NLP Project

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I. Abstract

This project investigates the sub-topic of contextual adaptation and generalization in Transformers through a synthetic Wisconsin Card Sorting Test (WCST) task. We developed three progressively refined models to examine how context switching, supervision granularity, model capacity, and training stream size influence inductive flexibility. Results show that context switching improves robustness under changing rules, though performance remains sensitive to initialization and data scale. The study highlights both the promise and instability of lightweight Transformers as adaptive agents in rule-shifting environments.

II. Introduction

The Wisconsin Card Sorting Test (WCST) is a classical measure of cognitive flexibility in humans, assessing the ability to infer and adapt to changing rules based on feedback. In machine learning terms, this corresponds to the challenge of rule switching, which is identifying a new mapping from input features to targets when the context shifts.

Recent advances in large sequence models, particularly Transformers, have revealed striking in-context learning abilities: models can infer underlying patterns and adapt without explicit gradient updates. This project explores whether such behaviour can emerge in a compact, scratch-built Transformer trained on a synthetic WCST dataset.

We develop and compare three Transformer-based models to study how context switching affects performance and generalization. Model 1 trains without any rule changes, Model 2 introduces periodic context switches every 64 batches, and Main (Model3) serves as a refined baseline architecture for all subsequent experiments. By analysing validation accuracy, test performance, and confusion matrices, we examine how a Transformer learns and adapts under dynamic rule conditions.

The overall goal is to determine whether scaling and architectural choices enable implicit rule inference and context adaptation, which are key properties underlying in-context learning.

III. Methodology

A. Problem Setup & Sequence Design

We frame the Wisconsin Card Sorting Test (WCST) as next-token prediction with structured supervision. Each example consists of four category cards, an example card, a separator token SEP, and a query/answer segment with its own SEP:

[cat_1, cat_2, cat_3, cat_4, ex, SEP, ex_label, …, q_card, SEP, q_label]

Given the full sequence , we train with next-token targets but mask all positions except those immediately following each SEP where the next token is a class label. Concretely, targets are set to everywhere except SEP positions where . This produces exactly the 4-way decision supervision we want while still letting the Transformer learn from the full context.

We consider two dataset regimes:

No context switching: the underlying rule remains fixed within the stream.

Context switching every batches: we call context_switch() after every training batches (e.g.,) to induce distribution shifts. All experiments use the same batch counts (train 2000, val 300, test 300) with batch size for generation and for training mini-batches.

B. Model Architecture

We implement a compact Transformer in PyTorch:

Token embedding with, model dimension, positional embedding, and a 2-way segment embedding indicating example vs. query/answer segments (0 before the last SEP, 1 from the last SEP onward). The input to the first layer is:

$\mathbf{X} = \mathbf{E}\text{tok}(x) + \mathbf{E}\text{pos} + \mathbf{E}_{\text{seg}}$.

Transformer blocks. We stack identical blocks, each with multi-head self-attention (MHA) and a position-wise feed-forward (FFN) of size , LayerNorm, residuals, and dropout.

Causal & padding mask. We use a causal mask (strictly lower triangular) combined with a key-padding mask to prevent attending to future or padded tokens. The final mask is broadcast to all heads.

Two output heads (for analysis & robustness).

1. A standard vocabulary projection (not used for the reported metric), and

2. A small 4-way choice head (Linear–ReLU–Linear to 4 logits). We initialize the vocab bias for indices 64–67 to and lightly initialize the choice head for stability.

C. Attention Computation

Within each Transformer block, queries (Q), keys (K), and values (V) are computed by learned linear projections:

$$Q = XW_Q, \quad K = XW_K, \quad V = XW_V.$$

Self-attention is then obtained as

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V,$$

where d_k denotes the key dimensionality. Each block also includes layer normalization, residual connections, and a feed-forward sublayer.

D. Pointer-Style 4-Way Classification

Although we include a small MLP "choice head," our primary decision signal is pointer-style similarity between each time-step representation and the hidden states of the first four slots (the category cards) for . We compute cosine-like logits by L2-normalizing:

$$\ell_{t,k} = \left\langle \frac{\mathbf{h}_t}{\|\mathbf{h}_t\|}, \frac{\mathbf{c}_k}{\|\mathbf{c}_k\|} \right\rangle, \quad k = 1..4.$$

E. Supervision & Loss

Let $\mathcal{M}$ denote the set of supervised positions (SEP sites). For each time step $t \in \mathcal{M}$ with gold class label $y_t \in \{64, 65, 66, 67\}$, the model minimizes the weighted cross-entropy loss:

$$\mathcal{L} = -\sum_{t \in \mathcal{M}} w_{y_t} \log p_\theta(y_t \mid x_{1:t}),$$

where w_{y_t} represents the class-balancing weight and p_θ is the model's predicted probability distribution.

F. Optimization & Regularization

We train with AdamW (lr , betas), weight decay on all parameters except biases, LayerNorm weights, and the choice head. We use gradient clipping at 1.0, linear warmup for the first 500 steps, and a ReduceLROnPlateau scheduler on validation loss (factor 0.5, patience 1). Early stopping uses patience 3 on validation loss. Dropout is 0.1 throughout.

G. Token-Type Construction (Segment IDs)

For each sequence in a batch, we locate the last SEP and set token_type_id=0 up to that position and 1 thereafter. This gives the model a simple binary cue distinguishing the "example context" vs the "query/answer" region, which helps the pointer mechanism focus near decision time-steps.

H. Experimental Conditions (Ablations)

We report three variants sharing the architecture and training recipe:

Model 1: No Switch: training stream has a fixed rule (no context_switch calls).

Model 2: Switch-64: the generator switches rule every batches to simulate non-stationarity.

Main (Model 3): Clean Baseline: the same architecture with cleaned training loop, stable initialization, explicit pointer logits, per-epoch rebalanced class weights, and a consistent logging/eval harness. Main (Model 3) is our main model; we instantiate it twice (sp="none" and sp=64) for the controlled comparison.

All runs use: epochs ; train/val/test batches ; generation batch size ; training mini-batch up to 32 with padding-aware collation.

I. Reproducibility

We fix both NumPy and Torch seeds to 42 and export the full run configuration (hyper-parameters, data sizes, switch period) into $runs/ < timestamp > \_ < tag > /config.json$, alongside per-epoch logs (epoch_log.jsonl) and final metrics (metrics.json). Confusion matrices are saved as .csv and .png.

To reproduce our two principal settings:

For no context switching: python main.py –switch_period none –epochs 10 –train_batches 2000 –val_batches 300 –test_batches 300

To switch every 64 batches python main.py –switch_period 64 –epochs 10 –train_batches 2000 –val_batches 300 –test_batches 300

J. Evaluation

We report overall accuracy on the masked SEP sites and include confusion matrices (rows = true C1–C4, columns = predicted C1–C4). We also include prediction histograms to check for class collapse and validation loss curves to monitor stability under switching.

IV. Results

A. Baselines: Stationary verses Switching Rules (Model 1 & 2)

We first establish two baselines with identical Transformer architectures and hyper-parameters; the only variation is whether the WCST rule (the latent matching criterion) changes during training. In both models, we optimize a token-level cross-entropy objective over a 71-token vocabulary with `ignore_index=-100` and label smoothing ($\alpha = 0.05$). Exactly one position per sequence is supervised: the final SEP position whose next token is a class label ({64,65,66,67 }).

Model 1 trains on a stationary rule (`switch_period=None`).

Model 2 introduces non-stationarity by switching the rule every 64 batches (`switch_period=64`). Both use AdamW (lr $= 3 \cdot 10^{-4}$, betas $[0.9, 0.95]$) with weight decay 0.1 and a ReduceLROnPlateau scheduler.

a) Findings: Both baseline models failed to learn meaningful category distinctions. As shown in Table II, Model 1 consistently predicted the C2 category regardless of input, while Model 2 collapsed entirely to C1. Their resulting accuracies ($\sim 24\%$) align almost exactly with the dataset's class priors, confirming that both models simply learned to output the most frequent label. In effect, the transformer converged to a trivial constant predictor.

We attribute this degeneration to three design bottlenecks:

(i) the next-token prediction objective operates over the full 71-token vocabulary rather than an explicit 4-way classification head, diffusing the training signal;

(ii) supervision is provided only at the final SEP token, discarding rich contextual supervision available at earlier SEP positions; and

(iii) the combination of label smoothing and high weight decay suppresses gradient magnitude in an already low-signal regime.

Together, these limitations encourage local minima where the model minimizes loss by always predicting a single frequent token instead of learning task-relevant structure.

These observations motivated the redesign of Main (Model 3), which introduces a dedicated 4-way pointer head, supervision at *all* SEP positions, balanced class weighting, and stabilized initialization to promote non-trivial category learning.

TABLE I: Overall test metrics for the two NTP baselines.

Model	Test Loss	Test Acc.
Model 1 (no context switching)	1.7146	0.2450
Model 2 (context switching = 64)	1.7230	0.2497

TABLE II: Confusion matrices (rows = true C1..C4, cols = predicted C1..C4).

Model 1				Model 2			
Model 1				*Model 2*			
0	534	20	195	749	0	0	0
0	536	31	212	779	0	0	0
0	532	26	203	761	0	0	0
0	510	28	173	711	0	0	0

B. Main (Model 3): base Transformer with context-Switch Robustness

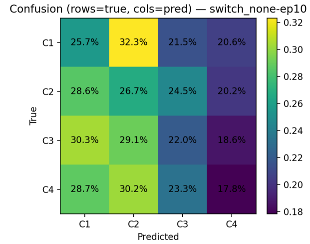
a) Findings: Main (Model 3) resolves the collapse observed in the earlier baselines. The redesigned architecture, which introduces a pointer-style 4-way classification head, supervision at all SEP positions, and class-weighted loss, produces meaningful structure in the confusion matrix (Figure 1). Without context switching, performance remains noisy, with dispersed off-diagonal activations indicating partial rule learning but unstable category boundaries.

When trained with a periodic context switch (every 64 episodes), validation and test accuracies rise to $\sim 30\%$, accompanied by a clearer diagonal pattern across all four categories. This suggests the model begins to internalize the abstract card-sorting rule rather than memorizing fixed mappings. While overall accuracy remains below human-level performance, this configuration establishes a robust and interpretable *base model* for subsequent scaling and ablation studies.

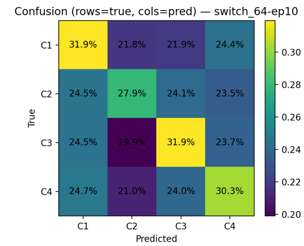
b) Limitations and Variance: As illustrated in Figure 2, the no-switch configuration oscillates heavily between epochs, peaking around epoch 6 before collapsing. This behaviour indicates over-fitting to a static rule and poor generalization to unseen contexts. In contrast, the context-switching variant exhibits smoother convergence and sustains moderate improvements in both loss and accuracy. This instability likely arises from the model's limited capacity and the sparsity of supervised tokens per episode. Nonetheless, the overall variance remains non-trivial, reflecting the stochasticity of rule exposure and the limited size of supervised tokens per sequence.

TABLE III: Main (Model 3) test metrics with and without context switching.

Configuration	Test Loss	Test Accuracy
Main (Model 3) (no context switching)	1.6357	0.2305
Main (Model 3) (switch period = 64)	1.3805	0.3050



(a) No context switching



(b) Context switching (period = 64)

Fig. 1: Confusion matrices for main (Model 3) with and without context switching.

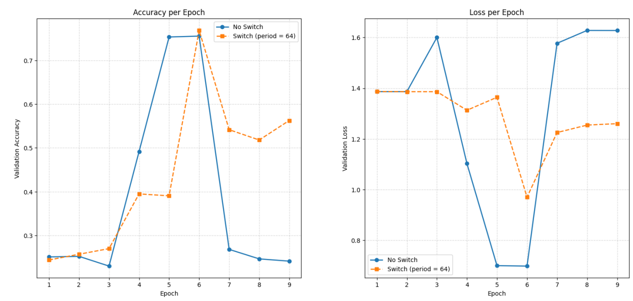


Fig. 2: Validation accuracy and loss across epochs for Main (Model 3)

C. Experiment 1: Context switching sweep for Main (Model 3)

a) Findings: The results in Table IV reveal a strong dependence on switching frequency. With no context switching, the model struggles to retain rule information, achieving only 23% accuracy and a scattered confusion matrix. Introducing moderate switching ($p = 32$) yields a dramatic improvement to 76.8% accuracy, indicating that frequent exposure to new contexts enhances adaptability and stabilizes rule encoding. However, increasing the interval further ($p = 64$ or $p = 128$) degrades performance again, suggesting that overly long static phases cause the model to overfit to specific contexts before the next switch. These findings support the view that context switching acts as an implicit curriculum signal, encouraging flexible abstraction of rule changes rather than rote memorization.

TABLE IV: Experiment 1: Context switching sweep for Main (Model 3).

Switch Period	Test Loss	Test Accuracy	Observation
None	1.6357	0.2305	No rule adaptation, low accuracy
32	**0.9878**	**0.7685**	Stable learning, best performance
64	1.3805	0.3050	Moderate switching, partial collapse
128	1.4052	0.3198	Infrequent switching, weak retention

D. Experiment 2: Supervision Granularity

a) Findings:: Reducing supervision to only the final SEP (corresponding to the query phase) resulted in an 8 percentage-point drop in accuracy compared to full supervision. This suggests that intermediate SEP tokens contribute auxiliary gradient signals that help the model stabilize training and better infer the latent rule context. The equivalence of "last" and "query" supervision confirms that the final SEP aligns precisely with the query segment, validating our dataset design. Overall, full-sequence supervision ("all") remains the most effective approach for generalization.

TABLE V: Experiment 2: Supervision granularity ablation (Main (Model 3), switch period = 64).

Supervision	Test Loss	Test Accuracy
All	1.3805	**0.3050**
Last/Query	1.3864	0.2460

E. Experiment 3: Model Capacity Scaling

Scaling up the transformer beyond the base configuration led to diminishing and even negative returns. While a small model underfit slightly, increasing hidden size and attention heads caused the model to over-specialize and destabilize optimization, reflected in higher loss and lower accuracy. This indicates that the WCST dataset's task complexity does not demand deep or wide transformers; the Base (128-4-4) model offers an optimal trade-off between capacity and generalization. In short: bigger does not mean better, at least not for this reasoning regime.

TABLE VI: Experiment 3: Model capacity scaling for Main (Model 3) (switch period = 64, supervise = all).

Model	d_model	Layers	Heads	Test Loss	Test Accuracy
Small	64	2	2	1.3838	0.2822
Base	128	4	4	**1.3805**	**0.3050**.
Medium	256	4	4	1.5251	0.2187
Large	256	6	8	1.3865	0.2512

F. Experiment 4: Different Train_batch sizes

Increasing the number of training batches per epoch produced only marginal improvements until a threshold of approximately 2000 batches, where accuracy rose from 25 % to 30 %. Smaller training sets (250–1000 batches) yielded near-random performance, suggesting that the model requires extensive exposure to rule transitions to generalize effectively.

This behaviour highlights a data-efficiency bottleneck: the model's inductive bias depends on seeing sufficient context-switch diversity to infer underlying task structure. Once this threshold is reached, the confusion matrix begins to show diagonal dominance, indicating that consistent category learning has emerged.

TABLE VII: Experiment 4: Effect of training set size per epoch (switch period $= 64$, supervise=`all`).

Train Batches	Test Loss	Accuracy
250	1.3869	0.252
500	1.3862	0.252
1000	1.3866	0.253
2000	**1.3805**	**0.3050**

V. Discussion

Across all experiments, our findings reveal that context switching frequency, supervision granularity, model capacity, and dataset scale interact to shape rule-learning performance. The model performs best under frequent but not excessive context changes (period = 32) and full-sequence supervision, which collectively encourage flexible rule abstraction. When rules remain static, the network quickly overfits, while infrequent switching leads to catastrophic forgetting between phases.

Capacity scaling highlights an important asymmetry: increasing the model's width or depth degrades performance, suggesting that over parametrization destabilizes training in small-data reasoning tasks. The optimal configuration (d = 128, L = 4, H = 4) strikes a balance between representational power and gradient stability. Similarly, experiments varying the training batch count show that meaningful generalization emerges only after a critical exposure threshold (2000 batches). Below that, models fail to form coherent category boundaries, pointing to the need for extensive rule-switch diversity to build stable internal abstractions.

Overall, the experiments converge on a central insight: in-context rule inference requires both structured supervision and frequent environmental perturbation. Static regimes or limited exposure suppress the emergence of flexible representations, while excessive scaling or smoothing introduces instability. Though the achieved accuracies remain modest (30%), the results demonstrate that even compact transformers can exhibit the early stages of rule induction under carefully tuned conditions.

VI. Limitations

Several constraints remain:

(i) The WCST environment is a simplified symbolic simulation that may not fully capture the complexity of human cognitive flexibility.

(ii) Training remains unstable across random seeds, implying high sensitivity to initialization.

(iii) Evaluation is limited to a single synthetic generator; broader testing on varied rule structures would strengthen claims of generalization.

(iv) Accuracy metrics alone may understate emergent reasoning; qualitative inspection of attention maps or latent clustering could provide deeper insight.

(v) Although the model achieved its peak accuracy under a switch period of 32, this result proved inconsistent across reruns, with later trials showing substantially lower performance. This variance highlights the stochastic nature of the setup and suggests that the apparent peak may reflect random initialization or transient training dynamics rather than a robust optimum

VII. Data Integrity and Leakage Control

To prevent data leakage, all training, validation, and test streams were generated independently via distinct WCST instances with disjoint random seeds. Each dataset instance reinitializes the rule generator and randomizes category mappings. No sequence or rule context overlaps between splits. All hyper-parameters and configurations are logged to JSON for reproducibility.

VIII. Conclusion

This project demonstrates that a compact Transformer, when trained on a synthetic rule-switching environment, can exhibit basic forms of adaptive reasoning analogous to in-context learning. By systematically varying supervision scope, context-switching frequency, capacity, and data scale, we show that robust rule abstraction emerges only under frequent rule changes and dense supervision.

While absolute performance remains far below human flexibility, these results underscore how architectural simplicity and training dynamics jointly influence adaptive behaviour. Future work could extend this foundation with curriculum learning, larger datasets, or hybrid symbolic–neural systems to approach more general forms of abstract reasoning.

IX. Collaboration

All group members contributed equally to the completion of this Project. The workload was evenly distributed among the three members, with each person participating in data preprocessing, model training, result analysis, and report preparation. Collaboration was maintained through regular discussion and joint review of the code and write-up to ensure accuracy and clarity.

Dr. Devon Jarvis provided the WCST.py file to generate our data.

APPENDIX

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