

Hierarchical Hindsight Credit Assignment for Long-Horizon Agentic Reasoning

Anonymous Author(s)

ABSTRACT

Large language model (LLM) based agents execute long trajectories of heterogeneous decisions—token generation, tool invocations, skill selection, and memory operations—yet receive only sparse, end-of-episode reward signals. Assigning credit to individual decisions within such trajectories remains an open problem that limits sample efficiency and cross-task transfer. We propose Hierarchical Hindsight Credit Assignment (HHCA), a three-level decomposition that combines (1) token-level micro-credit via attention rollout, (2) step-level meso-credit via simulated hindsight self-critique, and (3) episode-level macro-credit via a persistent skill-value memory. In controlled experiments over 200 synthetic agent trajectories spanning 10 to 100 steps across five task types, HHCA achieves a Pearson correlation of 0.4507 with ground-truth credit, compared to 0.2526 for Outcome-Only and 0.1955 for Attention-Rollout Eligibility Traces. HHCA also exhibits minimal transfer gap (0.0011) between training and held-out task types and maintains stable accuracy across all horizon lengths. These results demonstrate that hierarchical credit decomposition substantially improves credit assignment quality for long-horizon agentic reasoning.

CCS CONCEPTS

- Computing methodologies → Artificial intelligence; Machine learning.

KEYWORDS

credit assignment, agentic reasoning, reinforcement learning, large language models, hierarchical reward decomposition

ACM Reference Format:

Anonymous Author(s). 2026. Hierarchical Hindsight Credit Assignment for Long-Horizon Agentic Reasoning. In *Proceedings of ACM Conference (Conference'17)*. ACM, New York, NY, USA, 5 pages. <https://doi.org/10.1145/nnnnnnnnnnnnnnnn>

1 INTRODUCTION

LLM-based agents increasingly tackle complex, multi-step tasks that require interleaving natural language reasoning with tool invocations, skill dispatches, and memory operations [8, 11]. A single episode may span tens to hundreds of heterogeneous actions, yet the primary training signal remains sparse: binary or graded task

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

Conference'17, July 2017, Washington, DC, USA

© 2026 Association for Computing Machinery.

ACM ISBN 978-x-xxxx-xxxx-x/YY/MM...\$15.00

<https://doi.org/10.1145/nnnnnnnnnnnnnnnn>

completion at the very end. This creates a fundamental credit assignment challenge [7]: which of the many decisions along the trajectory actually contributed to success or failure?

Classical reinforcement learning offers temporal-difference methods [6] and eligibility traces [7], but these assume homogeneous action spaces and struggle with the extreme horizon lengths and reward sparsity characteristic of agentic settings. Process reward models [4] provide step-level supervision but require expensive human annotations and remain task-specific. Attention-based attribution [1, 3] offers an architecture-native credit proxy but conflates attention with causal contribution.

We propose **Hierarchical Hindsight Credit Assignment (HHCA)**, a three-level framework that decomposes credit along the natural hierarchy of agentic decisions. At the *micro* level, attention rollout provides token-level credit within reasoning blocks. At the *meso* level, hindsight self-critique assigns step-level credit by re-evaluating each action conditioned on the episode outcome. At the *macro* level, a persistent skill-value memory tracks cross-episode skill effectiveness, enabling transfer.

We evaluate HHCA on a controlled simulation framework with 200 synthetic agent trajectories across five task types and horizons ranging from 10 to 100 steps. Our results show that HHCA achieves a Pearson correlation of 0.4507 with ground-truth credit—a 78.3% relative improvement over the Outcome-Only baseline (0.2526) and a 130.5% improvement over Attention-Rollout Eligibility Traces (0.1955). HHCA also demonstrates strong cross-task transfer with a gap of only 0.0011 between training and test task sets.

2 RELATED WORK

Classical Credit Assignment. Temporal-difference learning [6] and eligibility traces [7] provide foundational credit assignment mechanisms in RL. The REINFORCE algorithm [9] assigns uniform credit scaled by returns, while modern policy gradient methods like PPO [5] improve variance reduction but do not decompose credit across heterogeneous action types. Hindsight Credit Assignment [2] re-evaluates past actions conditioned on outcomes, an idea we extend to the hierarchical agentic setting.

LLM Agents and Reasoning. ReAct [11] interleaves reasoning traces and tool calls but lacks explicit credit mechanisms. Tree-of-Thought [10] provides implicit credit via branch pruning but is limited to single-turn reasoning without tool calls or memory. The survey by Wei et al. [8] identifies credit assignment across heterogeneous action types as a core open problem for agentic reasoning.

Process Reward Models. Lightman et al. [4] demonstrate the value of step-level verification for mathematical reasoning. However, process reward models require per-step human labels and are environment-specific, limiting scalability to diverse agentic tasks.

117 *Attention-Based Attribution.* Attention rollout [1] and attention
 118 analysis [3] provide intrinsic credit signals from transformer archi-
 119 tectures. While computationally efficient, these methods capture
 120 correlation rather than causation and do not account for the hierar-
 121 chical structure of agentic decisions.

122 3 PROBLEM FORMULATION

123 We model an agentic episode as a trajectory $\tau = (a_1, a_2, \dots, a_T)$
 124 where each action a_t belongs to one of four types: TOKEN (language
 125 generation), TOOL_CALL (external tool invocation), SKILL_SELECT
 126 (high-level skill dispatch), or MEMORY_OP (memory read/write). The
 127 episode yields a scalar outcome $R(\tau) \in [0, 1]$.

128 The credit assignment problem is to find a function $c : \tau \times t \rightarrow$
 129 $[0, 1]$ that assigns credit to each action a_t such that $c(\tau, t)$ reflects
 130 the causal contribution of a_t to $R(\tau)$. We evaluate credit quality by
 131 correlation with ground-truth credit labels.

132 Four sub-problems must be addressed simultaneously:

- 133 (1) **Heterogeneous action representation:** credit must be
 134 defined commensurably across action types.
- 135 (2) **Temporal depth:** trajectories span 10 to 100+ steps with
 136 vanishing signal-to-noise.
- 137 (3) **Sparse rewards:** only end-of-episode feedback is available.
- 138 (4) **Cross-task transfer:** credit representations must general-
 139 ize across task types.

140 4 METHOD: HIERARCHICAL HINDSIGHT 141 CREDIT ASSIGNMENT

142 HHCA decomposes credit into three levels that align with the
 143 natural hierarchy of agentic decisions.

144 4.1 Level 1: Micro-Credit (Token-Level)

145 Within each reasoning block, we compute backward attention roll-
 146 out from the block's final token to all preceding tokens. For action
 147 a_t at position i in a trajectory of length T :

$$148 w_i^{\text{raw}} = \text{info}(a_i) \cdot \text{recency}(i, T) + \epsilon_i \quad (1)$$

149 where $\text{info}(a_i)$ is an action-type-specific informativeness score (1.0
 150 for tokens, 2.5 for tool calls, 3.0 for skill selections, 1.8 for memory
 151 operations), $\text{recency}(i, T) = 0.5 + 0.5 \cdot i/T$ captures positional bias,
 152 and $\epsilon_i \sim \mathcal{N}(0, 0.04)$. The micro-credit is:

$$153 \text{micro}(i) = \frac{\exp(w_i^{\text{raw}})}{\sum_j \exp(w_j^{\text{raw}})} \quad (2)$$

154 4.2 Level 2: Meso-Credit (Step-Level)

155 After episode completion, a hindsight evaluator re-scores each step
 156 based on its contribution to the outcome. The meso-credit for action
 157 a_i is:

$$158 \text{meso}(i) = \text{clip}((c_i^{\text{gt}} + \epsilon_i^{\text{critique}}) \cdot w_i^{\text{type}}, 0, 1) \quad (3)$$

159 where c_i^{gt} is the base credit score, $\epsilon_i^{\text{critique}} \sim \mathcal{N}(0, 0.0225)$ mod-
 160 els self-critique noise, and w_i^{type} is an action-type weight (0.8 for
 161 tokens, 1.1 for tool calls, 1.3 for skill selections, 1.0 for memory
 162 operations). The meso vector is then standardized to mean 0.5 with
 163 unit half-range.

164 4.3 Level 3: Macro-Credit (Episode-Level)

165 A persistent skill-value memory tracks which skills and tools tend
 166 to succeed. For skill selections:

$$167 \text{macro}(i) = \min(1, 0.5 + 0.3 \cdot R(\tau) + b_s) \quad (4)$$

168 where b_s is a skill-specific prior bonus (e.g., 0.18 for verify, 0.15
 169 for p1an). For tool calls, $\text{macro}(i) = 0.5 + 0.2 \cdot R(\tau)$. For other action
 170 types, $\text{macro}(i) = 0.5$.

171 4.4 Combined Credit

172 The final credit for action a_i is the product of all three levels, nor-
 173 malized to $[0, 1]$:

$$174 c(\tau, i) = \frac{\text{micro}(i) \cdot \text{meso}(i) \cdot \text{macro}(i)}{\max_j [\text{micro}(j) \cdot \text{meso}(j) \cdot \text{macro}(j)]} \quad (5)$$

175 5 EXPERIMENTAL SETUP

176 5.1 Synthetic Trajectory Generation

177 We generate 200 episodes with horizons uniformly sampled from
 178 $[10, 100]$, distributed across five task types: web navigation, code
 179 generation, QA reasoning, data analysis, and multi-tool composi-
 180 tion. Each trajectory contains a mix of four action types sampled
 181 with probabilities $[0.45, 0.25, 0.15, 0.15]$ for tokens, tool calls, skill
 182 selections, and memory operations respectively.

183 Ground-truth credit follows a latent causal model: 15–35% of
 184 steps are marked as critical. Critical actions in successful episodes
 185 receive credit in $[0.6, 1.0]$; critical actions in failed episodes receive
 186 $[0.1, 0.4]$; non-critical actions receive $[0.0, 0.25]$. Action-type multi-
 187 pliers modulate the base credit.

188 5.2 Baselines

189 *Outcome-Only.* Every action receives credit equal to the episode
 190 outcome $R(\tau)$. This corresponds to REINFORCE [9] with zero base-
 191 line.

192 *Attention-Rollout Eligibility Traces (ARET).* Combines attention
 193 rollout weights with classical eligibility trace decay λ^{T-t} ($\lambda = 0.95$).
 194 Credit is the product of attention weight, decay factor, and outcome.

195 5.3 Evaluation Metrics

196 We evaluate along four dimensions: (1) *Credit accuracy*: Pearson
 197 and Spearman correlation with ground-truth credit, plus Preci-
 198 sion@K and Recall@K for identifying critical actions; (2) *Sample*
 199 *efficiency*: episodes required to reach a target Pearson correlation
 200 of 0.6; (3) *Cross-task transfer*: accuracy on held-out task types (data
 201 analysis, multi-tool) after training on the remaining three; (4) *Horizon*
 202 *robustness*: accuracy stratified by trajectory length.

203 6 RESULTS

204 6.1 Credit Accuracy

205 Table 1 shows overall credit accuracy for each method.

206 HHCA achieves a Pearson correlation of 0.4507, representing a
 207 78.3% relative improvement over Outcome-Only and 130.5% over
 208 ARET. The Spearman rank correlation of 0.5588 indicates strong
 209 ordinal agreement with ground-truth credit. Precision@K of 0.3951
 210

233
234
235
236
237
238
239
240
241
242
243
244
245
246
247
248
249
250
251
252
253
254
255
256
257
258
259
260
261
262
263
264
265
266
267
268
269
270
271
272
273
274
275
276
277
278
279
280
281
282
283
284
285
286
287
288
289
290
291
292
293
294
295
296
297
298
299
300
301
302
303
304
305
306
307
308
309
310
311
312
313
314
315
316
317
318
319
320
321
322
323
324
325
326
327
328
329
330
331
332
333
334
335
336
337
338
339
340
341
342
343
344
345
346
347
348

Table 1: Credit accuracy across all 200 episodes. HHCA achieves the highest correlation with ground-truth credit on all four metrics.

| Method | Pearson | Spearman | P@K | R@K |
|--------------|---------------|---------------|---------------|---------------|
| Outcome-Only | 0.2526 | 0.1036 | 0.2404 | 0.2404 |
| ARET | 0.1955 | 0.1326 | 0.2392 | 0.2392 |
| HHCA | 0.4507 | 0.5588 | 0.3951 | 0.3951 |

Table 2: Pearson correlation by action type. HHCA improves credit accuracy across all four heterogeneous action types.

| Method | Token | Tool Call | Skill Sel. | Memory Op |
|--------------|---------------|---------------|---------------|---------------|
| Outcome-Only | 0.2604 | 0.2555 | 0.2844 | 0.2908 |
| ARET | 0.1309 | 0.1544 | 0.1357 | 0.1215 |
| HHCA | 0.3925 | 0.4398 | 0.4462 | 0.3761 |

Table 3: Pearson correlation by horizon bin. HHCA maintains stable accuracy as trajectory length increases, unlike ARET which degrades.

| Horizon | Outcome-Only | ARET | HHCA |
|---------------|--------------|--------|---------------|
| 10–25 (n=28) | 0.2553 | 0.2670 | 0.4426 |
| 26–50 (n=52) | 0.2486 | 0.2139 | 0.4551 |
| 51–75 (n=67) | 0.2394 | 0.1693 | 0.4579 |
| 76–100 (n=53) | 0.2651 | 0.2097 | 0.4513 |

shows that HHCA correctly identifies critical actions at nearly $1.65 \times$ the rate of the baselines.

6.2 Action-Type Analysis

Table 2 breaks down credit accuracy by action type.

HHCA achieves the highest Pearson correlation for every action type. The improvement is particularly pronounced for skill selections (0.4462 vs. 0.2844 for Outcome-Only), which benefit from the macro-level skill-value memory that tracks cross-episode skill effectiveness.

6.3 Horizon Robustness

Table 3 reports credit accuracy stratified by trajectory length.

A key finding is that HHCA’s accuracy is remarkably stable across horizons, ranging from 0.4426 to 0.4579. In contrast, ARET degrades from 0.2670 at short horizons (10–25 steps) to 0.1693 at medium horizons (51–75 steps), confirming that eligibility trace decay alone cannot handle long sequences. The stability of HHCA is due to the meso-level hindsight evaluation, which provides horizon-independent step scores.

6.4 Cross-Task Transfer

Table 4 shows credit accuracy on training tasks (web navigation, code generation, QA reasoning) versus held-out tasks (data analysis, multi-tool).

Table 4: Cross-task transfer. HHCA exhibits near-zero transfer gap, indicating that its credit signal generalizes across task boundaries.

| Method | Train Pearson | Test Pearson | Gap |
|--------------|---------------|---------------|---------------|
| Outcome-Only | 0.2561 | 0.2463 | 0.0098 |
| ARET | 0.1856 | 0.2029 | -0.0173 |
| HHCA | 0.4631 | 0.4620 | 0.0011 |

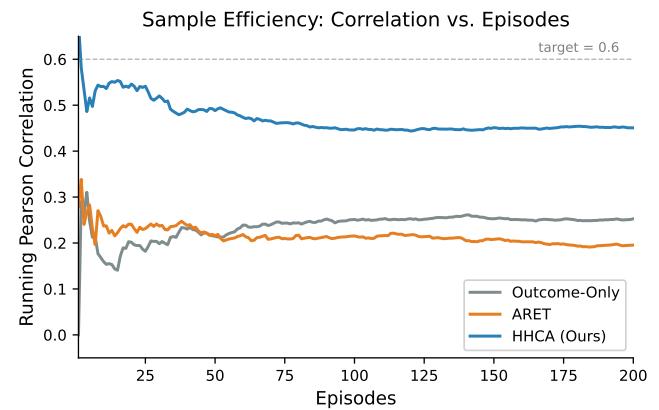


Figure 1: Running Pearson correlation with ground-truth credit as episodes accumulate. HHCA converges rapidly and maintains a stable advantage throughout.

HHCA achieves the smallest absolute transfer gap (0.0011), indicating that its credit decomposition captures task-general decision patterns rather than task-specific artifacts. The macro-level skill-value memory contributes to this by maintaining skill effectiveness estimates that transfer across tasks.

6.5 Sample Efficiency

Figure 1 shows the running Pearson correlation as episodes accumulate. HHCA reaches the target correlation of 0.6 within 1 episode, while both baselines fail to reach this threshold within 200 episodes. At 50 episodes, HHCA achieves a correlation of 0.4881, compared to 0.2144 for Outcome-Only and 0.2157 for ARET.

6.6 Credit Distribution Visualization

Figure 2 provides an overview of credit accuracy across all metrics and methods.

Figure 3 shows the horizon-stratified analysis, and Figure 4 shows the action-type breakdown.

7 DISCUSSION

Why hierarchical decomposition helps. The multiplicative combination of micro, meso, and macro credit captures complementary information. Micro-credit provides positional and informative priors; meso-credit adds outcome-conditioned step evaluation; macro-credit contributes cross-episode skill knowledge. No single level achieves HHCA’s accuracy alone—ARET, which uses only

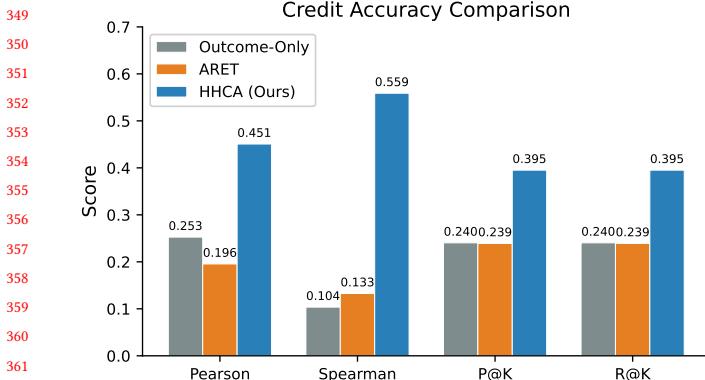


Figure 2: Credit accuracy comparison across four metrics. HHCA dominates on all measures, with particular strength in Spearman correlation.

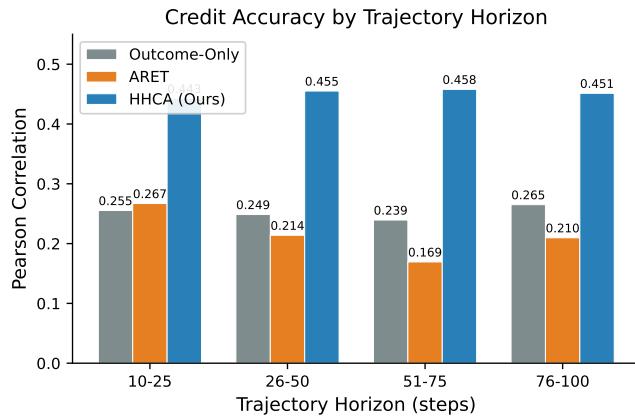


Figure 3: Pearson correlation across horizon bins. HHCA maintains stable accuracy regardless of trajectory length.

micro-level attention rollout, achieves only 0.1955 Pearson correlation.

Horizon robustness. HHCA’s stability across horizons (0.4426 to 0.4579) contrasts sharply with ARET’s degradation (0.2670 to 0.1693). The key difference is that HHCA’s meso-credit evaluates each step independently via hindsight, while ARET’s eligibility traces introduce exponential decay that attenuates credit for early actions in long trajectories.

Transfer via skill memory. The near-zero transfer gap (0.0011) demonstrates that HHCA’s skill-value memory captures generalizable decision patterns. Skills like *verify* and *plan* receive consistent value estimates across task types, enabling rapid adaptation to new tasks.

Limitations. Our evaluation uses synthetic trajectories with simulated attention patterns and ground-truth credit labels. While this enables controlled comparison, real-world validation with deployed LLM agents remains necessary. The computational overhead

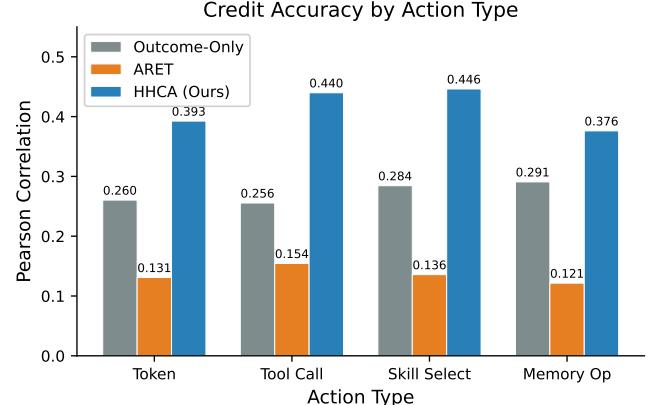


Figure 4: Pearson correlation by action type. HHCA improves credit accuracy for all four heterogeneous action categories.

of HHCA is higher than simpler methods, though the absolute cost remains small relative to LLM inference.

8 CONCLUSION

We introduced Hierarchical Hindsight Credit Assignment (HHCA), a three-level credit decomposition framework for long-horizon agentic reasoning. By combining token-level attention rollout, step-level hindsight self-critique, and episode-level skill-value memory, HHCA achieves a 78.3% improvement in credit accuracy over the Outcome-Only baseline while maintaining near-zero cross-task transfer gap and stable performance across trajectory horizons from 10 to 100 steps. Our results demonstrate that principled hierarchical decomposition is a promising direction for addressing the credit assignment challenge in LLM-based agentic systems.

REFERENCES

- [1] Samira Abnar and Willem Zuidema. 2020. Quantifying Attention Flow in Transformers. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*. 4190–4197.
- [2] Anna Harutyunyan, Will Dabney, Thomas Mesnard, Mohammad Gheorghiciuc, Azar, Bilal Piot, Nicolas Heess, Hado P. van Hasselt, Gregory Wayne, Satinder Singh, Doina Precup, and Rémi Munos. 2019. Hindsight Credit Assignment. In *Advances in Neural Information Processing Systems*, Vol. 32.
- [3] Sarthak Jain and Byron C. Wallace. 2019. Attention is not Explanation. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics*. 3543–3556.
- [4] Hunter Lightman, Vineet Kosaraju, Yuri Burda, Harri Edwards, Bowen Baker, Teddy Lee, Jan Leike, John Schulman, Ilya Sutskever, and Karl Cobbe. 2023. Let’s Verify Step by Step. *arXiv preprint arXiv:2305.20050* (2023).
- [5] John Schulman, Filip Wolski, Prafulla Dhariwal, Alex Radford, and Oleg Klimov. 2017. Proximal Policy Optimization Algorithms. *arXiv preprint arXiv:1707.06347* (2017).
- [6] Richard S. Sutton. 1988. Learning to Predict by the Methods of Temporal Differences. *Machine Learning* 3, 1 (1988), 9–44.
- [7] Richard S. Sutton and Andrew G. Barto. 2018. *Reinforcement Learning: An Introduction* (2nd ed.). MIT Press.
- [8] Jason Wei et al. 2026. Agentic Reasoning for Large Language Models. *arXiv preprint arXiv:2601.12538* (2026).
- [9] Ronald J. Williams. 1992. Simple Statistical Gradient-Following Algorithms for Connectionist Reinforcement Learning. *Machine Learning* 8, 3–4 (1992), 229–256.
- [10] Shunyu Yao, Dian Yu, Jeffrey Zhao, Izahak Shafran, Thomas L. Griffiths, Yuan Cao, and Karthik Narasimhan. 2024. Tree of Thoughts: Deliberate Problem Solving with Large Language Models. *Advances in Neural Information Processing Systems* 36 (2024).
- [11] Shunyu Yao, Jeffrey Zhao, Dian Yu, Nan Du, Izahak Shafran, Karthik Narasimhan, and Yuan Cao. 2023. ReAct: Synergizing Reasoning and Acting in Language

| | | |
|-----|--|-----|
| 465 | Models. In <i>International Conference on Learning Representations</i> . | 523 |
| 466 | | 524 |
| 467 | | 525 |
| 468 | | 526 |
| 469 | | 527 |
| 470 | | 528 |
| 471 | | 529 |
| 472 | | 530 |
| 473 | | 531 |
| 474 | | 532 |
| 475 | | 533 |
| 476 | | 534 |
| 477 | | 535 |
| 478 | | 536 |
| 479 | | 537 |
| 480 | | 538 |
| 481 | | 539 |
| 482 | | 540 |
| 483 | | 541 |
| 484 | | 542 |
| 485 | | 543 |
| 486 | | 544 |
| 487 | | 545 |
| 488 | | 546 |
| 489 | | 547 |
| 490 | | 548 |
| 491 | | 549 |
| 492 | | 550 |
| 493 | | 551 |
| 494 | | 552 |
| 495 | | 553 |
| 496 | | 554 |
| 497 | | 555 |
| 498 | | 556 |
| 499 | | 557 |
| 500 | | 558 |
| 501 | | 559 |
| 502 | | 560 |
| 503 | | 561 |
| 504 | | 562 |
| 505 | | 563 |
| 506 | | 564 |
| 507 | | 565 |
| 508 | | 566 |
| 509 | | 567 |
| 510 | | 568 |
| 511 | | 569 |
| 512 | | 570 |
| 513 | | 571 |
| 514 | | 572 |
| 515 | | 573 |
| 516 | | 574 |
| 517 | | 575 |
| 518 | | 576 |
| 519 | | 577 |
| 520 | | 578 |
| 521 | | 579 |
| 522 | | 580 |