"Worthwhile to Move" : Setting Intermediate Goals to Overcome Inertia and Routinization

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Abstract

(First draft, please do not cite).Behavioral imperfections are the rule, not the exception. This is true for human behavior, for decision-making process, and for problem-solving process. The world is complex, with a lot of frictions. Humans have limited physical resources, bounded cognitive abilities, psychological biais which distort their evaluation process and their motivations to search. Human preferences and beliefs are inconsistent. Motivations to act can be unconscious, or rather vague, or too low (depression) or too high (impulsive). Goals are ill defined, not well set. Human knowledge is incomplete, inadequate. Agents cannot digest all the information they receive each day. They must choose to ignore some part.In our world, frictions, bias, errors, anomalies, are everywhere. Imperfections can be of various types:(i) Cognitive imperfections: lack of knowledge, which is the main limitation for decision (cognition limits).(ii) Psychological imperfections which is the main problem for well directed motivation to drive action properly. They include goal setting imperfections, frustration feelings, unclear goals, impulsive behaviors, emotions bias.(iii) Physical and physiological imperfections: inertia and frictions (limited physical and physiological resources, Rumelt, 1990).The goal of this paper is to explain and formalize incremental decision-making process in real life settings.We characterize the efficiency loss of an incremental behavior in the context of an environnement which presents inertia-reactivity costs. To save space the other two main frictions, goal setting costs, and knowledge acquisition costs are not examined.We consider the "worthwhile to move" principle of incremental behavior, which we model as folows. In each step, the agent, before moving, and after exploration around the current state, compares intermediate advantages and costs of change. The agent is supposed to have a long term goal and limited needs. Each step, the agent chooses between (a) doing the same action as before, and (b) changing. He will move if the advantages to move are greater than some fraction of costs of moving move. This dynamic and reference-dependent incremental cost-benefit behavior leads to local

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actions and converges, if the agent's local costs of moving is sufficiently high. If the agent is more goal oriented (wants to "improve enough" at each step), the process shrinks (i.e., the diameter of the state-dependent "worthwhile-to-move set" decreases to zero), and reduces to one state if the goal function does not jump upward. The process ends in a permanent routine or a trap, where the agent prefers to stay there in spite of some residual frustration for not having reached his final goal. Efficiency losses concern both transition paths, the final state and the final goal. The agent uses qualitative enclosing heuristics to choose how much to explore around and to bound his control variables locally. The transition process is made of a punctuated succession of static exploration-exploitation phases, and dynamic moving phases. Each step, the process jumps from one temporary routine phase to an improving temporary routine phase, following a moving phase, until finally reaching some behavorial trap, a permanent routine, or even worst, a rest point lower than any local maximum. Convergence in finite time occurs if the agent chooses a finite total exploitation time.

1 Introduction

The goal of this paper is to explain and formalize incremental decision-making process in real life settings.We characterize the efficiency loss of an incremental behavior in the context of an environnement which presents inertia-reactivity costs. To save space the other two main frictions, goal setting costs, and knowledge acquisition costs are not examined.

We consider the "worthwhile to move" principle of incremental behavior, which we model as folows. In each step, the agent, before moving, and after exploration around the current state, compares intermediate advantages and costs of change. The agent is supposed to have a long term goal and limited needs. Each step, the agent chooses between (a) doing the same action as before, and (b) changing. He will move if the advantages to move are greater than some fraction of costs of moving move. This dynamic and reference-dependent incremental cost-benefit behavior leads to local actions and converges, if the agent's local costs of moving is sufficiently high. If the agent is more goal oriented (wants to "improve enough" at each step), the process shrinks (i.e., the diameter of the state-dependent "worthwhile-to-move set" decreases to zero), and reduces to one state if the goal function does not jump upward. The process ends in a permanent routine or a trap, where the agent prefers to stay there in spite of some residual frustration for not having reached his final goal. Efficiency losses concern both transition paths, the final state and the final goal. The agent uses qualitative enclosing heuristics to choose how much to explore around and to bound his control variables locally. The transition process is made of a punctuated succession of static exploration-exploitation phases, and dynamic moving phases. Each step, the process jumps from one temporary routine phase to an improving temporary routine phase, following a moving phase, until finally reaching some behavorial trap, a permanent routine, or even worst, a rest point lower than any local maximum. Convergence in finite time occurs if the agent chooses a finite total exploitation time. The model is able to describe a full range of behavior, moving from hill-climbing local behavior, to intermediate goal setting behavior which seeks to"improve enough" each step, intermediate satisficing process without too much sacrificing, problem-solving process (bounded rationality), a theory of needs and wants, routinization and habituation process, and finally traditional global optimization (substantive rationality) where all frictions have disappeared.

We emphasize the role of psychology and cognition to balance between motivation and fear of change, and the importance of speed in decision-making for reactive behaviors. We explain links with optimization and approximate-optimization theory, variational inequalities (the Ekeland variational principle and others), proximal algorithms, local search hill-climbing algorithms and global search models.

2 From Incrementalism to Instrumentalism to Optimization

In a world with frictions, a first incremental principle, the "worthwhile to move" principle, can handle the realistic case of an incremental decision-making process where the agent tries, each step, to do a little better than before. We show, adding an instrumental (goal setting) principle, called the "improving enough" principle, how our model can handle a huge variety on intermediate goal setting behavior.The traditional case of optimization is at the other extreme of this range of behavior, in a frictionless world.

In the Real World, Frictions are the Rule, not the Exception Behavioral imperfections are the rule, not the exception. This is true for human behavior, for decision-making process, and for problem-solving process. The world is complex, with a lot of frictions. Humans have limited physical resources, bounded cognitive abilities, psychological biais which distort their evaluation process and their motivations to search. Human preferences and beliefs are inconsistent. Motivations to act can be unconscious, or rather vague, or too low (depression) or too high (impulsive). Goals are ill defined, not well set. Human knowledge is incomplete, inadequate. Agents cannot digest all the information they receive each day. They must choose to ignore some part.

In our world, frictions, bias, errors, anomalies, are everywhere. Imperfections can be of various types:

i) Cognitive imperfections: lack of knowledge, which is the main limitation for decision (cognition limits).

ii) Psychological imperfections which is the main problem for well directed motivation to drive action properly. They include goal setting imperfections, frustration feelings, unclear goals, impulsive behaviors, emotions bias.

iii) Physical and physiological imperfections: inertia and frictions (limited physical and physiological resources, Rumelt, 1990).

Incremental Behavior: Balancing between Intermediate Advantages and Costs of Change Because imperfections are everywhere, most of our behavior is incremental. We work step by step, using small improving steps and local improving actions, local exploration devices, trials and errors.... We assupose that at each step, an agent balances between local advantages and local costs of moving. Incremental aspects are context-dependent and reference-dependent. The reference state is the current state.

Choosing to Change or to Stay Choosing is a dynamic process. The simplest way to choose between a given set of alternatives is to make a cost-benefit analysis, to compare advantages and costs, loss and gains, of each alternative. The basic unit of choice is comparison between a pair of options. The traditional optimization theory pre-supposes a known choice set of alternatives. The agent who wants to find the best alternative takes a pair of alternatives, compare their

advantages and costs over a list of criteria, rejects the alternative that has the less favourable balance between advantages and costs. He is supposed to do the same for each pair of alternatives, in one shot. Non-rejected alternatives will be chosen. This process of comparisons is not viewed as sequential.

In a more realistic sequential choice process, successive eliminations make the process of choice state-dependent, because choosing is between a new alternative and the existing state. The comparison process is anchored to previous choices. Choosing must consider repeated choices, with the possibility to change his choice from one period to the next. Very often, to choose to stay, is the reference-dependent choice. The possibility of repeated choices matter much if we consider every choice as a dynamic process. This leads to the concept of temporary routines where the agent repeats the same action during some time, and changes from time to time, moving from one temporary routine to a new temporary routine, to finally ending in a trap, a permanent routine, or a final choice.

Incremental Intermediate Goal Setting Behavior If, because of lack of knowledge, an agent cannot optimize, he must explore around the current state to discover his local environment to try to improve each step. This is a local search optimizing process (hill-climbing). If the agent wants to improve his motivation to try to "improve more and more quickly" each step, he can set intermediate goals (intermediary aspiration levels) to help him to drive his exploration process to "explore enough" but "not too much" . This is the "gradual satisficing" process of Soubeyran A (2006), without inertia and frictions, (see also Martinez-Legaz JE-Soubeyran A, 2002).

If there are inertia forces ("costs of moving"), the agent must do more to sustain his intermediate motivation: he must "improve even more" each step to be able to compensate intermediate costs of moving, by intermediate "advantages of moving". Then, it is "worthwhile to move". This is a way to limit intermediate sacrifices. This process leads to local action in an endogenous way. Local action is not an hypothesis as it is for a high climbing algorithm, it is now a consequence of inertia. It leads to convergence if the agent "improves enough". The process converges to a rest point (trap, routine) if the agent "improves more than enough" each step.

Modelizing the Inter-related Aspects of a Decision Making Process Our model examines why agents do something or not, and how they choose to do it. Their choices concern both actions and "ways of doing". Agents can choose to do nothing. They can choose to repeat what they have done before, or can choose to change. The reference point is "what and how" things where done before.

Our model shows that a behavior has at least six interrelated characteristics:

1) Incrementalism aspect,
2) Instrumentalism aspects
3) Local exploration and search aspects

4) Qualitative aspects, using economizing (fast and frugal) heuristics to localize and enclose the process and cut the cost regression paradox (to "know how to know how..".). In the context of a complex world of radical uncertainty, we do not use probabilities, but rather set inclusions, i.e., inequalities to modelize the degree of flexibity, fuzziness and adaptation of a behavior,

5) Punctuated dynamical aspects: where transitions matter, because they are necessary to reach the final goal (a succession of jumps from a temporary routine to an other temporary routine).

6)Finally our model can incorporate without much effort physical, physiological, psychological, cognitive, and social features of a behavior.

Main Findings: Behavioral Implications Our model defines a general "adaptive decision and making" behavior by linking in a unique framework complementary "motivation building", goal setting, "exploration around" and moving (changing, learning) tasks. In this paper we emphasize first the inertia context for incremental behaviors, then, the goal setting and inertia contexts for intermediate goal setting behavior. To save space we do not explore (!) very deeply the determinants and characteristics of the local exploration task (the information and knowledge acquisition process).

Our first goal is to modelize in a very simple way these incremental process of decision and making as a succession of balances (comparisons) between state dependent intermediary advantages and costs to change, with respect to intermediary advantages and costs to stay.

Using a topological approach, we show tha, if the state space is a metric space (only a proximity concept is needed, no concept of direction is required), if the per unit of time utility (valence) is bounded above, and if the agent can enclose his "worthwhile to move relation" within a reflexive and transitive enclosing relation, putting bounds on his control variables, by choosing, each step, a not-too-long exploitation period, using a minimum per-unit-of-distance effort of moving, taking a not-too-low sacrifice index, putting not-too-high weights over temporary contentment and deception, then:

a) for a low-goal-oriented process where the agent follows a "worthwhile to move" dynamic and just wants to improve step by step, the "worthwhile to move" relation has the local action property, is nested, and the process converges to some state if the state space is complete. It converges in finite time if the agent spends a finite time for exploitation and the speed of moving is high enough

b) for a higher-goal-oriented process where, starting from a given initial state, if the agent follows a "worthwhile to move" dynamic and "explores enough" around the current state to be able to "improve enough", the process not only converges, but shrinks and finally stops at a trap (a rest point) where the agent prefers to stay than to move again. Routines represent a specific example of traps where an agent stops thinking before doing.[1]

[1]There are very few papers showing the formation of routines. In this context our paper generalizes to a procedural framework the specific exploration-exploitation process of rou-

Calibrating Imperfections and Inefficiencies: How far from Optimization do Agents Behave ? Our model can help to estimate, in a given context, the departure of a given behavior from the standard formulation of an optimization model. It helps to calibrate the size of the inefficiencies. This will give us a tool to know when, depending of the context, the "as if hypothesis" is justified, i.e., when optimization is a good enough approximation of a given behavior. To succeed in this goal our model must

i) modelize lack of knowledge, frictions and goal setting inefficiencies. This problem will become more complicated when we will introduce inertia inefficiencies.

ii) define dynamic inefficiency indexes, i.e., to calibrate the inefficiencty gaps of a behavior with respect to its substantive formulation.

iii) link the inefficiency gaps of a behavior to the anomalies (characteristics) of both the agent and his environment (the context).

Concerning an inertia context (costs of moving), inefficiencies indexes will include also the total costs of moving (i.e., the total energy spent along the process, or the size of intermediate sacrifices), the mean speed of moving. Several quality-cost ratio can be defined.

At a more mathematical level, our model gives a cognitive proof of the celebrated "epsilon approximation theorem" or variational principle" of Ekeland (Attouch H-Soubeyran A, 2006). It also provides a general framework to study up-to-date general proximal algorithms (Attouch H- Bolte J, 2006, Attouch H-Redont P-Soubeyran A, 2006) and second order dynamic optimization models with memory (Attouch-H- Goudou X and Redon P, 2000, Attouch H -Soubeyran A, 2006).

From Behavioral Imperfections to Behavioral Traps and Anomalies We study whether all these dynamically interlinked behavioral imperfections converge. What are the kind of behavioral traps where the process can gradually move? Let us list some of them: path dependency, lock-in effects, aspiration traps, local maximum, high climbing traps, irregular dynamics, stop-and-go process of static and dynamic phases, routinization process moving from temporary routines to permanent routines, intermediate goal formation to help to sustain motivation.Optimization will appear as a pure limit special case, when all imperfections are ignored.

3 Incrementalism: "Worthwhile to Move" Principle Helps to Bound Intermediate Sacrifices

The material for this section will be made available at the seminar.

tinization of Sinclair-Desgagné and Soubeyran (2000) which use a traditional optimal control model. They show the formation of routines when, each period, an agent takes benefit of both learning by thinking (exploration) and learning by doing (exploitation and learning).

4 The Punctuated "Exploitation-Exploration and Moving" Process

The material for this section will be made available at the seminar.

5 A Topological and Tychastic Approach, Using Inclusions

This section will be made available at the seminar.

6 Incrementalism via Enclosing

This section will be made available at the seminar.

6.1 Using an Enclosing Heuristic to Enclose the "Worthwhile to Move" Inclusion

6.2 More on Incrementalism: Convergence in Finite Time

Enclosing Using an enclosing heuristic we can show, as we have done for incremental behavior, that the "worthwhile to move" process exhibits local actions, local moves, convergence of the goal (per unit of time utility), and convergence of the states if the state space is complete. We consider now convergence in finite time.

7 Instrumentalism: Improving Enough and Shrinking

We consider now a more goal-oriented "worthwhile to move" process (more than just improving) where, in an inertia context, the agent wants both

i) to follow a "worthwhile to move transition" $y \in W(x) = \{A(x,y) \geq \xi(x)C(x,y)\}$ where, during the transition, the agent must compensate intermediate costs by intermediate advantages that are are higher than a given fraction of costs, i.e., where sacrifices are low enough during the transition,

ii) and to "improve enough", i.e., meeting the intermediate satisficing level, $g(y) - g(x) \geq \varepsilon(x)$.

We will show that if (a) the per unit of time utility function is bounded above, and (b) the agent has been able to enclose the "worthwhile to move" inclusion $y \in W(x)$ within an enclosing inclusion $y \in S(x)$, then such a "worthwhile to move" and temporary satisficing process will shrink, i.e., the radius of the enclosing inclusion, $radiusS(x_n) \geq 0$, converges to zero. Hence the enclosing inclusion shrinks, and so does the "worthwhile to move" inclusion.

7.1 Improving Enough

Intermediate "Improving Enough" Behavior Consider first a more oriented goal-setting process which does not follow a "worthwhile to move" process. This defines an intermediate satisficing process where the agent wants to "improve enough" (see Soubeyran A., 2006). Each step, say starting from $x \in X$, the agent sets first a new aspiration level $\widehat{g}(x) > g(x)$, then sets an adjoint satisficing level $\widetilde{g}(x)$, $g(x) < \widetilde{g}(x) < \widehat{g}(x)$, and tries to reach it. To succeed, he must explore within an exploration set $E[x, r(x)] \subset X$ around $x \in X$ to find some $y \in X$ such that $g(y) \geq \widetilde{g}(x)$. Finally, at each new step, the agent will adapt his aspiration level. Let $\overline{g} = \sup\{g(y), y \in X\} < +\infty$ be the finite supremum of the bounded above per unit of time utility function $g(.)$. To save space, suppose that the agent sets a feasible aspiration level, $\widehat{g}(x) \leq \overline{g} < +\infty$. If not, he will not reach it and, sooner or later, will be obliged either to explore more around the current state, or to relax his aspiration level.

Both "Worthwhile to Move" and " Intermediate Improving Enough" Behavior Suppose now that the agent follows both i) a "worthwhile to move" and ii) an intermediary satisficing (improving enough) process. Then, the agent follows a worthwhile to move process $y \in W(x)$. Suppose that he has succeeded to enclose it within the enclosing process $y \in S(x)$. By exploration around the current state, the agent will discover locally his utility function as well as the enclosing inclusion $S(x) = \{y \in X, g(y) - g(x) \geq \theta d(x, y)\}$. Let $s(x) = \sup\{g(y), y \in S(x)\} \leq \overline{g} < +\infty$ be the highest unknown aspiration level that the agent can reach within the enclosing inclusion. Let $\widehat{g}(x) = g(x) + p(x)[s(x) - g(x)]$, $p(x) > 0$, be the unknown relation between the aspiration level $\widehat{g}(x)$ and $s(x)$.

Starting from any $x \in X$, it is always possible to find an "improving enough" and "worthwhile to move" state $y \in S(x) \subset W(x)$, such that $g(y) - g(x) \geq \sigma(x)[s(x) - g(x)]$, $0 < \underline{\sigma} < \sigma(x) < 1$,because of the definition of $s(x)$ as a supremum.

7.2 Shrinking

Let $radiusS(x) = \sup\{d(x, y), y \in S(x)\} \geq 0$ be the radius of the subset $S(x) \subset X$. Then, $s(x) - g(x) \geq g(y) - g(x) \geq \theta d(x, y)$ for all $y \in S(x)$ implies that $s(x) - g(x) \geq \theta radiusS(x)$. We are now prepared to show how the worthwhile to move process will shrink.

A "Worthwhile to Move" Behavior which "Improves Enough" at each Step Shrinks Suppose that, at each step, the agent finds $x_{n+1} \in S(x_n) \subset W(x_n)$ which improves enough, i.e., such that $g(x_{n+1}) - g(x_n) \geq \underline{\sigma}[s(x_n) - g(x_n)]$.

The Shrinking Proposition:

Suppose that the per unit of time utility function is bounded above. Suppose, as before, that the agent has succeeded to define and enclose his worthwhile to

move process. Suppose finally that, each step, the agent explores enough around to be able to find $x_{n+1} \in S(x_n) \subset W(x_n)$ which improves enough, i.e., such that $g(x_{n+1}) - g(x_n) \geq \underline{\sigma}\,[s(x_n) - g(x_n)] \geq 0$.Then, the worthwhile to move process shrinks, which means that the radius $radiusW(x_n)$ of the worthwhle to move set converges to zero.

Proof:: $g(x_{n+1}) - g(x_n) \geq \underline{\sigma}\,[s(x_n) - g(x_n)] \geq \theta radiusS(x_n)$. We have seen that a worthwhile to move process is such that $g(x_n) \longrightarrow g^*$. This implies that $radiusS(x_n) \longrightarrow 0, n \longrightarrow +\infty$.

Remark: Here we have instrumentalism: the goal changes along the process, because the unsatisfied needs $\widehat{g}(x_n) - g(x_n)$ change (decrease) each time.

8 Convergence Towards a Trap: Stopping with no Residual Frustration

In this section we want to know in which cases the agent prefers to stop moving, with no residual frustration feelings, because at the end of the process his aspiration gap will vanish: $\widehat{g}(x^*) - g(x^*) = 0$.

Behavioral Traps (Stable Routines) As seen before, a performance $x^* \in X$ is said to be a behavioral trap, or a stable routine if, for any $y \in X$ with $y \neq x^*$, it is not worthwhile to move from x^* to y. This is equivalent to say that $x^* \in X$ is a rest point element of the "worthwhile to move" relation $x \in X \longmapsto W(x) \subset X$, i.e., $W(x^*) = \{x^*\}$. In this case, the agent has no further incentives to move.

The Worthwhile to Move Theorem *Suppose that the state space X is a metric space with metric d, a the instantaneous utility function $g(.)$ is bounded above, and the agent uses an enclosing heuristic which encloses the worthwhile to move inclusion $y \in W(x)$, $W(x) = \{y \in X, A(x,y) \geq \xi(x)C(x,y)\}$ within the inclusion $y \in S(x), S(x) = \{y \in X, g(y) - g(x) \geq \theta d(x,y)\}, \theta > 0$.* [2]

Then, the worthwhile to move (but, for the moment, not satisficing) process $y \in W(x)$ can be enclosed within the nested enclosing process $y \in S(x) : W(x) \subset S(x)$,for all $x \in X$.Let $x_{n+1} \in W(x_n), n \in N$ and $x_{n+1} \in S(x_n), n \in N, x_0 \in X$ given, be the worthwhile to move and the enclosing process.

a) If the state space is complete the worthwhile to move process converges, $x_n \longrightarrow x^* \in X, n \longrightarrow +\infty$ whatever the starting state $x_0 \in X$. It converges in finite time if, along the process, the total time spend for exploitation is finite

[2] This means that the agent puts limits on the following choixe variables (controls): he sets a maximum lenght of exploitation $0 < t(y) \leq \overline{t}$, a minimum per unit of time effort of moving $e(x,y) \geq \underline{e} > 0$ and a minimum rate of non sacrificing $\xi(x) \geq \underline{\xi} > 0$. He also puts maximum weights over contentment and deception, and $0 \leq \delta(x) \leq \overline{\delta}$. Then, the acceptable transition ratio is higher than a strictly positive level, $\theta(x,y) \geq \theta > 0$, where the minimum acceptable transition ratio is $\theta = (\underline{\xi}\underline{e})/\left[\overline{t}(\overline{\delta}\right] > 0$.

and the speed of moving $v(x,y) = d(x,y)/t(x,y)$ *is higher than a strictly positive level.*$v > 0$.

b) If the worthwhile to move process is "improve enough", which is always the case if the agent "explores enough" around, each step, the process not only converges, but also shrinks: $radiusS(x_n) \longrightarrow 0$. *If the per unit of time utility function is upper semi continuous, then, the limit state* $x^* \in X$ *is a trap (a routine):* $S(x^*) = \{x^*\} \Longrightarrow W(x^*) = \{x^*\}$.

The agent will stop moving at $x^* \in X$ *and has no residual frustration:* $\widehat{g}(x^*) = g(x^*)$.

The "Clairvoyance Theorem" (Clear-sightedness Theorem) *Suppose that, each step, the agent chooses the same radius of exploration* $r(x_n) = r > 0, n \in N$. *Our result shows that after some finite time the worthwhile to move set will lies inside the exploration ball of constant radius, because the radius of the worthwhile to move set skrinks to zero. Then, after a finite time the agent will optimize.*

This is a very powerful result which shows when, under inertia frictions , an agent optimizes.This help to understand the degree of validity of the "as if " hypthosesis (even if agents do not optimize, the substantive approach says: we suppose that it is as if agents optimize).

9 Concluding remarks

Inertia is everywhere. Our approach modelizes intermediate goal -etting behavior with inertia. It can be seen as a local search optimization model in an inertia context which makes local action a result, not an hypothesis. It adds an intermediary goal setting process which helps to built a bridge between local search models and global search models of renforcement learning, via a deterministic exploration-exploitation and moving process, in an inertia context.

The synoptic power of our model is that it articulates in a dynamic way around the exploration-exploitation trade off, three main blocks: goal setting (motivation-exploitation), exploration (search, knowledge and information seeking), and moving (inertia, reactivity costs). Our model is related to a huge list of decision and making models, static and dynamic model of decisions, and then, dynamic models of decision and dynamic model of decision and action, either deterministic or stochastic.

What matters is the interrelation between three blocks : goal setting, motivation and exploitation, exploration (knowledge and information acquisition), and changing (costs of moving, learning).

Our model considers the case of a large state space case (not compact). It adopts a toplogical view, the very general case of a metric space, with no directions. It can be easily extended to a quasi metric space. Our model anchors each step, decision and action, actions changing the context of decision each step.

Appendix 1: Links with Regularization Theory for Ill Behaved Problems

Available upon request

Appendix 2: Links with Local and Global Search Optimization Algorithms

Available upon request

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