Strategy Formation as Solving a Complex and Novel Problem

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ABSTRACT

In this paper, we seek to better understand how executives can intelligently combine modular and integrated problem solving processes to form the best possible strategy in entrepreneurial environments. To do so, we compare the efficacy of strategies formed via different processes under various market conditions, exploring the sources of significant performance differences. We address this question using NK simulation methods. We show that the 'decision weaving' strategy formation process leads to more effective strategies than either local or 'chunky search' processes across a variety of problem specifications. We also offer insight into two key concepts of the decision weaving framework; stepping stones and learning plateaus, which allow executives to balance the tradeoff between quality and the speed of the strategy formation process. This provides practical points for executives forming strategy to overcome their own bounded rationality and contributes to literature on strategy processes and complex problem solving within organizations.

Keywords:

Strategy formation, problem solving, strategic decision making, behavioral theory, simulation

Introduction

In 2007, Brian Chesky and Joe Gebbia were struggling to pay rent in San Francisco so they rented out their apartment to three conference attendees to help make ends meet (Tame, 2011). With this success, they began to believe they had stumbled onto a promising business opportunity for solving short-term housing needs. Yet recognizing this opportunity was a far cry from actually forming a strategy to capture it. The founders toiled for three years to determine the activities for hosts, guests, locations, and services that would become Airbnb. The process was difficult because no one had previously attempted what they were trying to do and each new activity they tried seemed to require changes to what they were already doing (Hempel, 2012).

Airbnb's story is far from unique. It is not uncommon for executives in entrepreneurial settings to see a promising business opportunity, but then falter in the course of strategy formation to capture that opportunity. Here, we define strategy formation as the process by which executives decide on a unique set of interdependent activities to create and capture value (Porter, 1996). By entrepreneurial settings, we mean contexts where both young and established firms compete in nascent markets or with innovation-driven strategies (Ott, Eisenhardt, and Bingham, 2017).

Strategy formation in entrepreneurial settings is particularly difficult for executives because it is both a novel and a complex problem (Ott *et al.*, 2017). On the one hand, the novelty inherent to new ideas and nascent markets means executives cannot know which individual activities will be superior without exploring a breadth of innovative possibilities for each strategic activity (Gavetti, Levinthal, and Rivkin, 2005). On the other hand, the complexity of fitting the various interdependent activities into a coherent strategy, where each activity adds value to the others, is difficult for executives because any single change may have unintended consequences for other activities (Porter, 1996; Siggelkow, 2001). In other words, strategy formation is difficult because high-performing strategies need to contain superior activities (for the given opportunity) *and* be a coherent whole.

As such, strategy formation is an example of the more abstract process of solving novel, complex problems. Other examples include challenges like product innovation or logistics system design (Baldwin

and Clark, 2000; Ethiraj and Levinthal, 2004; Simon, 1996). A problem is complex if it can be viewed as a whole that consists of numerous elements which are distinct, but interact with one another richly (Rivkin, 2001). This includes creating products with interacting features, organizations with interacting units, and strategies with interacting activities. Complex problems are most difficult when they are also novel, where novelty is defined as something new, original or unfamiliar (Gavetti *et al.*, 2005). For example, when creating a new product or forming a new strategy, executives have a harder time drawing on prior experience for solutions or reasoning about the interactions among parts of the problem (Simon, 1997; Ulrich and Eppinger, 2015).

Prior research has focused on two possible ways to solve a novel, complex problem. On one hand, an executive could solve a complex problem in a modular way – that is by breaking the problem into distinct pieces or "modules." Modular problem solving is beneficial for finding innovative, superior solutions to each piece of the problem because it allows for exploration of many alternatives for each module. This makes it more likely that superior alternatives are found (Ethiraj and Levinthal, 2004; Ulrich and Eppinger, 2015). However, it can be difficult to fit the separate pieces together which leads to oscillation between solutions that are optimal for different pieces (Mihm, Loch, and Huchzermeier, 2003). On the other hand, an executive could solve a complex problem in an integrated way, by evaluating the entire problem holistically all at once. Integrated problem solving is beneficial for making the pieces of the problem fit together into coherent, value-adding solutions (Burton and Obel, 1998; Siggelkow, 2001). Yet, it may not be possible for any individual to hold all the necessary information in their mind which leads to inferior solutions (Baldwin and Clark, 2000). Given the benefits and drawbacks of each approach, there is still a dilemma as to which process is more effective for finding superior, coherent solutions to novel, complex problems, like forming strategy.

Literature on solving the complex problem of strategy formation suggests three approaches that may address this dilemma by combining modularity and integration (Ott *et al.*, 2017): local search, chunky search, and decision weaving. *Local search* is the strategy formation process by which an executive evaluates the strategy as a whole but limits exploration of performance improvements to local

alternatives – i.e. they change one activity at a time, determine if that change improves overall strategy performance, and, if so, adopt that change (Levinthal, 1997). It is the most basic form of combining modular and integrated strategy formation (Cyert and March, 1963). *Chunky search* is the process by which an executive finds the best strategy for a small "chunk" of activities (e.g. product) and then slowly increases the number of considered activities (e.g. adds consumers, then suppliers, then operations) until the entire strategy is assessed (Baumann and Siggelkow, 2013). It is modular strategy formation at the beginning, but with gradually increasing integration over time. *Decision weaving* is the process by which an executive sequentially focuses on adapting one strategic domain (set of activities) at a time to improve overall strategy performance while also using infrequent, low resource changes in other domains (Ott and Eisenhardt, 2017). It is *simultaneously* modular and integrated strategy formation because it separates the problem into domains but evaluates performance based on the whole strategy. Overall, while prior literature suggests these three processes, it is unclear which process leads to better strategies and when.

With this in mind we ask, *how do executives most effectively engage in strategy formation in entrepreneurial settings*? We address this question using simulation methods, which is effective for topics like ours where the basic framework of the process is understood but the theory needs to be fleshed out (Davis, Eisenhardt, and Bingham, 2007). The process of solving a novel, complex problem using either modular or integrated search is well enough developed to create a model but further analysis is needed to examine how the two types may be best used in a single strategy formation process. Additionally, simulation allows for experimentation with key constructs that allow us to produce new, internally valid theoretical insights in a controlled setting (Cook and Cambell, 1979; Davis *et al.*, 2007). Using simulation, we compare the performance of strategies formed via three processes and explore the origins of the performance differences. We then systematically experiment by changing aspects of the strategy problem as well as key aspects of the decision weaving process to further unpack the performance differences of the various processes.

Our analysis yields several important insights, contributing to literature on strategy processes and complex problem solving more generally. First, we show decision weaving leads to higher performing

strategies than either local or chunky search processes. This contributes to literature on strategy processes that highlights the importance of combining "doing" and "thinking" in strategy formation by showing there are more and less effective combinations. Second, we dig into these performance differences by detailing the roles of stepping stones and learning plateaus in forming better strategies. We show that executives can infrequently use stepping stones to maintain an integrated view of their strategy across domains and increase the performance of the strategy formed. Additionally, decision weaving forms high-performing strategies faster than chunky search, making it more adept in entrepreneurial settings. Decision weaving is faster because switching focus at a learning plateau (as opposed to searching for a local optima) allows executives to balance the tradeoff between performance and speed. Lastly, we show that these results are robust to changes in the complexity of the strategy problem that executives face. Thus, we contribute to literature on complex problem solving by filling a gap in our current understanding of how executives balance the benefits and challenges of modular and integrated problem solving. Overall, this study advances understanding of how executives intelligently set up processes to aid their strategic decision making and strategy formation.

Prior Research & Hypotheses

Modular or integrated problem solving processes for strategy formation

As noted above, strategy formation in entrepreneurial settings requires executives to simultaneously battle *novelty* in learning about a new opportunity or activity, and *complexity* in combining the many different activities needed for a viable strategy. More generally, this is an example of a novel, complex problem solving task where the solution is a strategy that is high-performing by virtue of having superior parts that combine to make a coherent whole. Several strands of research address how such problems may be solved.

One strand of research on complex problem solving contends that executives may be able to take a modular approach by breaking it apart and solving each piece of the complex system individually. Prior research shows that modular problem solving is high performing when the system is (nearly) decomposable such that decisions can be grouped into relatively independent modules (i.e. sets of

decisions) (Baldwin and Clark, 2000; Ethiraj and Levinthal, 2004; MacCormack, Rusnak, and Baldwin, 2006; Simon, 1996). Additionally, attacking the problem in a modular way should be particularly favored over more integrated approaches when flexibility and rapid innovation of individual modules are equally or more important than system-level performance (i.e. coherence) (Ulrich and Eppinger, 2015). In these settings, a modular process can lead to high-performing solutions if problem solvers can overcome the difficulty of putting the separate pieces back together without them conflicting (Mihm *et al.*, 2003).

For instance, Ethiraj and Levinthal (2004) explore the relationship between modular problem solving and innovation. Using a formal model and simulation, they explore the ramifications of solving complex product design problems with a modular process by breaking the design into smaller sets of features. Their model shows that modular product design can allow executives to avoid locking-in an inferior solution for a particular module early in the design process. This occurs because these executives search more extensively for innovative solutions to each module. However, this performance advantage is dependent on the executives being able to separate the problem into modules (i.e. sets of features) based on the "true underlying structure" of the product. Some executives may "over-modularize" the problem by breaking it into too many small pieces. In these cases, the search for advantageous solutions to the modules is actually restricted rather than enhanced, and overall performance suffers. This suggests that modular problem solving can be effective for forming superior, coherent strategies if and only if the executives are able to break the strategy problem up based on the "true" underlying interdependencies of the opportunity.

Another strand of research on complex problem solving instead contends that executives should take an integrative approach to problem solving whereby they consider all of the pieces of the problem at once rather than breaking it into modules (Burton and Obel, 1998; Ulrich and Eppinger, 2015). Integrated problem solving allows for greater coherence in the solution by avoiding partial solutions that conflict with one another. Problem solvers who use an integrated approach find a coherent solution where all the pieces fit well together. In contrast, those who do not end up oscillating between solutions that are optimal for different parts of the whole but cannot be combined (Mihm *et al.*, 2003; Terwiesch and Loch,

1999). However, an integrated approach can be extremely challenging for executives due to the sheer amount of information that needs to be processed (Baldwin and Clark, 2000) and the number of possible solutions (Simon, 1997). The result can be a coherent, but not necessarily superior or innovative solution. For strategy formation in particular, integrated approaches are beneficial to avoid misfits among various parts of the strategy that decrease firm performance (Ozcan and Eisenhardt, 2009; Siggelkow, 2001).

For instance, Siggelkow (2001) offers one example of the benefits of an integrated approach to strategy formation. He describes how Liz Claiborne attempted to re-form their strategy after changes in the environment. In the face of retailer demands and changing consumer preferences, the executives at Liz Claiborne initially tried to change only their ordering activities (to electronic) without changing production, financial reporting, and inventory management activities. "Playing an incomplete game," as Siggelkow termed it, was akin to trying to solve the strategy problem modularly. This caused the different modules of Liz Claiborne's strategy to become incompatible with each other. This ultimately led to a performance decline. Liz Claiborne got back on track strategically when their executives took a more integrated approach to strategy formation. When they linked decisions about their design, clothing portfolio, production, distribution, and selling process together they were able to form a coherent strategy for the new environment and increase performance. So an integrated approach for forming strategy is necessary to avoid misfits that may arise through modularity.

In sum, prior research suggests that modular problem solving may lead to superior alternatives for parts of solutions if the problem is broken apart correctly. But it can be problematic if the parts do not form a coherent whole. In contrast, integrated problem solving is more likely to lead to coherent solutions but the cognitive difficulty of parsing the necessary information may lead to satisficing and subpar solutions. This suggests that in order to form a strategy that is high-performing, with both superior parts and coherence, executives must somehow combine modular and integrated problem solving processes.

Combining modular and integrated problem solving

The problem solving literature reviewed above suggests two categories of processes – modular and integrative – but cannot adjudicate between them when the problem is both novel and complex.

However, the strategy formation literature suggests three possible approaches for combining modular and integrated problem solving for the purpose of forming a strategy in entrepreneurial settings, and more broadly solving novel, complex problems. These approaches are: local search (Cyert and March, 1963; Levinthal, 1997), chunky search (Baumann and Siggelkow, 2013), and decision weaving (Ott and Eisenhardt, 2017). We now review each of these in turn, and build hypotheses that address their relative performance in forming strategy (see table 1 for a summary).

First, executives using *local search* form a strategy by looking at "local" solutions, i.e. strategies that have been used before or which are close to the current strategy, rather than seek a higher performing "distant" solution (Cyert and March, 1963; March and Simon, 1958). This process is a result of assumptions about the bounded rationality of executives. Because executives are cognitively limited, strategies are formed by altering only one module of the strategy at a time. If this modular change improves integrated performance then they keep the new strategy, if it does not the executive tries to change a different module of the strategy. Thus in local search, the exploration of alternatives for a piece of the strategy is moderately modular because only one component changes at a time but executives choose that component from the strategy as a whole. Meanwhile, the evaluation of performance remains completely integrated. This can limit the performance of individual components as executives never explore distant solutions. But, the strategy remains coherent as only changes that improve integrated performance are made (Gavetti and Levinthal, 2000). In highly complex environments, the strategies that executives find with local search can be largely dependent on where they start their search. This makes performance differences largely attributable to luck (Levinthal, 1997) rather than the decision making skills of executives.

Second, executives using *chunky search* to form strategy begin by finding the best strategy for a small "chunk" of activities. They then slowly add activities to that chunk until the entire strategy is considered (Baumann and Siggelkow, 2013). For example, if the Airbnb executives had used chunky search, then they would have started by choosing a small subset of activities - say how to recruit attendees to conferences in Chicago as guests - and optimizing their strategy for that set of activities. When

performance could no longer be improved within that chunk, they would then add one new activity, like using LinkedIn to reach possible guests. They would then optimize with larger and larger chunks until they reach fully integrated search at the end of the process.

There are two main differences between chunky search and local search. First, while the evaluation of performance is integrated from the beginning in local search, chunky search begins with modular evaluation (i.e. only the performance of the activities in the current chunk are evaluated) and then has gradually increasing integration[1] as the search progresses. Second, while the exploration of alternatives is moderately modular in local search (because it is restricted to a single local change within the entire set of activities), chunky search is more modular in exploration because it also restricts changes to occur within the current chunk of activities. So executives forming strategy with chunky search begin with a modular problem solving process, and then gradually increase integration over time.

These differences between chunky search and local search help chunky search to form equally coherent strategies, but with superior activities, than local search. Gradually increasing integration allows chunky search to avoid getting stuck in a locally optimal, but not high-performing, strategy early in the process (Baumann and Siggelkow, 2013). In other words, executives are more likely to find more advantageous modules for their strategies with chunky search because they will experiment with more alternatives for each strategic component. Meanwhile, chunky search also maintains high coherence in strategies because it eventually evaluates strategic performance in a fully integrated manner. Other factors, like starting with a less influential component, or a less complex problem will decrease the advantages of chunky search but never erase it. Thus:

H1: Executives using chunky search will form strategies with higher average performance than local search[2].

[1] The authors describe this as "gradually decreasing parochialism" where evaluations are neither based on each individual component's performance only (parochial) nor on the entire system (non-parochial), but rather start at the former and gradually move toward the latter. For our purposes "gradually increasing integration" is an easier term to compare to the other processes, but it is the same process.

[2] Note this is a replication hypothesis as Baumann & Siggelkow (2013) have already shown this with simulation. We use this to verify the correct operation of our implemention.

Finally, executives using *decision weaving* to form strategy use a two-pronged approach of sequential focus and stepping stones (Ott and Eisenhardt, 2017) to combine modular and integrated problem solving processes. That is, executives sequentially focus on modularly exploring one of several strategic domains (e.g. supply, demand, product, and geographies) until they reach a "learning plateau" in that domain. This learning plateau occurs when the executives have learned the basic structure of the domain, not necessarily an optimal strategy. They then switch focus to a new domain. Simultaneously with this focus, executives pay enough attention to background domains to respond to any serendipitous opportunities and problems that arise in those domains by making use of stepping stones. Stepping stones are easy, low resource actions taken in background domains. These responses keep background domains loosely integrated with the focal domain. Thus, exploration of individual domains is simultaneously modular, due to repeated focus on single domains (i.e. sequential focus), and integrative, due to the periodic use of low resource actions in background domains (i.e. stepping stones). Similarly, evaluation of performance is simultaneously modular, in the decision of when to switch domains, and integrative, in the assessment of if the overall strategy is working well. This simultaneity of modular and integrative problem solving is different from both local and chunky search.

This simultaneity is key to why entrepreneurs who use decision weaving form an effective strategy while others continue to flounder in their markets, act haphazardly, and ultimately fail (Ott and Eisenhardt, 2017). Like chunky search, decision weaving begins with a focus on only a subset of decisions. This allows executives to explore each domain in more depth than with local search, and to find superior alternatives for each domains. Additionally, decision weaving does not optimize the strategy for each domain early on in the process. Instead, it switches domains at learning plateaus. Moving on from a domain before optimizing it, combined with integrated evaluation (using whole strategy performance) avoids the "over-modularized" state possible with modular problem solving. This state decreases adaptation (Ethiraj and Levinthal, 2004). In other words, decision weaving maintains the coherence of the strategy. Thus:

H2: Executives using decision weaving will form strategies with higher average performance

than local search.

While both chunky search and decision weaving are better processes for finding effective strategies than local search alone, it is less obvious how they compare to each other. Which of these two processes forms higher-performing strategies may depend on the context of the strategy problem, in particular, on the complexity of the strategy problem. In high complexity problems, while it is especially important for strategies to be coherent, it is also very easy to get locked into a sub-optimal solution early on. There, executives using chunky search benefit from gradually increasing integration where they eventually use a completely integrated process. In contrast, executives using decision weaving maintain some level of modularity throughout the process, increasing the chance of a misfit in strategy. This may give executives using chunky search an advantage over decision weaving in forming strategies for highly complex problems. By the same logic, decision weaving should hold the advantage for very low complexity problems because it more closely mimics a modular problem solving process by sequentially forming strategy one domain at a time. Modular processes like this have been shown to be excellent when the problem is nearly decomposable (low complexity) (Baldwin and Clark, 2000; Ethiraj and Levinthal, 2004; MacCormack *et al.*, 2006) because executives can explore each part of the problem in more detail. Thus,

H3: Executives using chunky search will form strategies with higher (lower) average performance than decision weaving for relatively high (low) complexity strategy problems.

We now turn to our simulation model.

Model

The theoretical focus of our paper is on strategy formation in entrepreneurial settings. Executives face novel, complex strategy problems where they are challenged to find individually advantageous activities that combine into a coherent strategy. More specifically, our goal is to explore the implications of executives choosing to form strategy via one of three processes, each of which combine modular and integrated search in different ways (local search, chunky search, and decision weaving). As with all good simulations, we seek to address this focus using the least complex conceptualization possible (Burton and

Obel, 1995). However, for the simulation to fully unpack the mechanisms of interest, we minimally require: (1) a complex strategy problem, (2) a representation of the strategy of a firm as a set interdependent domains, each of which contains multiple interdependent decisions, and (3) models of each of the three strategy formation processes. In modeling these aspects, we are primarily concerned with the relationship between a chosen strategy formation process and its subsequent performance in a range of settings. In discussing our model, we will call the simulated actors *strategizers* in order to delineate them from our discussion of real life executives.

Complex Strategy Problems and Interdependent Domains

To model a complex strategy problem, we create high dimensional solution spaces, or landscapes, on which strategizers will search for an optimal strategy using one of the three modeled strategy formation processes. To do so, we adapt the NK Model (Kauffman, 1993, 1995) that was originally developed in evolutionary biology but has since been used to model complex problem solving processes within organizations (Gavetti and Levinthal, 2000; Gavetti *et al.*, 2005; Levinthal, 1997). NK modeling is appropriate for questions of strategy formation because just as *executives* engaged in strategy formation search to find the best *strategy* from an unknown set of possible strategies, *strategizers* on NK landscapes search for the highest *peak* existing on the NK terrain. Thus, the NK landscape appropriately captures the core features of the phenomenon of interest, strategy formation, in a simple but robust way – an important criterion for valid simulation (Lave and March, 1975; Rivkin and Siggelkow, 2003).

We conceptualize strategizers as having to choose a set of interdependent activities that their firm will perform in order to create and capture value (i.e. a strategy). These activities are separated into interdependent strategic domains (e.g. supply activities, product activities, etc). As such, in our elaboration of the NK model the typical N decisions for an NK model are broken into smaller subsets. We represent a strategy as N binary elements that are grouped into S strategic domains such that each domain has the same number of decisions, D (e.g. If S=3 and D=4 then N=12). For example, if S = 3 we can think of executives considering decisions in three domains: product (s1), supply (s2), and demand (s3). Strategizers make decisions within each domain (Gavetti *et al.*, 2005). For example, in the supply domain

executives may make choices such as whom to target as suppliers, what types of partners to engage for help with supply, or which marketing channels work best for increasing supply. Note that individual strategizers do not choose these domains but rather domains are defined as part of the strategy problem. Each strategy can then be represented as a binary string of length *n*. For example if N=9, S=3, and D=3 then n could be (s1{1,0,1}, s2{0,1,1}, s3{1,0,0})[3].

As is standard in NK models, each decision makes a contribution, c_i, to the overall strategy performance V(n) (Baumann and Siggelkow, 2013; Levinthal, 1997). Each contribution c_i depends on how decision i is configured as well as the configuration of some set of other decisions. Unlike standard NK models where the contribution of each decision depends on K other decisions, we follow Gavetti et al. (2005) in decomposing K into two values. The interdependence of decisions within a domain (K_w) is the probability that each decision's contribution is dependent on each other decision in the focal strategic domain. The interdependence of decisions between domains (K_b) is the probability that the focal decision's contribution is dependent on each other decision outside the focal strategic domain. In most cases, we model K_b as strictly less than K_w because the strategic domains represent theoretically natural domains, i.e. it is unlikely that a given decision related to supply will be more dependent on decisions related to demand than it is to other supply decisions.

As is typical in NK models (Baumann and Siggelkow, 2013; Levinthal, 1997), the performance of a given strategy n is the average of each of the N performance contributions: $V(n) = (c_1(n) + c_2(n) + \ldots + c_N(n))/N$. Thus, we can compare the efficacy of the three strategy formation processes by comparing the performance values of the final strategies formed by each. This measure of performance is particularly useful for our research because it implies both superior pieces and coherence of the whole strategy. That is, performance is only high when the strategy contains decisions with high individual contributions and also is coherent such that the individual decisions actually enhance the contributions of their related

[3] This is different than Gavetti et al.'s (2005) model which also breaks the N decisions into groupings. In their model decisions are aggregated into policies and the policies drive action. Here the decisions within a domain do not aggregate to a policy for that domain. Rather, domains reflect the "true underlying structure" of the particular problem (landscape).

decisions. As is standard (Baumann and Siggelkow, 2013), all reported performance measures are normalized based on the maximum performance for the given landscape.

Search processes

We now discuss how strategizers search to find high-performing sets of activities to create and capture value (i.e. strategy). Each strategizer is modeled as following one of three strategy formation processes: local search, chunky search, or decision weaving. Sets of three strategizers, one using each process, begin with the same randomly chosen set of decisions (initial strategy) and then search.

Following prior models (Levinthal, 1997; Rivkin, 2000), *Local search* strategizers are given the initial strategy as a starting point, and then consider changes of one decision at a time, accepting changes that improve the strategy's performance. This strategy formation process assumes boundedly rational executives who want to use integrated problem solving but lack the capabilities to do so. They instead end up taking one action at a time, learning from that action, and adapting their strategy if overall performance has increased. When the strategizers no longer find a local decision set that improves the performance of the current strategy, they have reached a local peak and settle on that set of decisions as their final strategy.

Following Baumann & Siggelkow (2013), *Chunky search* strategizers rely on local search over a predetermined subset (or chunk) of decisions (4 decisions) and then expand their search to include more and more decisions over time for a (4+1+1…) expansion pattern (Baumann and Siggelkow, 2013). While the strategizers are searching a subset, they also only evaluate the performance contributions from those decisions, resulting in gradually increasing integration. This strategy formation process is theoretically similar to modularly solving the strategy problem for the core firm activities and then "thickening" that core strategy over time. When the strategizers have integrated all decisions into the search and no longer see a local change that will increase performance, the process stops and the final strategy is found.

Following Ott & Eisenhardt (2017), *Decision weaving* strategizers combine sequential focus on a foreground domain with stepping stones in background domains. Domains are defined as disjoint and exhaustive modules, which are randomly chosen when the landscape is built. To model sequential focus,

we allow the strategizers to randomly choose a strategic domain on which to focus. They explore only new sets of alternatives that change decisions within their focal domain. But, they evaluate those alternatives based on the performance of the entire system (strategy). The strategizers continue to search within the focal domain until they reach a learning plateau. This is modeled as a threshold level of changes to the decision set, L, made within that domain. They then randomly choose a new focal domain. To model stepping stones, we allow strategizers to periodically make decisions outside of the focal domain. This captures executives exploring opportunities that arise in background domains. We implement stepping stones by having strategizers periodically (stochastically determined based on a Bernoulli trial with probability ss_prob) change a random decision outside of the focal domain to see if performance improves. If it does, that change is accepted. The strategizers then resume search in the focal domain. When the strategizers have iterated through each strategic domain once, the final strategy is found.

Results

Our simulation results broadly indicate that decision weaving is a more effective strategy formation process than either local search or chunky search. Our results also unpack this performance gap by exploring the key factors that make decision weaving effective for strategy formation. These factors include the complexity and size of the strategy problem, how stepping stones are used, and the threshold level for learning plateaus.

We begin reporting our results for moderate levels of the various inputs to our model, N=12, S=3 (So D = N/S = 4), K_w=0.75, K_b=0.25, L=4, and ss_prob=0.75. We chose this set of inputs as our core result because the size of the strategy problem is large but computationally tractable, and complexity is moderate across the whole set of decisions. Additionally, these inputs adhere to the assumption described above that decisions within a domain are likely to be more interconnected than those between domains.

Unless otherwise noted, we report average results for each experiment across 100 landscapes with 100 searchers of each type on each landscape. This ensures that our results are due to differences in the search processes rather than from any stochastic influence. Where possible, we report 95% confidence

intervals rather than significance levels in line with the emerging practice in the field (Bettis *et al.*, 2016). We first test our base hypotheses about strategy performance by comparing the performance results of decision weaving and chunky search to each other and to local search. We then explore how the results change when the strategy problem changes in complexity or size. Lastly, we extend the decision weaving model by unpacking two key components of the process: stepping stones and learning plateaus.

Performance differences between strategy formation processes

Core result

We begin our analysis with a comparison of the performance of the three strategizers. To do this, we simulate a Local Searcher, a Chunky Searcher, and a Decision Weaver forming a strategy on each performance landscape with moderate levels for each model specification (S=3, D=4, K_w=0.75, K_b=0.25, ss_prob = 0.75). See Table 2 for a summary of the core result.

First, we examine the average performance of the final strategy that each strategizer finds. Here we see that both Chunky Searchers and Decision Weavers outperform Local Searchers as expected in H1 and H2. Surprisingly, there is also a large performance advantage for Decision Weavers over Chunky Searchers. Decision Weavers, on average, settle on a strategy with a performance of 0.927 (0.926, 0.928), while Chunky Searchers settle on a strategy with a performance of 0.908 (0.907, 0.909) and Local Searchers settle on a strategy with the lowest performance of 0.904 (0.903, 0.905). This performance difference occurs as a result of a difference in the efficacy of the search processes because all three strategizers begin at the same random initial strategy.

For added robustness measuring strategy performance, we also report the percentage of firms reaching the global peak (i.e. highest possible performance) of the landscape. Again, Decision Weavers outperform the other strategizers with 13.3% of Decision Weavers finding the highest performing strategy possible while only 8.7% of Chunky Searchers and 8.5% of Local Searchers do so. Thus, strategizers using decision weaving are more likely to reach the best possible strategy for a given strategy problem. Moreover, even when Decision Weavers do not reach the global maximum, they average a performance of 0.916 (0.915, 0.917) which is higher than Chunky Searchers' 0.899 (0.898, 0.901) and Local

Searchers' 0.895 (0.894, 0.896). The results indicate that decision weaving leads to higher-performing strategies than chunky search for our base input levels.

Core result – Number of evaluations and strategy changes

We can dig deeper into the performance differences by evaluating how the different strategizers get to their final strategies. To do so, we compare the average number of strategies (decision sets) evaluated and the number of changes made from initial to final strategy. The number of strategies evaluated has been used in NK simulations as both a measure of the breadth of search (Baumann and Siggelkow, 2013) and of the amount of time it takes to find a final strategy (Gavetti *et al.*, 2005). A higher number of evaluations could be interpreted in two contrasting ways. First, more evaluations may be deemed as preferable because strategizers who explore more possibilities are likely to find a higher performing strategy. However a higher number of evaluations may also be considered detrimental since more evaluations means it takes longer to get to a final strategy. Ideally an executive would want to increase breadth of search while decreasing time spent searching, or find the correct balance on the edge of chaos (Davis, Eisenhardt, and Bingham, 2009). Given that the number of strategies evaluated is directly tied to time spent searching, the best strategizers can do is to balance this tradeoff of finding the highest performing strategy in the fewest number of evaluations.

As shown in Table 2, Local Searchers are the fastest to settle on a final strategy, evaluating just 18.437 (18.232, 18.642) strategies. This occurs because, as prior research laments, Local Searchers tend to get "stuck" on local peaks early in the search process. In contrast, Chunky Searchers are the slowest to reach a final strategy and explore more strategies by evaluating 90.281 (90.012, 90.550) strategies. Decision Weavers fall almost directly between the two, averaging 46.346 (46.299, 46.393) strategies evaluated. This result is extremely interesting when paired with the finding above: it shows that decision weaving finds higher performing strategies *and* is faster than chunky search. In other words, decision weaving is better at balancing exploration of a variety of strategies with the ability to find a strategy quickly.

To further understand what the three strategizers are doing differently in their strategy formation

processes we also look at the number of changes made to the initial strategy. Whereas the number of evaluations corresponds to the number of alternative strategies considered, the number of changes corresponds to implementing a new strategic activity because the strategizer has actually moved in that direction. This measure may be more relevant theoretically than evaluations for capturing time and resources spent during exploration because strategy implementation is more costly than simply evaluation (Bingham and Davis, 2012). Table 2 shows that Decision Weavers make the fewest changes to their strategy (5.322 (5.277, 5.367)) and Local Searchers make only slightly more (5.713 (5.668, 5.758)). In contrast, Chunky Searchers make many more changes (14.764 (14.705, 14.822)) than the other strategizers. The lower number of changes combined with higher average performance indicates that decision weaving allows strategizers to make more influential (i.e., smarter) changes to their strategies than their counterparts. Thus, the increase in average performance is not just a matter of taking more time to evaluate the strategy problem. Instead, decision weaving helps executives to explore more intelligently (i.e., efficiently).

Experiments with Complexity of the Strategy Problem

We next extend our analysis to examine the performance of each strategizer for strategy problems of various levels of complexity. As discussed above, complexity in our model is split into interdependence of decisions within a domain (K_w) and interdependence of decisions between domains (K_b). We experiment by varying both types of complexity from our moderate levels (figures 1 & 2).

Interdependence of decisions between domains

We first vary the interdependence of decisions between domains (K_b), holding all other parameters constant. We see that when the strategic domains are independent from one another ($K_b = 0$) all strategizers perform well relative to more complex problems. However, Decision Weavers perform best – i.e. finding the optimal strategy for the given problem (figure 1). We expect this result based on prior research on decomposable problems, e.g. no decision about supply affects the product (or other domains). In such settings, modularly solving each domain (e.g. making all decisions about supply and then making all decisions about product) is the ideal process (Baldwin and Clark, 2000). Sequential focus

allows Decision Weavers to take advantage of this problem structure to find the best strategy. This supports H3 that decision weaving will outperform chunky search for low complexity problems.

More interestingly, decision weaving unexpectedly maintains its advantage over both chunky and local search as interdependence between domains increases (decreasing decomposability). This is surprising because modular attention to domains would be predicted to perform poorly. As figure 1 shows, the performance advantage of decision weaving decreases with the introduction of interdependence of decisions between domains (K_b=0.25). However, as the interdependence of decisions between domains continues to increase (i.e. domains are more tightly coupled), decision weaving maintains a consistent performance advantage over both chunky and local search. In other words, decision weaving is most advantageous for decomposable strategy problems, but it also still leads to higher performing strategies when strategic domains are tightly interconnected.

Interdependence of decisions within domains

We see an even stronger trend in the performance advantage of decision weaving as we hold interdependence of decisions between domains (K_b) constant and instead vary the interdependence of decisions within a domain (K_w). Figure 2 shows that decision weaving enjoys an increasing performance advantage over the other processes as the interdependence between decisions within a domain (K_w) increases. As complexity increases, the final strategies of both chunky and local search strategizers decrease in performance relatively faster than decision weaving strategizers. So even when the contributions of every decision within a domain depend on every other decision in that domain (e.g. all supply decisions influence one another) decision weaving will allow executives to form coherent strategies while the other formation processes lose coherence and therefore performance. Thus H3 is not supported. Instead, decision weaving is the most effective combination of modular and integrated problem solving for high complexity strategy problems.

Experiments with Number of Decisions and Domains within the Strategy Problem

We next turn our analysis to comparing the performance of the three strategizers across different size strategy problems. In many NK simulations the size of the problem, or landscape, is defined solely by

the number of decisions (N) that make up each agent's current strategy. However, for our model, decisions are broken into S strategic domains, each with D decisions (i.e., N=SxD). As a result, the size of the strategy problem in our simulation can change in multiple ways. An increase in N can be caused by either an increase in the number of strategic domains that decisions are broken into (S) or the number of decisions per domain (D). We extend our analysis by looking at both these cases (Figures 3 & 4).

Number of decisions per domain

Figure 3 shows that all strategizers form worse performing strategies as the number of decisions per domain (D) increases. That is, as executives have more decisions to make in each domain, they are less likely to find a high-performing strategy. As D increases, the number of possible strategies that a strategizer has to consider increases exponentially, and so there will be a higher likelihood of finding a satisfactory but not optimal strategy (i.e., a local peak). Looking more closely at these results, all three strategizers perform about the same when there are only two decisions per domain. But, as strategizers make more decisions per domain, the performance advantage of decision weaving over the other two processes grows. This means that if the strategy within each domain is relatively simple, then decision weaving may not be necessary (though it does not hurt). This may be the case, for instance, if there is a lone supplier of a key part, or if the government is the only buyer. However, many, if not all, of the domains would need to be this simplistic which seems unlikely in a real strategy problem. In most settings, executives have to make myriad decisions in each part of the business, which is what makes strategy formation difficult. For instance, the AirBnB founders had to make many decisions like how to build supply, ensure great listings, and take payments for hosts, all of which fell under the "supply" domain. Thus, when there are many decisions per domain, decision weaving is particularly advantageous and outperforms the other processes.

Number of domains

Figure 4 then shows that, as the number of strategic domains (S) increases from two (2) to five (5), decision weaving remains advantageous but that advantage decreases. When the number of domains becomes very large but the number of decisions per domain remains relatively small, the difference

between decision weaving and chunky search disappears entirely. In other words, decision weaving does not perform as well when executives mistakenly "over-modularize" their strategy problem (Ethiraj and Levinthal, 2004). This result reinforces that executives using decision weaving should break the problem into relatively few modules based on the natural boundaries of different parts of the business. If executives instead try to carve up the business into too many separate pieces they lose the advantage of integrated exploration via stepping stones because there are too many background domains to track even superficially.

Taken together, the results of the experiments on complexity and size of the strategy problem indicate that the number of decisions to be made within a domain relative to the number of domains is the most relevant factor for how much better decision weaving performs than chunky search (table 4). When many decisions occur in each domain, decision weaving balances in-depth exploration within a domain with coherence across domains in a way which the other two processes cannot match. Additionally, in extremely complex environments decision weaving maintains a large performance advantage over chunky search even if executives err on the side of having too many domains. Comparing Figure 5 to Figure 4 shows decision weaving holds onto its performance advantage over other processes in highly complex settings, even as the number of domains increases. So decision weaving is most advantageous in situations where there are many decisions per domain and fewer domains. However, if complexity is very high, as is often the case in entrepreneurial settings, decision weaving still outperforms the other two processes in the theoretically less likely scenario of a few decisions in a greater number of domains.

Unpacking the Advantage of Decision Weaving

Combining sequential focus and stepping stones for performance

Given the high relative performance of decision weaving across a range of strategy problems, we next turn to understanding *why* decision weaving works so well. Ott & Eisenhardt (2017) theorize the *combination* of stepping stones with sequential focus makes decision weaving integrative and leads to the formation of better strategies. The key is that executives deliberately move non-focal domains to the background, and conduct only low-resource (relative to other alternatives) actions in those domains when

an opportunity arises. We now examine how much having *both* sequential focus and stepping stones matters by comparing the performance of sequential focus with and without stepping stones[4] (Figure 6).

When Decision Weavers rely only on sequential focus (ss_prob = 0) they attempt to form a strategy within each domain separately and then piece them together. There is no high level integration of exploration across domains. These strategizers form strategies with an average performance level of 0.900 (CI = [0.899, 0.902]). But, when stepping stones are added (at our base level of ss_prob = 0.75) the average performance level increases to 0.927 (CI = [0.926, 0.928]). This confirms that the *combination* of sequential focus and stepping stones makes decision weaving a powerful process for forming effective strategies. Without stepping stones, strategizers are using only modular exploration[5] rather than simultaneously modular and integrative exploration and cannot form effective strategies in even moderate complexity.

We extend this analysis to show that performance increases as soon as stepping stones are introduced (even at very low frequencies) to decision weaving (Figure 7). This advantage grows as the frequency of looking for stepping stones increases. At the extreme (ss_prob=1), each time a decision weaving strategizer examines a possible new set of activities in the focal domain they also look for a stepping stone by examining a change in a decision in a non-focal domain. The performance is highest at this extreme, showing that if resources (including attention) were not an issue strategy formation may benefit from keeping domains even more tightly integrated.

Interestingly, there are decreasing marginal returns to performance for continued increases in the frequency of looking for stepping stones. This suggests that executives do not need to constantly look for opportunities to enact stepping stone activities while they are focused on sequentially learning in each strategic domain. Instead, it is enough to be open to stepping stones to address a problem or opportunity that arises in a background domain. Infrequent use of stepping stones is enough to keep an integrated

[4] Analyzing stepping stones alone is uninteresting since that process is precisely that of a Local Search strategizer.
[5] Note that this is not completely modular problem solving as there is no *parochialism*. In other words, strategizers are integrative in their evaluation of performance by evaluating the system performance of possible changes, even though they only explore within a single domain at once.

view of how domains are linked together. This balance between focused learning and integrative decision making is what leads to the formation of more coherent strategies.

Learning plateaus to balance speed and performance

Thus far we find that decision weavers formed higher performing strategies for most strategy problems, and also reached a final strategy faster than chunky search with fewer changes than both local and chunky search processes. To understand why decision weaving is a more "intelligent" way to problem solve, we turn our analysis to another key part of the decision weaving process: using learning plateaus for knowing when to switch from focusing on one domain, say supply, to a new domain, like the product. Ott & Eisenhardt (2017) find executives switch domains when they have learned the basic structure of the focal domain, instead of an optimal point. In other words, executives hit a "learning plateau." We modeled the learning plateau by having Decision Weavers stop searching within a domain when they make a threshold number of changes in that domain, rather than continue to search until they find a local optimum like other strategizers. We can vary this learning threshold level to explore how performance changes as Decision Weavers enageg in more or less learning within each domain.

As figure 8 shows, the performance of strategies formed through decision weaving levels off as the threshold for switching is increased (i.e., learning plateau). If a strategizer switches focus after making four (4) changes to the strategy, there is only a small increase in performance over switching after three (3) changes. In other words, strategizers are not much better off continuing to search within a domain after they have made several changes (three in our model). At this point, they have learned the basic structure of the focal domain and should move on. The core insight is that decision weaving strategizers are more efficient in terms of the speed versus performance tradeoff when they recognize that they have learned the basic structure of a domain and then switch focus without the domain being perfect. That is to say, executives save time without sacrificing performance when they switch focal domains at a learning plateau, not optimum.

To further illustrate this result, we add the number of strategies evaluated to figure 8 (shown in figure 9). As we see, switching the learning threshold from four (4) to three (3) decreases performance

very marginally but does decrease the average number of evaluations made. This helps to balance the tradeoff between quality and speed that every strategic decision maker must face.

That said, if time is available it is better to lean towards too much time spent in a single domain than towards too little. As Figure 7 shows, the performance penalty for switching focus before learning about the structure of the domain is extreme. Strategizers who move to a new domain after learning a single lesson perform much worse on average than those that maintain focus longer. That is, executives who frequently switch between domains or become distracted from their focus will not form high performing strategies. Learning the structure of a domain requires learning multiple lessons (e.g., supply will join a platform for a $200 incentive *and* stay engaged for six months). Individual lessons must be tied together for a coherent strategy.

Staying focused slightly too long rather than too short is especially true early in the search process. As shown in Table 3, when the learning threshold is increased, many of the changes to strategy occur while a strategizer is focused on the initial domain. Therefore, if an executive has to choose how to allocate time between domains, then spending more time learning about the initial domain and using stepping stones in the background domains is more beneficial than switching out of that first domain too soon. However, the results also show that lower thresholds increase the number of changes made later in the decision weaving process. Thus, implementing a learning threshold leaves more room for experimentation in later domains. This highlights the importance of the balance between remaining focused long enough to learn but not so long that a firm locks into activities too soon.

Discussion and Conclusion

Using simulation modeling we add to theory on strategy formation in entrepreneurial settings. Our core contribution is a direct comparison of the effectiveness of multiple strategy formation processes. Specifically we unpack the performance differences among local search, chunky search, and decision weaving. Existing literature shows strategy formation is difficult for executives because it is both a novel and complex problem (Gavetti *et al.*, 2005; Ott *et al.*, 2017; Siggelkow, 2001). We show how executives can best handle those competing demands by using decision weaving to form strategy. This process yields

strategies that contain superior activities but still combine those activities into a coherent, value adding whole. In our simulation, decision weaving forms higher-performing strategies than local search and higher-performing strategies faster than chunky search for almost all strategy problems. By extending theory on strategy formation in entrepreneurial settings we contribute to literature on strategy processes and complex problem solving more generally, opening up several interesting avenues for future research in each.

Strategy processes

First, our analysis contributes to the topic of strategy processes by offering concrete details of *how* decision weaving improves the performance of strategies formed with the use of stepping stones. Existing literature describes the difficulty of forming a strategy that has superior pieces (Gavetti *et al.*, 2005; Gavetti and Rivkin, 2007) and which is also coherent (Ozcan and Eisenhardt, 2009; Siggelkow, 2001). It suggests that taking an approach that is both modular and integrated is ideal but difficult (Baumann and Siggelkow, 2013; Ott *et al.*, 2017). We are able to provide convincing evidence that decision weaving combines modular and integrated problem solving more effectively than the other processes in almost all settings. Additionally, we offer a more nuanced understanding of why the process of decision weaving leads to coherent strategies with superior activities. Our simulation shows sequential focus without stepping stones does not form high-performing strategies. Thus the *combination* of sequential focus and stepping stones is vital. Yet executives do not need to constantly be looking for stepping stone alternatives. Instead, executives can infrequently use stepping stones to support the formation of high-performing strategies. As long as they are alert enough to recognize opportunities in background domains they can conserve resources for learning in the focal domain. This infrequent use of stepping stones balances the tension between in-depth learning for superior activities and having the necessary coherence between domains. This balance leads to higher performing strategies.

Second, we contribute to our understanding of strategy processes by showing that a firm does not need to sacrifice strategy performance in order form their strategy quickly because learning plateaus make quality and speed both possible. Our simulation reveals that strategizers using decision weaving form

high performing strategies while evaluating and changing fewer activities than chunky search. This balance between performance and speed implies a more intelligent experimentation with strategic alternatives. We go on to show that this intelligence comes at least in part from relying on the concept of the learning plateau for knowing when to move on from a focal domain. We show that there is a definite plateau to performance gains where remaining focused beyond learning the basic structure provides little additional benefit. Using a moderate number of lessons learned as a switching criteria (i.e. learning plateau), allows executives to move faster and keep their strategy more flexible than the optimization goals of either local or chunky search. Thus, if entrepreneurs are cognizant of how they set up strategy formation processes and follow the old adage of not to "let the perfect be the enemy of the good" they will form higher performing strategies faster than their competitors. More research is needed to determine when entrepreneurs are able to set up such quality processes, in particular if they recognize the time pacing of their stepping stones and how they recognize learning plateaus.

Third, we highlight the importance of executives being able to block the strategy problem into separate domains while also viewing strategy broadly across those domains. We advance recent research showing that executives have to combine "doing" and "thinking" to effectively form strategy (Ott and Eisenhardt, 2017; Ott *et al.*, 2017). The advantage that decision weaving gives to executives is built on the combination of sequential focus and stepping stones, not just one or the other. This means decision weaving is impossible to put to use in real life unless an executive can *think* about the opportunity in terms of interconnected strategic domains and *also act* by exploring those domains sequentially. Executives with too holistic of a mindset might try to do too many things at once while those with too narrow of a mindset (e.g. just worrying about the product and assuming customers will come) might miss opportunities for creating value by combining activities. Exploring how and when executives combine "doing" and "thinking" remains an exciting area for future research.

Complex problem solving in organizations

Our experiments with strategy problem size and complexity go beyond strategy formation to contribute to complex problem solving more generally. First, we offer a theoretically valid search process

that performs well *across* complexity levels. Prior research on complex problem solving processes has shown that whether integrated or modular search processes are more effective largely depends on the complexity level of the environment (Baldwin and Clark, 2000; Frenken, Marengo, and Valente, 1999; Ulrich and Eppinger, 2015). In contrast, our model shows that decision weaving performs well at low, moderate, and high complexity levels. Executives do not have to choose between the advantages of a modular or an integrated approach because decision weaving is simultaneously modular and integrated in both exploration and evaluation of alternatives. As long as executives do not artificially carve up decisions into too many domains, decision weaving will balance domain-by-domain learning alongside decision integration across domains in a way other processes cannot. In other words, decision weaving takes advantage of the problem structure of strategy formation (i.e. many tightly connected decisions in a few loosely connected domains). This result should have implications for other complex problems beyond strategy formation where the structure of the problem is similar such as product design or collaboration processes.

Second, and relatedly, we contribute to complex problem solving within organizations by updating our view of the executives who are the problem solvers. Prior research, largely out of the behavioral theory of the firm tradition, contends that boundedly rational executives must simplify complex problems and that this simplification leads to errors (Cyert and March, 1963). The only way such limited executives can form strategy, or solve other complex problems, is through a local search process that often relies as much on luck as it does on understanding (Levinthal, 1997). However, more recent research has shown that using cognitive tools, such as analogy, to abstract up from the details of the particular problem (Gary, Wood, and Pillinger, 2012; Gavetti *et al.*, 2005) can make complex problem solving easier for executives. We continue this line of work by showing that executives can overcome their own limitations by setting up intelligent decision processes for complex problem solving. With decision weaving, executives do not always need to simplify complexity away in order to bring a strategic problem within the bounds of their rationality. Instead they rely on the combination of sequential focus and stepping stones to more intelligently attack the problem. We hope that this spurs future research to

explore other ways in which executives can craft processes to overcome cognitive limitations such that we can create a more complete understanding of cognition as a microfoundation of strategy.

Conclusion

Forming a strategy by putting together a unique set of interconnected activities to create and capture value is one of the most important organizational processes to understand because it can lead to performance differences among competitive organizations. This study extends previous theory on strategy formation by showing that decision weaving leads to effective strategies, with both superior and coherent activities, and unpacking several of the key concepts within the process. In doing so, we offer insights into how executives should seek to combine modular and integrated processes for solving complex problems. This expands the repertoire of actions executives have for overcoming bounded rationality beyond simplification and satisficing to the intelligent design of decision making processes.

Table 1: Three strategy formation processes combining modular and integrated problem solving

	Local search	**Chunky search**	**Decision weaving**
Process summary	Change one component, evaluate system performance, accept if an improving change, repeat till optimum	Focus on subset of decisions, change one component in subset, evaluate subset performance, accept if an improving change, repeat till optimum then expand subset	Focus on single domain (Sequential focus) until several performance improving changes made. At same time, periodically explore local change in other domain (Stepping stones). Repeat till all domains addressed
Exploration for new strategic activities	Moderately modular (1 change at a time across all possible changes)	Modular first (1 change at a time across a subset of possibilities) -> Moderately modular later (Local search)	Simultaneously Modular (Sequential focus) & Integrated (Opportunistic stepping stones)
Evaluation of strategy	Always Integrated	Modular first -> Integrated later (Gradually increasing integration)	Modular (Learning plateaus to switch) & Integrated (overall performance) simultaneously
Stop	At a (local) optimum	Fully integrated, at a (local) optimum	Basic structure of domain understood, all domains addressed
Pros	Strategy remains coherent. Fast.	Avoid getting stuck in local peak early, eventually is fully integrated	More depth to exploration of modules, but avoids "over-modularization." Fast & high-performing
Cons	Get "stuck" on local peaks early	Slow, too integrative in low complexity	Chance of misfit in highly complex environments

Table 2: Core results (N=12, S=3, D = N/S = 4, K_w=0.75, K_b=0.25, L=4, and ss_prob=0.75) - 95% confidence intervals are shown in brackets

Searcher	**Local searcher**	**Chunky searcher**	**Decision weaver**
Average Performance	0.904 [0.903, 0.905]	0.908 [0.907, 0.909]	**0.927** [0.926, 0.928]
% of searchers to reach highest possible performance (global peak)	8.52	0.871	**13.32**
Average performance of strategizers who do not reach highest possible performance (global peak)	0.895 [0.894, 0.896]	0.899 [0.898, 0.901]	**0.916** [0.915, 0.917]
# of activity sets (strategies) evaluated	**18.437** [18.232, 18.642]	90.281 [90.012, 90.550]	46.346 [46.299, 46.393]
# of changes to get from initial to final strategy	5.713 [5.668, 5.758]	14.764 [14.705, 14.822]	**5.322** [5.277, 5.367]

Table 3: Strategy changes per focal domain at varying learning thresholds

Learning Threshold Level (S=3, D=4)	**2**	**3**	**4**	**5**
Avg. Total Changes [95% confidence interval]	5.100 [5.060, 5.140]	5.262 [5.218, 5.305]	5.315 [5.270, 5.361]	5.393 [5.347, 5.438]
# of changes while focused on first domain	2.925 [2.903, 2.948]	3.621 [3.593, 3.649]	3.912 [3.879, 3.946]	4.057 [4.022, 4.093]
# of changes while focused on second domain	1.501 [1.476, 1.526]	1.145 [1.120, 1.170]	0.969 [0.945, 0.992]	0.909 [0.887, 0.932]
# of changes while focused on third domain	0.674 [0.655, 0.693]	0.496 [0.479, 0.513]	0.434 [0.418, 0.451]	0.426 [0.410, 0.442]

Table 4: Summary of strategy problem experiment results

	Experimental input				
	Complexity		**Problem size**		**Number of domains when complexity is high**
	Between domains (Kb)	*Within domains (Kw)*	*Number of decisions per domain (D)*	*Number of domains (S)*	
Best process when Low value	Decision weaving	Decision weaving & Chunky search	Decision weaving, Chunky search, & Local search	Decision weaving	Decision weaving
Best process when High value	Decision weaving	Decision weaving	Decision weaving	Decision weaving & Chunky search	Decision weaving
As value increases the performance gap…	Decreases initially and then remains steady	Increases	Increases	Decreases to nothing	Decreases but holds

Figure 1: Experiment with changing between domain interdependence (K_b)

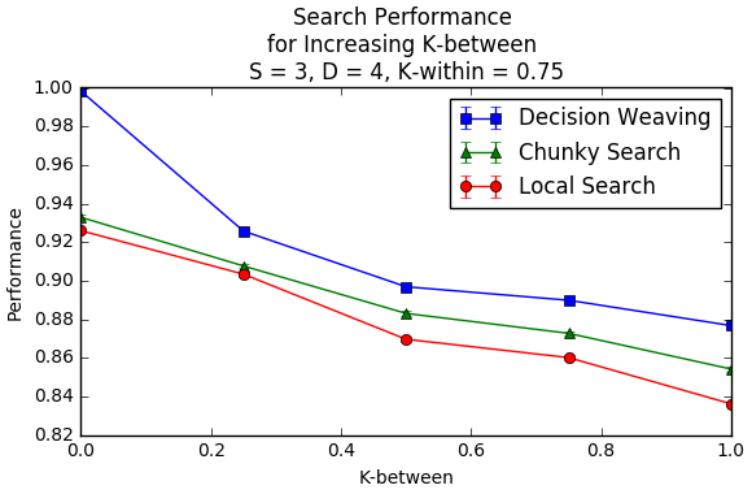


Figure 2: Experiment with changing within domain interdependence (K_w)

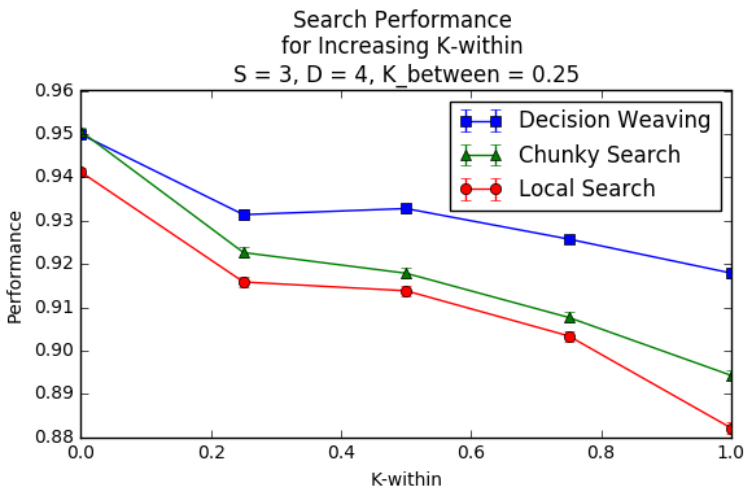


Figure 3: Experiment with changing number of decisions per domain

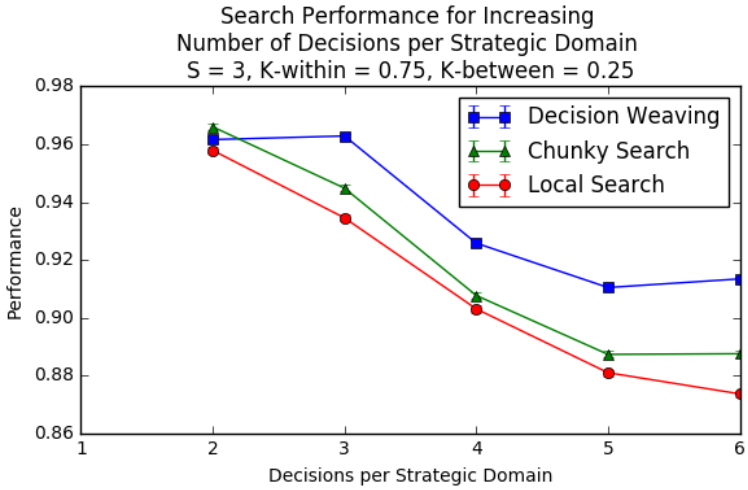


Figure 4: Experiment with changing number of strategic domains

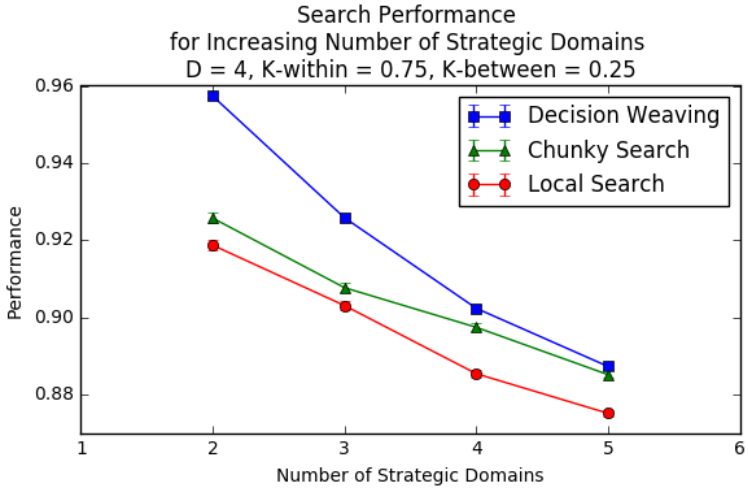


Figure 5: Experiment with changing number of domains at complexity = 1

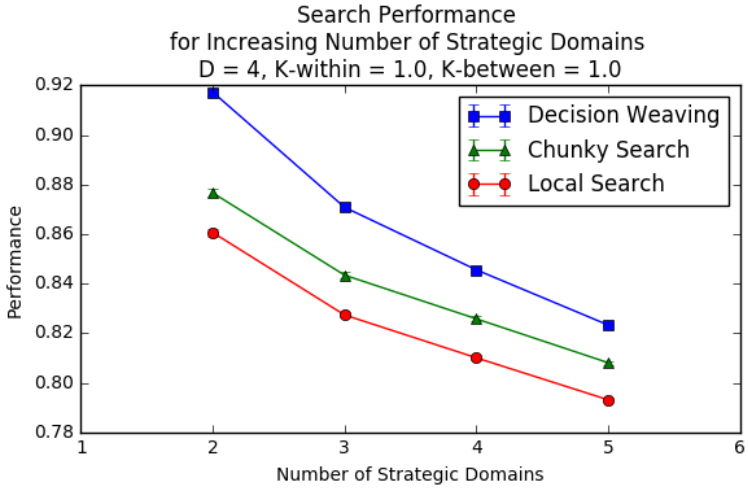


Figure 6: Decision weaving performance with and without stepping stones

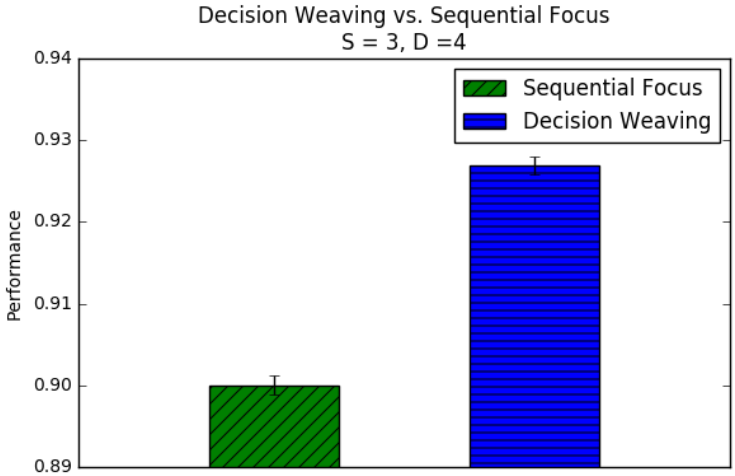


Figure 7: Decision weaving performance at varying frequencies of stepping stones

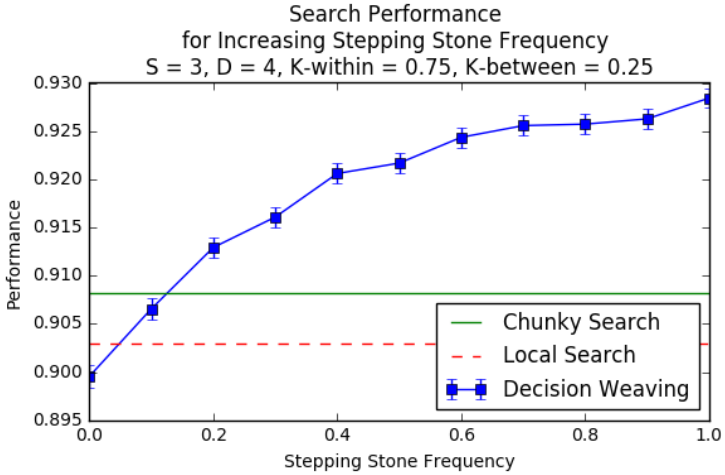


Figure 8: Performance at varying learning thresholds

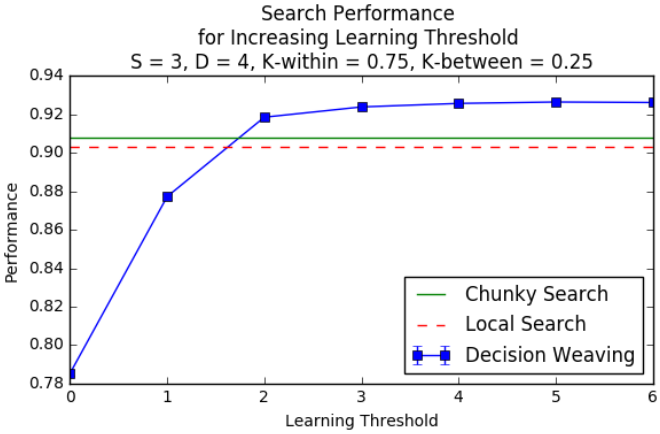
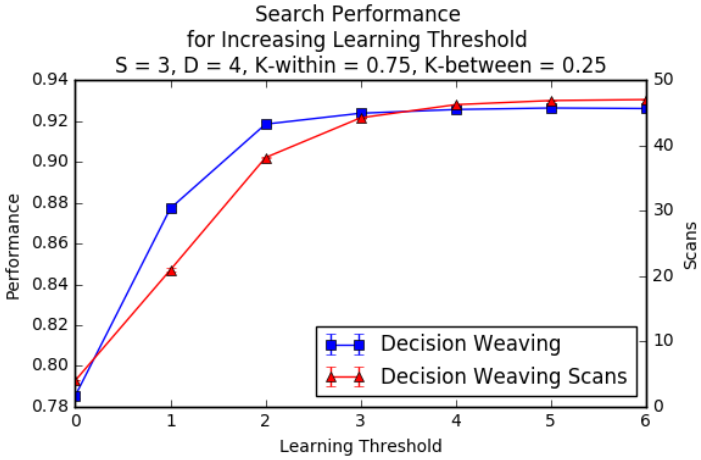


Figure 9: Number of evaluations made at varying learning thresholds



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