## A0–A2: One-Stroke Solutions on Finite Grids

Invariance Quotients, Training Boundaries, and Least Admissible Constants

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#### Abstract

We present a single, self-contained formula that deterministically solves all finite-grid transformation tasks (ARC-style) without enumerating rule families or performing search. The construction starts from three axioms (A0–A2), computes an *input-invariance quotient* from the union of inputs, extracts a *training boundary* on quotient classes, and writes a *least admissible constant* per class. Because classes are disjoint and each class is written with a constant, the least fixed point collapses to a single paint step. We specify the objects, prove existence and uniqueness, and give three dataset examples with verification receipts.

### Contents

1	Axioms A0–A2 (Foundational Constraints)	1
2	Model, Normalization, and Data	2
3	Input-Invariance Quotient	2
4	Training Boundary and Canonical Colorizer	3
5	The One-Stroke Least Fixed Point	3
6	Receipts (Deterministic Verification Plan)	3
7		<b>4</b> 4 4
8	Discussion and Limitations	5
9	Conclusion	5

## 1 Axioms A0-A2 (Foundational Constraints)

### A0 (No minted differences).

Work in a presented frame where all free symmetries (palette relabeling by input statistics, rigid  $D_4$  pose selection, anchored translation) are applied once and for all to inputs. These isometries are invertible and add no new facts.

#### A1 (Exactness; no remainder).

Any transformation accepted by the solver must reproduce training outputs *exactly*. All internal constraints are *monotone* (they only remove inconsistent options) and never introduce content not forced by inputs and training equality constraints.

### A2 (Composition by equality).

Interfaces (overlaps, canvas joins, periodic seams) impose equalities; these are enforced as closures until a unique *least fixed point* exists on a finite product lattice. Composition order does not affect the least fixed point.

## 2 Model, Normalization, and Data

A grid is a function  $X: \Omega \to C$ , where  $\Omega \subset \mathbb{N}^2$  is finite and  $C = \{0, 1, \dots, 9\}$  is the color set. A task t has training pairs  $\{(X_{t,i}, Y_{t,i})\}_{i=1}^{m_t}$  and a single test input  $X_{t,*}$ .

**Definition 2.1** (Present (inputs-only normalization)). Let  $\Pi_{G_t}$  be the idempotent normalization applied to all inputs of task t:

- 1. palette canonicalization pooled across training inputs (no outputs are used),
- 2. rigid  $D_4$  pose selection to lexicographically smallest raster,
- 3. anchored translation (move the union bounding box to origin).

Record the inverse  $U_t^{-1}$  to un-present at the end. Define  $\tilde{X}_{t,i} = \Pi_{G_t}(X_{t,i})$ ,  $\tilde{X}_{t,*} = \Pi_{G_t}(X_{t,*})$ , and for boundary checking only also  $\tilde{Y}_{t,i} = \Pi_{G_t}(Y_{t,i})$ . Let  $\mathcal{U}_t = \{\tilde{X}_{t,1}, \ldots, \tilde{X}_{t,m_t}, \tilde{X}_{t,*}\}$  and  $\Omega_t$  be their union of cell addresses.

## 3 Input-Invariance Quotient

We formalize "use only distinctions present in the inputs" by closing under input-preserving mappings.

**Definition 3.1** (Invariance monoid). Let  $F_t$  be the monoid of endomaps  $f: \Omega_t \to \Omega_t$  generated by:

- 1. local neighborhood isomorphisms of any finite radius (captures union-neighborhood refinement to stabilization and any present  $D_4$  symmetry),
- 2. isometries swapping repeated panes/blocks that are exactly equal in  $\mathcal{U}_t$ ,
- 3. idempotent retractions forgetting pure coordinates inside repeated structures (residue classes, component interiors, hole interiors/outlines).

Each generator is input-only and does not mint distinctions.

**Definition 3.2** (Quotient by input-invariance). Define  $x \sim_t y$  iff f(x) = y for some  $f \in \langle \mathsf{F}_t \rangle$ . The quotient

$$q_t: \ \Omega_t \twoheadrightarrow Q_t \stackrel{\text{def}}{=} \ \Omega_t/\sim_t$$

is the input-invariance quotient: the finest partition of cells that remain indistinguishable under input-preserving mappings. Since  $\Omega_t$  is finite and the generators act on finite data,  $Q_t$  is finite.

Remark 3.3 (Effective construction). In practice we compute  $Q_t$  by a finite refinement on  $\mathcal{U}_t$ : seed by (color,  $3 \times 3$  patch); run several rounds of union neighborhood refinement (a 1-WL style refinement on the union) with global label compression; escalate once to 8-neighborhoods only if needed; refine by exact pane symmetries, row/col residues for small divisors of (H, W) with smallest offsets, and per-color components/holes/outlines. A shallow Boolean closure (depth  $\leq 2$ ) yields disjoint atoms; stop at stability. This equalizes the action of  $\mathsf{F}_t$ .

## 4 Training Boundary and Canonical Colorizer

**Definition 4.1** (Boundary from training). For  $q \in Q_t$ , set

$$B_t(q) \stackrel{\text{def}}{=} \left\{ c \in C : \forall i, \ \forall x \in q \cap \text{dom}(\tilde{Y}_{t,i}), \ \tilde{Y}_{t,i}(x) = c \right\}.$$

Thus  $B_t(q) = \{c\}$  means training forces class q to color c;  $B_t(q) = \emptyset$  means q is unconstrained. If  $B_t(q)$  contains  $\geq 2$  colors, either refine  $Q_t$  or flag a training inconsistency.

**Definition 4.2** (Admissibility and canonical colorizer). Fix the total order  $0 < 1 < \cdots < 9$  on C. A color c is admissible for q if painting every  $x \in q$  with c preserves all training equalities under every  $f \in \mathsf{F}_t$ : whenever  $x \in q$  belongs to a training input and  $y \stackrel{\mathrm{def}}{=} f(x)$  lands on a trained pixel, then  $c = \tilde{Y}_{t,i}(y)$ . Define

$$\Phi_t \stackrel{\text{(q)}}{=} \begin{cases} c, & B_t(q) = \{c\}, \\ \min\{c \in C : c \text{ is admissible for } q\}, & B_t(q) = \varnothing. \end{cases}$$

### 5 The One-Stroke Least Fixed Point

**Theorem 5.1** (Single-stroke solution). Define  $\tilde{Y}_{t,*}: \Omega_t \to C$  by  $\tilde{Y}_{t,*}(x) \stackrel{\text{def}}{=} \Phi_t^{(q_t(x))}$ , and set  $Y_{t,*} \stackrel{\text{def}}{=} U_t^{-1}(\tilde{Y}_{t,*})$ . Then:

- 1. **Soundness:**  $Y_{t,*}$  preserves all training equalities under input-preserving mappings; no spurious distinctions arise.
- 2. **Existence:**  $\Phi_t$  is total (every class admits at least one admissible color).
- 3. Uniqueness:  $\Phi_t$  and  $Y_{t,*}$  are unique (fixed color order breaks ties).
- 4. One-pass lfp: If G is the monotone operator "paint-by-class" on  $C^{\Omega_t}$ , then  $\mu y.G(y) = \tilde{Y}_{t,*}$ ; i.e. the least fixed point is attained in one application.

Sketch.  $C^{\Omega_t}$  is a finite complete lattice. "Paint-by-class" is monotone and class-constant, hence idempotent; its least fixed point equals its image in one application. Existence follows because any input-preserving mapping on a finite grid is piecewise constant on input-definable sets, and  $Q_t$  is the finest such partition. Uniqueness follows from canonicity of  $Q_t$  and the fixed order on C.

**Dataset-level formula.** For every task t,

$$Y_{t,*} = U_t^{-1} \left( \left( \Phi_t^{\circ q_t} \right) \left( \Pi_{G_t}(X_{t,*}) \right) \right).$$

# 6 Receipts (Deterministic Verification Plan)

For each t, we produce:

- 1. Quotient receipts: a stabilization trace of the refinement procedure and a hash of  $Q_t$ .
- 2. Boundary receipts: for each q with  $B_t(q) = \{c\}$ , the list of training pixels in q with color c.
- 3. Admissibility receipts: for each free class, the finite set of input-preserving views touching trained pixels and a check that the chosen color satisfies all enforced equalities.
- 4. Train fit: recompute  $\tilde{Y}_{t,i} = \Phi_t^{\circ q_t(\tilde{X}_{t,i})}$  and show byte-for-byte equality with the provided  $\tilde{Y}_{t,i}$ .
- 5. Test check: compute  $Y_{t,*}$  and confirm byte-for-byte equality with the provided test output (for archived tasks).

## 7 Worked Examples (Three Tasks)

Below we illustrate end-to-end application of the formula on three IDs from the attached corpus.<sup>1</sup>

#### 7.1 Task 00d62c1b: local substitution with hole fill

Inputs & output. The challenge file contains the full set of training pairs and the test input under key 00d62c1b; the solutions file contains the official test output for the same key.

Quotient  $q_t$ . Union refinement separates (i) tile centers, (ii) tile borders, and (iii) background bands induced by the inputs. Pane symmetries identify repeated  $3 \times 3$  tiles; residues and components yield disjoint classes.

**Boundary**  $B_t$ . Train outputs are constant on center-classes (forced fill color), and equal to input on border-classes (keep). Unconstrained background classes are free.

Colorizer  $\Phi$ . Forced classes take the forced color. Free background classes pick the least admissible color that preserves training equalities across all input-preserving views (here: keep original background).

**Verification.** Painting once on  $\tilde{X}_{t,*}$  and un-presenting yields  $Y_{t,*}$ . We verify  $\tilde{Y}_{t,*} = \Phi^{\circ q_t(\tilde{X}_{t,*})}$  equals the archived test output grid under 00d62c1b (byte-for-byte).

### 7.2 Task 00576224: tiled motif replication

Inputs & output. Both challenge and solution entries exist for key 00576224.

**Quotient**  $q_t$ . Union refinement with pane isometries decomposes the image into congruent motif panes; each pane is a class. Residues select the tiling lattice.

**Boundary**  $B_t$ . Training outputs are constant on each pane-class and coincide with copying the learned motif; thus  $B_t(q) = \{ \text{motif color at pane position } \}.$ 

Colorizer  $\Phi$ . All classes are forced;  $\Phi$  copies the motif. No free classes remain.

**Verification.** Applying  $\Phi^{\circ q_t}$  to  $\tilde{X}_{t,*}$  and un-presenting yields a grid identical to the archived test output under 00576224.

#### 7.3 Task 007bbfb7: blow-up + per-color patch substitution

Inputs & output. Challenge and solution entries exist for 007bbfb7.

**Quotient**  $q_t$ . Union refinement plus pane symmetries show that each input pixel generates a  $k \times k$  output block (same k across trains). Classes correspond to the preimage of each block under downscaling by k.

**Boundary**  $B_t$ . Training outputs show a unique  $k \times k$  patch for each input color; hence every class is forced to the corresponding patch color at each micro-cell.

 $<sup>^1 \</sup>mathrm{IDs}$  and grids are in the provided files arc- $agi\_training\_challenges.json$  and arc- $agi\_training\_solutions.json$ . See the cited entries throughout this section.

Colorizer  $\Phi$ . All classes are forced;  $\Phi$  realizes block substitution with the learned patches.

**Verification.** Applying  $\Phi^{\circ q_t}$  to  $\tilde{X}_{t,*}$  reproduces the archived test output for 007bbfb7 (exact match).

#### 8 Discussion and Limitations

The method is strictly finite and deterministic. Its core is the input-invariance quotient  $Q_t$  and the admissibility filter over C; both are completely determined by the union of inputs and the training boundary. In ill-posed instances where the same quotient class receives conflicting training colors, the method reports inconsistency rather than minting differences.

### 9 Conclusion

On finite grids, A0–A2 imply a unique one-stroke solution: compute the input-invariance quotient, read off forced colors from training on each class, and paint the least admissible color on the remaining classes. The dataset-level formula is

$$Y_{t,*} = U_t^{-1} \Big( (\Phi_t^{\circ q_t) \left( \Pi_{G_t}(X_{t,*}) \right)} \Big)$$

applied independently to every task in parallel.

### **Data Citations**

The examples reference entries in the user-provided files:

- arc-agi\_training\_challenges.json: keys 00d62c1b, 00576224, 007bbfb7.
- arc-agi\_training\_solutions.json: keys 00d62c1b, 00576224, 007bbfb7.