output is correct or not. Specifications are powerful for divide-and-conquer design strategies, for modular reasoning, and for assigning blame.

Let us contrast the ML captioning system with the most boring non-ML system we can think of: *computing taxes*. Also here, we probably do not want to do all computations in a single step, but break the system down into components. For symmetry let us just stick to three components again, illustrated in Figure 6: one for computing the adjusted gross income (some notion of what income counts for tax purposes, do not ask), one for computing deductions (where some deductions depend on the income brackets), and one module to generate the text of the actual tax return.

We can again define an interface for each component (`computeAGI: Data -> Int`; `compute-deductions: Data -> Int -> Int`; `report: Int -> Int -> String`), but more importantly, we know exactly what the system and each component is supposed to do, what its responsibilities are, and what it expects from other components.

Based on provided inputs, a computed tax return is *either correct or wrong*. It is not "pretty good" or "95% accurate" as judged by a human expert; it either works as specified and produces the right result or it does not. We also would not accept it producing correct tax returns for 98% of all users, but would instead consider it as a

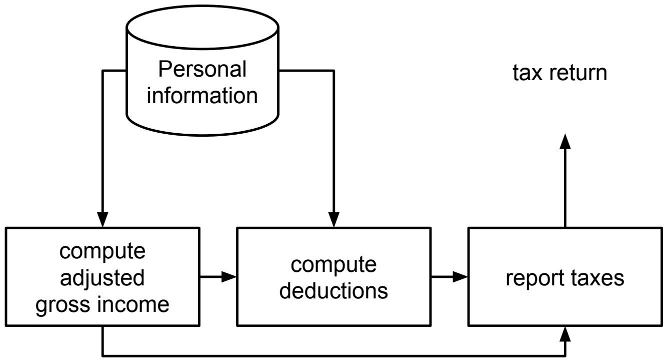

Figure 6: Possible system decomposition for computing taxes

problem if it produced a wrong result for any single valid input.

If the output is wrong, we can *assign blame* by checking whether the income, the deductions, and the report were computed correctly based on their respective given inputs. Again, each component's output is either correct or wrong for the provided inputs. If a person's reported deductions are wrong, but that's due to incorrectly computed adjusted gross income, we would not blame the deductions or reporting component (they work correctly for the inputs they were given) but would blame the compute-adjusted-gross-income component that produced the wrong value used by the others.

Similarly, if we fix a bug in a component to produce the correct component output, this should never decrease the correctness of the system. We may expose further bugs in other components that previously were suppressed by the bug that is now fixed upstream, but those other bugs were already there.

Decomposition works often in traditional software systems because we can specify the behavior of individual components. With *deductive reasoning* based on logic, we can understand the consequences from combining two modules in terms of the composed specifications. This is a cornerstone to a sound divide-and-conquer strategy and *modularity*. If each component produces the correct outputs for the given inputs, so does the composed system—this is, at least, the idea. If something breaks, we analyze which component is responsible. Specifications even open the door for *modular reasoning* and *information hiding*, where to understand a component, one only needs to understand its inputs and the interfaces and specifications (but not internal implementations!) of all other used components. This is how software engineers were able to build and compose so much reusable code in libraries and software ecosystems, where we can compose layers and layers of abstractions, but this is a discussion for another day.

Real Specifications. . . To be frank, we should acknowledge that, in practical software engineering, we almost never see the strong formal specifications as covered in computer-science textbooks. Most specifications are textual and informal, such as API documentation for most libraries. We also routinely work with systems that have only weak or implicit specifications that cover only part of the behavior, miss side effects, or do not cover important qualities like resource consumption—if we have any written specifications at all. The fact that most specifications are informal or not even written down at all does not prevent us from reasoning about compositions: We still can *in principle* provide a specification on demand, and we can use that understanding of the specification to assign blame (or renegotiate with the component's consumer what the specification should be).

3 Back to Machine Learning...

For machine-learned components, we do not have any meaningful specifications in the traditional sense that could tell us whether an output is correct for any given input which we could use to judge whether a model works correctly for all possible inputs. For many problems, we already have a hard time capturing what it means for a single prediction of a model to be "correct" (multiple humans may not agree).

Even if we had a strict binary notion of correctness for any single prediction, we would *not* expect a model to make correct predictions for every possible input. In traditional software engineering, if we find an input-output pair that does not match the specification, we consider this as a *bug*. In contrast, in machine learning, we know to expect occasional wrong predictions. For some hard problems, we would actually be quite happy if even just 30% of all answers were correct, for other problems 99% accuracy is okay but not great. In line with the aphorism *"all models are wrong, but some are useful,"* we do not evaluate the *correctness* of a model but whether the model mostly *fits* our problem. We evaluate fit as a relative measure, typically some form of *prediction accuracy* over some (hopefully representative) input-output example, not as a binary correctness criteria for the model. This does not compose nicely.

While they do not have specifications in the traditional sense that relate any inputs and outputs, there are still some things we know and can reason about. We still have an intuition or goal for what a model is supposed to do, be it detecting objects or generating plausible sentences. We may have some invariants, such as fairness requirements that we can even state formally. And we usually also have an intuition of how we expect components to behave when composed, as in our image captioning system, even though we may not be able to logically deduce that behavior from the component's behavior. That is, practical non-ML software and machine-learned models are not at opposing extreme ends on a spectrum between strong and no specifications and our activities in developing and assuring them should reflect this. While there are important differences, there are also lots of similarities, as we will see.

Side note: In the broader field of artificial intelligence, there are numerous techniques that go beyond learning heuristics from observations. Beyond machine learning, *symbolic* AI techniques are often based on deductive reasoning [Russell and Norvig, 2020], often with nice compositional properties, for example, many traditional planning and control problems encoded as constraint satisfaction problems. Also probabilistic reasoning about uncertainty is compatible with specifications and facilitates clear reasoning about composition, though researchers still actively work on technical challenges to scale technical inference or verification steps needed for many problems [Pfeffer, 2016].

4 The Limits of Decomposition: Feature Interactions (Emergent Behavior)

While it may seem that decomposition in traditional software systems is obvious and clean, unfortunately, that is not always the case either. It is not even just a question of whether we write formal or informal, strong or weak specifications, but a question of whether this would be possible in the first place. The study of the *feature interaction problem* in software engineering has made this ample clear.

So what are feature interactions actually? Sometimes a mandated decomposition of a system is simply way too optimistic, and we are missing interactions that should have been obvious from a component's specifications, but were not. In most of these cases, we make, accidentally or even intentionally, wrong assumptions about the environment and about how a component interacts with the environment and other components (see environmental assumptions in *the World vs the Machine* [Jackson, 1995]). We say that two components (or features) *interact* in unanticipated ways, giving rise to a *feature interaction* or say that new behavior *emerges* from the composition of multiple components, referred to as *emergent properties* in systems engineering. Note "feature interactions" here is not to be confused with interpreting how data features interact within an ML model [Molnar, 2020].

There are many examples of feature interactions, and they typically follow a common pattern: We decompose the system into components, then design, develop and test these components separately, but finally observe unexpected behavior when composing them. The canonical example is a *call forwarding* feature in a phone system that competes with a separately developed *call waiting* feature on how to respond to the same call on a busy line, but there are many examples where components in cars or smart home systems interfere with each other when combined. We can usually blame each problem on weak specifications that did not anticipate the interaction, but in general the problem is much bigger.

4.1 Decomposition fallacies in complex systems

In complex systems, especially systems that live in the real world, it is often not possible to nicely separate behavior and divide a problem into subproblems cleanly. Behavior in many real systems is antimodular.

Let's postpone problems with the real world for a second and consider an example of feature interactions at the software level: two WordPress plugins that try to transform the same part of a blog post: "`[:weather:]`" and "`:]`" but, depending on their order, the output may differ. The behavior of both plugins can seemingly be well specified in isolation in that each plugin takes the blog post and modifies it in an intended way, but we may not get the result we expect if we compose them. Conceptually the problem is that the plugins do not necessarily get the original blog post, but instead may receive input already modified by other plugins, without being aware of these plugins, possibly resulting in mangled output like "`[:weather`☺" (see Fig. 7). The interaction is clearly foreseeable if we had known about the other plugin and thought about it (overlapping

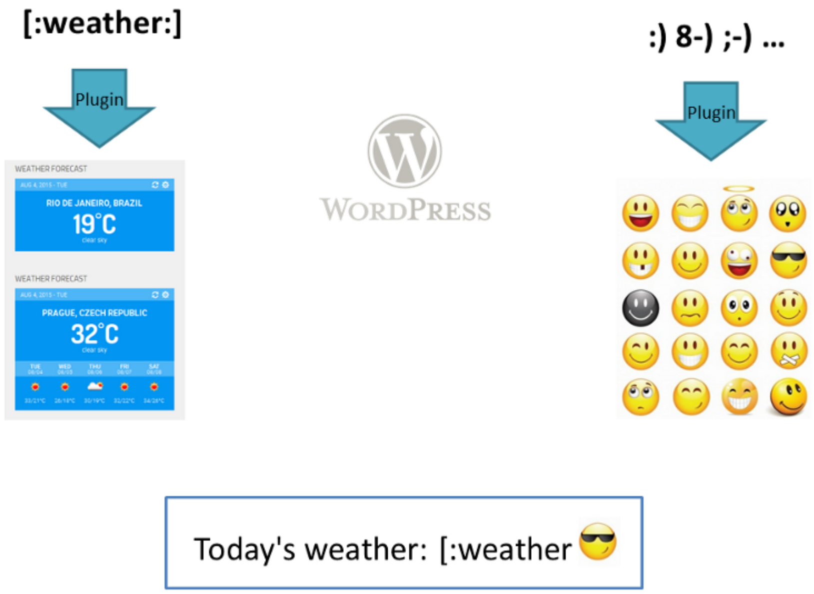

Figure 7: Interaction between two independently developed and tested plugins in a blogging software

preconditions, resolvable by explicit ordering), but there are just so many plugins and potential interactions to consider—after all, the number of potential interactions among plugins grows exponentially with the number of plugins. It is not obvious, though, how one could come up with a better specification for each plugin, without thinking through all possible plugin compositions upfront: If both plugins explicitly assumed the original blog post as input, they would not be composable; alternatively, if plugins always had to assume arbitrary other transformations on their input first, they could make no meaningful specifications about how their behavior relates to the user's blog post. That is, we have to look at specific combinations of components and cannot just reason about them separately, largely breaking our divide and conquer strategy.

It gets much worse when the *real world*™ is involved, as in cyber-physical systems: Consider a home automation system with a heating component, a ceiling fan component, and a component to control opening windows. We could specify the behavior of each controller to some extent and reason about how each component interacts with the environment. However, in the environment, the actions of the different components may influence each other through physical processes (e.g., warm air from the heater moves through the ceiling fan to the open window). They may also compete for the same resources, such as electricity or human attention. To truly understand how the different components behave in concert in the home automation system, we would need to fully understand the environment, in addition to the actual components. For example, if we wanted to fully specify how each component influences the room temperature, such

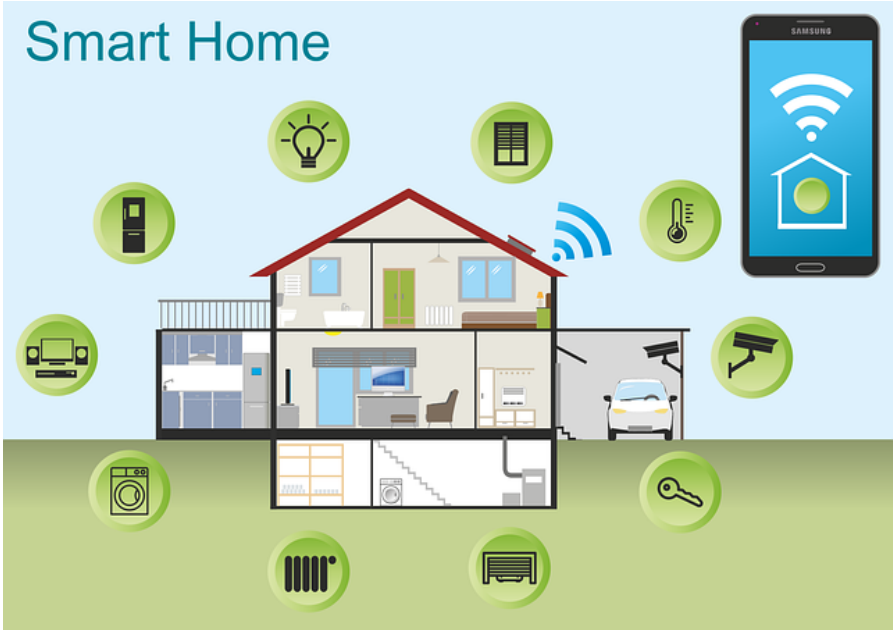

Figure 8: Smart home system in which all kinds of independent devices can make decisions, possibly interacting in unintended ways.

specification may need to involve aerodynamic physics and the specific layout of the house and a clear understanding of how other components behave—such a full environment model is clearly unrealistic in practice. And even if we could model the environment, we could not reason about components individually, but only about the system as a whole. As requirements-engineering researcher Michael Jackson framed it during a discussion at a Dagstuhl seminar: *"the physical world has no compositionality."*

4.2 Decomposing anyway

A key insight from the study on feature interactions and systems engineering broadly is that, even when systems are complex, we decompose them anyway, and, necessarily, we make simplifying assumptions that may not actually hold. Humans simply cannot deal with complexity beyond a certain scale—we do not have the *cognitive capacity*. We need to abstract and decompose. We may make simplifications out of ignorance, but we may also make them knowing very well that our decompositions are not perfect. We may intentionally create specifications that are weak or even wrong for specific cases. We may do this intentionally for good reasons, hoping that we can resolve issues at composition time.

For example, in WordPress, we may pass a partially processed blog post through multiple plugins knowing that we cannot cleanly separate their effects. In the home automation setting, we separately design components knowing that we are unlikely to ever understand how exactly they interact in a specific environment. In fact, the feature interaction problem gained popularity when, in the early 1990s, telephone systems became more and more sophisticated and added more features, such as call forwarding, that were deployed in different hardware components of larger interconnected telephone networks with different network providers, customer devices, and many device manufacturers—complexity soon exceeded the cognitive capacity of developers, and it became hard to foresee interactions within a single device, let alone between networked devices from different manufacturers. In all cases, a divide-and-conquer approach is unavoidable to cope with complexity, even knowing that decompositions are not clean. We simply have no other choice to deal with real-world complexities in current engineering practices.

While humans are forced to decompose complex systems to handle complexity, the good news is that, *most of the time*, a divide-and-conquer approach pays off and imperfect decompositions work. Most of the time, we decompose systems, making a number of assumptions that we know are not perfectly true, hope to catch inadvertent interactions at composition time or at runtime, and mostly it works out in practice. For example, most plugins work well together in complex systems such as WordPress, Chrome, and Thunderbird. In the home automation system, we can use control mechanisms and dynamically adjust for interactions rather than to plan the exact interactions of components. The problem are those remaining unanticipated interactions from too weak or wrong specifications that surprise us, sometimes badly with severe consequences, such as a fire control system malfunctioning.

5 Coping with Feature Interactions

Feature interactions are not a new phenomenon. They have been actively studied, at least, since the 90s' focus on telecommunication systems, and as *emergent properties* they are an important aspect of system engineering. The community has learned how to build systems that work reasonably well despite weak or even partially wrong component specifications. Dedicated analysis, design, and control techniques anticipate and compensate for these kinds of modularity problems.

While not a silver bullet, it is likely that there are insights from a long tradition of coping with feature interactions that may help us to better understand and build systems composed with multiple machine-learned components and traditional components. In both worlds, we explicitly deal with modularity and composition problems stemming from weak or missing specifications. The thoughts and parallels below are a starting point.

5.1 Detection through testing

The first most obvious insight is that unit testing or component verification are clearly not sufficient, even in traditional software systems. That is, it cannot be sufficient to check whether each component meets its specification, but we also need to test whether the composed system as a whole indeed behaves as expected. This is where the importance of *integration testing* and *system testing* comes from.

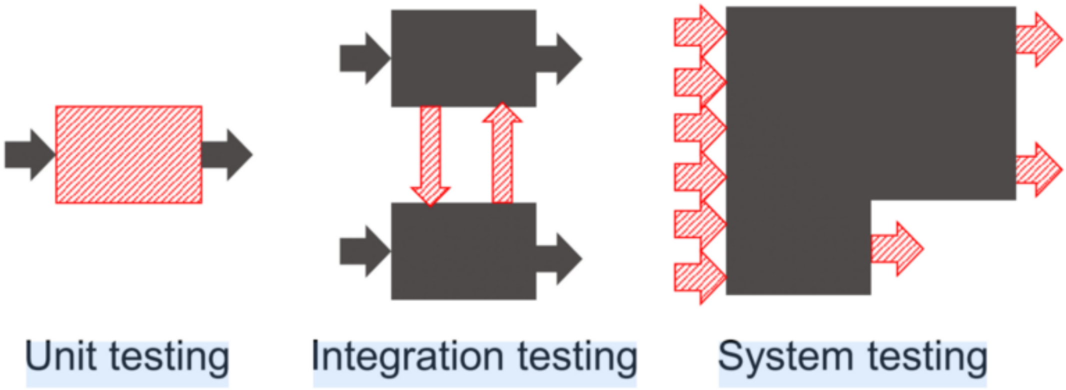

Figure 9: Testing at different levels: Unit testing, integration testing, system testing

This observation holds also for systems with machine-learning components, which is just another reminder not to stop at measuring prediction accuracy on a test dataset (which itself can already be challenging to do well), but to evaluate the entire system in production and measure system goals (e.g., sales, customer satisfaction).

Considering feature interactions can also influence what kind of tests to write for integration testing. Anticipating potential feature interactions, we may want to write tests for behavior that should be invariant whenever the component is included in a system. For example, both plugins of the WordPress example could come with a test case checking that the plugin correctly transforms a relevant blog post independent of any other plugins installed (e.g., the Weather test would fail if the Smiley plugin is active at the same time, thus detecting the interaction) [Nguyen et al., 2014]:

```
function testWeather() {
   if (plugins.contains('weather')) {
       output = runWebPage('index.php', 'Today is [:weather:].');
       assertMatch(output.getElementByXPath('/html/body/div[1]'),
                   'Today is \D+ degree.');
   }
}
function testSmiley() {
   if (plugins.contains('smiley')) {
       output = runWebPage('index.php', 'Hey there :]');
       assertMatch(output.getElementByXPath('/html/body/div[1]'),
                   '.*<img "...">');
   }
}
```

In systems with machine-learned components, one can imagine similar tests of contributions of individual components to the overall system behavior, for example, the image captioning system should always produce short descriptions independent of what objects are detected or how the results are ranked. The traffic light detection in a self-driving car should reliably detect obvious examples of traffic lights independent of other components that may, say, involve detection under challenging conditions involving a map or filter inputs against adversarial attacks. Here, the test case could be represented with a test dataset on which to achieve consistently high prediction accuracy, independent of other components.

5.2 Detection through better specifications, formal specifications

A long history of research on feature interactions has shown that better requirements engineering can help to anticipate interactions, often through systematic inspection of potential interaction points, or actually writing down and mechanically checking compatibility of specifications.

With strong specifications, we can detect conflicts between multiple component specifications and the system specification. For example, we could notice overlapping preconditions of the WordPress plugins' transformations and thus detect a conflict at design time. If specifications are written in a machine-readable format, various analysis tools such as theorem provers and model checkers can help to reason about potential composition problems.

Weak and informal specifications can still be useful to detect many problems. For example, *goal models* that describe the goal of each component can help to identify overlapping and conflicting goals (e.g., heating, cooling, and opening windows in the home automation scenario). Similarly *resource models* that describe which external resources components consume or control can help to detect conflicts, such as multiple home automation components competing for electricity or human attention in certain situations or a smart switch controlling the power supply depended on by a space heater.

Even without tools and formal specifications or models, just by looking at pairs of components, it is often possible to detect possible interactions during a manual inspection step. Such a manual pairwise analysis is quite common in practice for detecting possible interactions (researchers have actually held competitions to find interactions within requirements in the 90s [Calder and Magill, 2000]), and it is often guided by looking at probable interaction points, accessed resources, environment assumptions, goals, and preconditions of components. In their survey paper, Nhlabatsi et al. [2008] provide a concise overview of common kinds of conflicts and different kinds of interactions that can help to guide an inspection. If a possible interaction has been detected, it may be worth writing down additional specifications about how to resolve it appropriately at runtime (e.g., the weather plugin having priority over the smiley plugin).

In a machine-learning context, we may be able to reason to some degree about goals, resources, and maybe even weak specifications to detect certain kinds of possible interactions, especially if models interact through the environment and shared resources. However, given how hard it is to provide even weak specifications, leveraging system design might be a more promising solution.

5.3 Design for isolation and domain-specific resolutions

Likely the most powerful strategy in addressing the feature interaction problem is to prepare for unknown interactions as part of the design process. That is, instead of trying to identify specific interactions with testing or requirements analysis, we anticipate the possibility of some unknown interactions as part of the system design: We design the system to (1) prevent certain interactions by *isolating* components or (2) prepare for automatically *resolving* interactions when they eventually take place.

Isolation: A common strategy to avoid interactions is to isolate the effects of individual components. For example, in WordPress, plugins do not transform the entire page, but individual parts, such as the blog post or the header links, such that plugins changing different parts do not interfere (though technical enforcement is not as strong as it could be). In Android, apps are largely sandboxed and cannot access each other's internal state, each other's files, or each other's screen output.

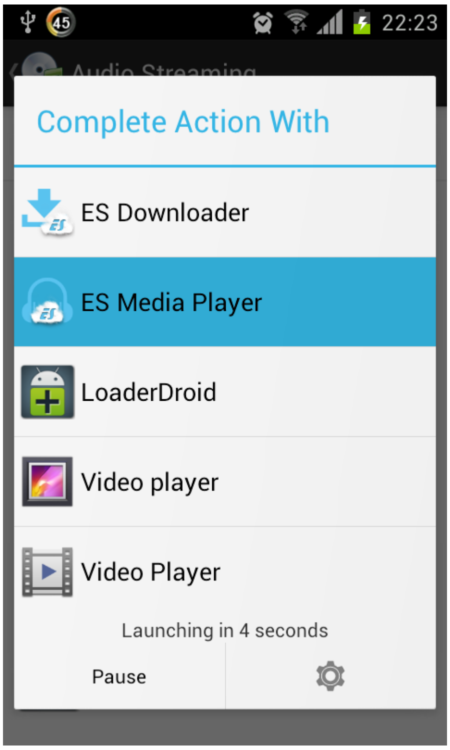

Figure 10: System-wide interaction resolution in Android: When multiple apps can respond to a request, the system asks the users.

Even when possible, *full* isolation is rarely desired, as components should often work together in intended ways. Such designs will therefore typically allow specific kinds of interactions, but often require to use permitted and possibly controlled communication channels. For example, WordPress allows multiple plugins to extend individual extension points, each allowing only limited transformations. Android provides well-defined communication channels ("Intents" and system APIs) controlled by the operating system, which ensures that only certain messages in certain formats can be exchanged; the system can even intercept, modify, or block messages at runtime if it serves the system specifications, such as not making phone calls without the corresponding app permissions. This design limits interactions to much more controllable points.

Resolution: An interaction can be resolved manually once it has been detected by adding *coordination logic.* Resolution typically consists of one component overwriting the behavior of another (e.g., disable cooling while the heater is running), ordering components (e.g., always run the smiley plugin last), adding some logic combining results (e.g., when multiple components suggest conflicting target temperatures, take the average). Anticipating the need for resolution, e.g., by enabling flexible reordering, will make it easier for developers or end users to resolve interactions when found.

Beyond resolving interactions once they are detected, clever system designs can automatically select default resolutions. That is, while we may not be able to anticipate specific interactions or prevent interactions through isolation, we can anticipate that some interactions will eventually happen and design the system to handle unknown interactions gracefully. Automated resolution is usually preferred over manual resolution if possible, as resolving every interaction individually is tedious and we may not detect an interaction in time before some harm is done.

In several domains, automatic *domain-specific default resolution* mechanisms have been very successful [Bocovich and Atlee, 2014, Jackson and Zave, 1998, Zave et al., 2015]. For example, in self-driving cars, multiple components (cruise control, emergency braking, map) may provide possibly conflicting suggestions for the target speed (i.e., interaction through a specific target variable). Anticipating these conflicts, the system can be designed to resolve these conflicts by *always* picking the lowest (safest) suggested speed [Bocovich and Atlee, 2014]. In Android, it is impossible to foresee all app interactions, but the system is designed to ask the user when multiple apps can respond to a request, such as playing a video in Figure 10—again a default resolution strategy is baked into the system design. It is important to note that these strategies usually need to be designed for a specific problem, which is their strength and weakness at the same time: on the one hand, the system can resort to resolutions that leverage domain knowledge, but, on the other, it is difficult to transfer this type of solution to other domains.

Default resolution strategies are usually designed for a target domain such that they usually yield a good, best-effort result, without having to foresee all possible interactions. Even if the result may not be the perfect answer, because the component specifications are truly incompatible (e.g., overlapping preconditions, conflicting goals), a resolution strategy is typically designed to pick a consistent answer (e.g., following priorities) that is safe for the task at hand.

The design of many machine-learning systems that are composed of multiple models seem to already align quite well with this strategy of resolving interactions at specific communication points: Machine-learned components are already largely isolated (and wouldn't directly access or modify each other's internal state) and communicate only through limited messages. For example, *data fusion* steps to combine outputs of multiple models are common (e.g., visible explicitly in the Apollo architecture above). The fusion strategy can either be defined manually (like picking the lowest speed) or learned with another machine learning model (often called a meta model)—in both cases, it is usually a custom solution for the specific task at hand rather than a general-purpose fusion strategy. For example, a smart thermostat can learn the behavior of various smart home components and their interactions to learn to coordinate them better.

Interestingly, in our motivating image captioning scenario, the ranking component can be seen as a domain-specific fusion mechanism that combines outputs of object detection and language model. This ranking component is trained on task-specific data, so it may very well learn how to cover for inaccuracies in other components and how to resolve possible interactions. For example, it could learn to not trust sentences with "persons" in it, because it has identified problematic interactions of how the language model interacts with inaccuracies of the object detector on those entities. In this sense, the ranking component is carrying out coordination logic to resolve interactions that has been learned itself!

We suspect there are many opportunities to think very deliberately about communication channels and formats to restrict the kind of data exposed from models and more importantly data fusion steps to define or even learn default resolutions for interactions.

6 Different Reasons for Decomposition

In traditional software systems, we need to use a divide and conquer approach to handle complexity with our limited human cognitive capacity, and specifications are essential to make this work so that we can focus on one component at a time. Interestingly, machine learning algorithms do not share the same capacity limits; they excel at learning models with millions of parameters, finding patterns in high-dimensional feature spaces in huge data sets.

The primary reasons for decomposing machine learning problems seems to be (1) to infuse *structure* and *domain knowledge* into the solution and (2) to reuse models. By decomposing the image captioning problem, we can make it explicit that we think object detection and creating common-sense sentences with those objects are important ingredients in a solution, e.g., that we only present results generated by the language model. We can also reuse ML components trained on different data sets, such as learning the language model on a much larger dataset of captions without requiring corresponding images. By reusing ML components trained on other data, we may transfer some form of domain knowledge that we think will be a useful part of a solution. However, decomposition is only one of multiple possible design strategies to encode domain knowledge and reuse, others including feature engineering, tailoring deep neural network architectures and inductive biases, transfer learning, and augmenting training data.

The fact that decomposition is a *design option* in machine learning and *not a necessity* is very visible in the different submissions for the image captioning competition: some use decomposition, others learn a single model. Similarly, in research on self-driving cars, there is a tension between composing many models (as the Apollo architecture shown above) and learning a single end-to-end model that predicts outputs like steering angle directly from raw sensor inputs [e.g., Bojarski et al., 2016].

Furthermore, we use machine learning usually to reason about the world instead of abstract mathematical concepts. However, when reasoning about humans, vision, or languages, we have to accept that we are working with real-world concepts that do not compose nicely, concepts we cannot specify well, and concepts we might not even understand even when a model has learned them well. Hence it is not surprising that learned models do not compose nicely either.

7 A Call for Systems Thinking and Designing for Interactions

Even though the lack of proper specifications may make machine-learning models appear special as compared to traditional software systems, there are many parallels around how to design a system to anticipate interactions with a healthy dose of system thinking. That is, we need to focus on *system* design, not just the design of ML model architectures. Even though the reason for decomposition may be different, feature interaction thinking is still important, maybe more than ever.

The key point is to realize that decomposition without perfect modularity is okay. Decomposition is a best effort approach, but we need to anticipate interactions, prepare for them as part of the system design and development process, and make feature interactions a first-class concern to reason about them when they occur. We need to embrace design methods of managing interactions, and machine learning itself may provide a powerful tool in our toolbox for learning interaction resolution strategies.

At the same time, it is worth exploring what kind of specifications, however partial, we can provide for machine-learned models. Describing goals of models or assumptions made in training data selection or modeling can help to reason at least partially about compositions. Recent adoption of more structured documentation like model cards [Mitchell et al., 2019] and datasheets [Gebru et al., 2020] can provide inspiration for providing structured and possibly even machine-readable information about models.

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