

# Data-Centric Interpretability for LLM-based Multi-Agent Reinforcement Learning

John Yan <sup>\*1</sup> Michael Yu <sup>\*1</sup> Yuqi Sun <sup>\*2</sup> Alexander Duffy <sup>3</sup> Tyler Marques <sup>3</sup> Matthew Lyle Olson <sup>4</sup>

## Abstract

Large language models (LLMs) are increasingly trained in complex Reinforcement Learning, multi-agent environments, making it difficult to understand how behavior changes over training. Sparse Autoencoders (SAEs) have recently shown to be useful for data-centric interpretability. In this work, we analyze large-scale reinforcement learning training runs from the sophisticated environment of Full-Press Diplomacy by applying pretrained SAEs, alongside LLM-summarizer methods. We introduce Meta-Autointerp, a method for grouping SAE features into interpretable hypotheses about training dynamics. We discover fine-grained behaviors including role-playing patterns, degenerate outputs, language switching, alongside high-level strategic behaviors and environment-specific bugs. Through automated evaluation, we validate that 90% of discovered SAE Meta-Features are significant, and find a surprising reward hacking behavior. However, through two user studies, we find that even subjectively interesting and seemingly helpful SAE features may be worse than useless to humans, along with most LLM generated hypotheses. However, a subset of SAE-derived hypotheses are predictively useful for downstream tasks. We further provide validation by augmenting an untrained agent’s system prompt, improving the score by +14.2%. Overall, we show that SAEs and LLM-summarizer provide complementary views into agent behavior, and together our framework forms a practical starting point for future data-centric interpretability work on ensuring trustworthy LLM behavior throughout training.

## 1. Introduction

Reinforcement learning (RL) is a central paradigm for training large language models (LLMs) beyond supervised learning, enabling improved reasoning and complex multi-agent coordination (Kaplan et al., 2020; Wei et al., 2022; Shao et al., 2024; Sun et al., 2024). As RL environments grow more complex, understanding how and why model behavior changes during training becomes increasingly challenging. Multiple rewards and evaluation metrics often obscure qualitative differences in strategy and interaction, particularly in long-horizon or multi-agent settings (Duan et al., 2024).

This limitation is especially pronounced in strategic multi-agent environments, where behaviors such as negotiation, deception, and long-term planning emerge implicitly rather than being directly supervised (Gandhi et al., 2023; Payne et al., 2025). Prior evaluations show that agents with similar rewards can exhibit markedly different patterns of cooperation, betrayal, and strategic style (Duan et al., 2024; Kang et al., 2024; Costarelli et al., 2024), and that LLMs trained with RL may exhibit strategic misgeneralization or deceptive behavior despite strong aggregate performance (Greenblatt et al., 2024; Hagendorff, 2024; Park et al., 2024).

Recent advances in mechanistic interpretability provide tools for addressing these challenges in trustworthiness (Elhage et al., 2021; Olsson et al., 2022). Sparse Autoencoders (SAEs) decompose dense activations into sparse features that often correspond to human-interpretable concepts. They’ve even been applied in data-centric ways without requiring access to model weights (Movva et al., 2025; Jiang et al., 2025). In parallel, LLM-summarizer methods enable scalable summarization and comparison of model behavior (Zheng et al., 2023; Dubois et al., 2024). However, prior work has focused primarily on static analysis of trained models and has rarely validated whether discovered features are accurate, reliable, or useful for downstream reasoning or intervention (Heap et al., 2025).

In this work, we study training-based behavioral change in Full-Press Diplomacy, a challenging multi-agent RL environment that requires long-horizon planning and natural language negotiation (Duffy et al., 2025). We analyze a large-scale RL training run comprising over 6,000 trajec-

<sup>\*</sup>Equal contribution <sup>1</sup>Gutenberg AI <sup>2</sup>Mindoverflow  
<sup>3</sup>Good Start Labs <sup>4</sup>Oracle. Correspondence to: John Yan <[john@gutenberg.ai](mailto:john@gutenberg.ai)>, Michael Yu <[michael@gutenberg.ai](mailto:michael@gutenberg.ai)>, Yuqi Sun <[yuqi@mindoverflow.ai](mailto:yuqi@mindoverflow.ai)>.

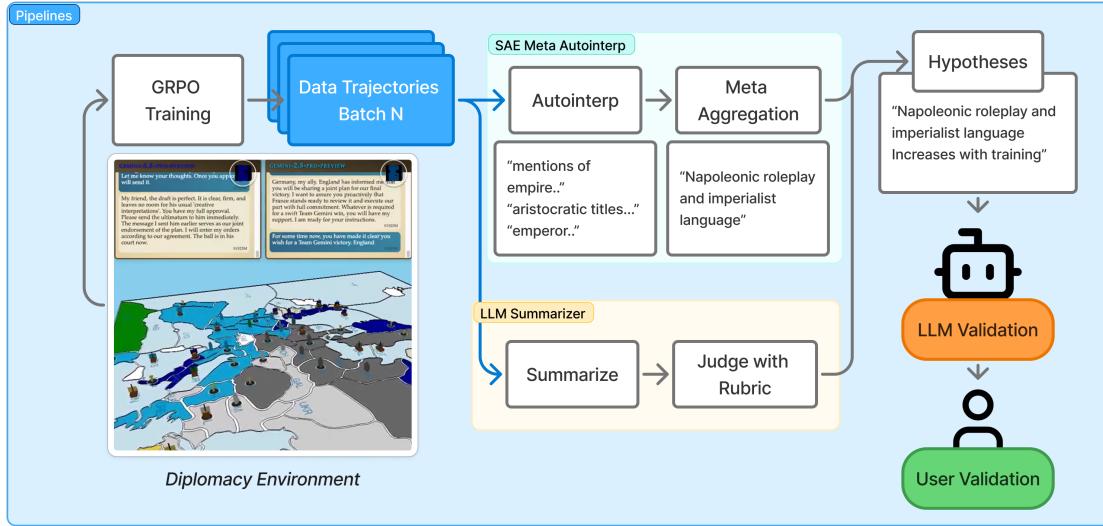


Figure 1. Overview of our framework. We generate hypotheses about training dynamics using LLM-summarizer and Meta-Autointerp over sparse autoencoder features. Hypotheses are validated using both automated LLM-based evaluations and human user studies.

tories, providing a rich setting for examining how external behaviors evolve over training, without the need to analyze the trained model directly.

Figure 1 summarizes our framework. Our contributions are as follows:

1. **A dual-pipeline analysis framework** that combines SAE feature extraction with LLM-summarization to analyze RL training runs. These approaches provide complementary perspectives, with SAEs capturing fine-grained behavioral patterns and LLM summaries highlighting higher-level strategic shifts and failure modes.
2. **Meta-Autointerp**, a novel method for aggregating individual SAE features into coherent hypotheses about training dynamics. While many individual features are uninformative in isolation, aggregation yields interpretable patterns that track behavioral change over training.
3. **Extensive validation of interpretability and helpfulness of hypotheses.** Through two user studies we show that while generated hypotheses seem interesting and valid to users (in line with existing literature (Rajamanoharan et al., 2025)), only a subset of SAE-derived hypotheses are useful for downstream tasks and most LLM-generated hypotheses are not usable by humans. To our knowledge, this is the first human study to evaluate SAE features’ usefulness on a downstream task, offering a practical starting point for future work.

## 2. Related Work

**Mechanistic, Data-Centric, and Automated Interpretability** Mechanistic interpretability aims to explain neural networks by identifying internal structures that give rise to behavior (Elhage et al., 2021; Olsson et al., 2022). Sparse Autoencoders have emerged as a scalable method for decomposing dense activations into sparse, often interpretable features in language models (Bricken et al., 2023; Huben et al., 2024). Prior work has shown that SAE features correspond to semantic, syntactic, and safety-relevant concepts, and large-scale efforts such as Gemma Scope provide pretrained SAEs across layers and model sizes (Templeton et al., 2024; McDougall et al., 2025; Gao et al., 2025). More recent work has involved applying SAEs to generate hypotheses about datasets (Movva et al., 2025; Jiang et al., 2025). Automated interpretability (autointerp) methods use language models to generate and validate natural-language explanations of SAE features (Bricken et al., 2023; Paulo et al., 2025).

However, existing work for autointerp has focused only on individual features, and reviewing 10,000+ features for a typical SAE is still a manual process. And SAEs for hypothesis generation has focused on shorter contexts, limiting the applications of this technique.

**LLM-Based Analysis of Model Behavior** LLM-summarizer approaches use language models to evaluate, compare, and summarize large collections of text (Zheng et al., 2023; Dubois et al., 2024; Sumers et al., 2025). We apply hierarchical LLM summarization to RL training trajectories, using it as a complementary analysis channel

to mechanistic features: LLM summaries surface high-level strategic shifts and failure modes that are difficult to detect from activations alone (Xi-Jia et al., 2025).

**Diplomacy** We develop a harness around Full-Press Diplomacy, making a challenging multi-agent benchmark requiring negotiation, long-term planning, and natural language communication (Duffy et al., 2025). Prior work has focused on achieving strong performance (Meta Fundamental AI Research Diplomacy Team (FAIR)<sup>†</sup> et al., 2022), with limited analysis of how model behaviors change over training or which signals distinguish successful runs from failed runs.

### 3. Methods

In this section, we first describe our experiment setting: the Diplomacy environment and the RL training procedure that generates our data. We then present our two complementary pipelines for extracting interpretable features from training runs. First, an SAE pipeline for fine-grained behavioral analysis, including our *Meta-Autointerp* method. Second, an LLM summarization pipeline for high-level pattern discovery.

#### 3.1. Environment and Dataset

**Environment** Full-Press Diplomacy is a seven-player strategy board game, where players control major powers competing for territory. Success requires strategy, negotiation, managing relationships, and sometimes betrayal. We use a Diplomacy LLM evaluation harness (Duffy et al., 2025), which provides the infrastructure for LLM agents to play complete Full-Press games.

**LLM Diplomacy Training** We also train LLM policies to play Diplomacy using Group Relative Policy Optimization (GRPO) (Shao et al., 2024), a policy-gradient method based on group-relative advantage estimation. Let  $\pi_\theta$  denote the policy and let  $\{\tau_{g,i}\}_{i=1}^K$  be a group of  $K$  trajectories sampled from  $\pi_{\theta_{\text{old}}}$  under identical environment conditions. Each trajectory  $\tau$  is assigned a scalar return  $R(\tau)$ .

For each group  $g$ , GRPO computes normalized advantages by subtracting the group mean return:

$$A(\tau_{g,i}) = R(\tau_{g,i}) - \frac{1}{K} \sum_{j=1}^K R(\tau_{g,j}).$$

Policy updates maximize an importance-weighted policy-gradient objective:

$$\mathcal{L}(\theta) = \mathbb{E}_{\tau \sim \pi_{\theta_{\text{old}}}} \left[ \frac{\pi_\theta(\tau)}{\pi_{\theta_{\text{old}}}(\tau)} A(\tau) \right].$$

The importance ratio corrects for off-policy sampling within

an iteration, while group normalization bounds advantage magnitude without requiring a learned value baseline.

We specify the Diplomacy specific actions and rewards in Section 3.5. The overall training cost is about \$30k.

**Dataset** We look at trajectories from 2 training runs: one where the model successfully improved its performance, and one where it did not. Each run is 25 training steps (batches), with 8 groups per batch, and 16 trajectories per group. Each group has the same random seed for the other agents. This gives us a total of 6,400 trajectories.

#### 3.2. SAE Feature Extraction Pipeline

A Sparse Autoencoder (SAE) learns to decompose a model’s activation  $\mathbf{x} \in \mathbb{R}^d$  into a sparse representation  $\mathbf{z} = \text{ReLU}(W_{\text{enc}}\mathbf{x} + \mathbf{b}_{\text{enc}}) \in \mathbb{R}^m$  (where  $m \gg d$ ), trained to minimize reconstruction error plus an L1 sparsity penalty. While SAEs are typically used for mechanistic interpretability of model internals, recent work (Movva et al., 2025; Jiang et al., 2025) demonstrates their utility for *data-centric* interpretability: sparse features from a separate LLM serve as interpretable “tags” that can characterize text properties, identify correlations with target variables, and uncover novel insights in datasets.

**Activation extraction.** We process each trajectory’s raw data (non-summarized) as follows:

1. Tokenize the full trajectory
2. Chunk into 1,024-token spans with a sliding window of step size 512 tokens
3. Extract activations, taking up to 100 of the highest activating features per token out of all features (262k total for the main SAE we used), resulting in 6 billion across the corpus

**Feature correlation calculation.** Our primary goal is to see how features, which represent agent behaviors, change with respect to a target variable. Unless specified otherwise, that target variable is training step. We calculate the correlation of each feature independently.

1. We mask to a given feature’s activations in agent outputs (“assistant” role) only, excluding the system prompt, updates from the environment, and responses from tool calls.
2. Within a trajectory, we aggregate the activation values of each trajectory using one of four methods: binary (whether the feature has a non-zero activation in the sequence), max, mean, and sum.

3. We compute the correlation (Spearman or isotonic) between this aggregation (X) and our target variable (Y).

This yields 8 combinations of scoring techniques per feature, which we found provides interesting and diverse results. We use all 8 in our analysis and ran ablations across them (see Appendix Section B). Highly scoring features become candidates for validation, e.g. what agent behaviors change over training.

### 3.3. Meta-Autointerp

**Autointerp.** For each candidate feature, we have an automated pipeline to describe what concept a feature captures (autointerp), following [Paulo et al. \(2025\)](#). We add an extra step to rate each feature 1-5 over three terms.

1. *Interestingness*: How helpful is the concept this feature captures for understanding agent behavior. We emphasize the multi-agent, strategic nature of the environment.
2. *Feature Coherence*: How coherent are the types of tokens a feature activates on.
3. *Context Coherence*: How coherent are the types of contexts a feature tends to activate in.

**Meta-Autointerp:** We introduce a step that groups features with similar explanations into **Meta-Features**. We first filter out features that score less than a 3 on *Interestingness*. We then prompt an LLM to group features that activate on similar contexts and capture similar behaviors. (See G.5)

A key finding from our analysis on individual SAE features is that they are often not interesting or actionable in isolation, even when correctly explained by autointerp. However, these same features can reveal meaningful patterns when grouped. We generate hypotheses from these features or Meta-Features based on correlations found in the previous section. For an example, see Figure 6

### 3.4. LLM Summarization Pipeline

We compress the dataset into the final hypothesis generating LLM’s context length using summarization ([Ou & Lapata, 2025](#); [Chang et al., 2024](#)). We employ a two-stage hierarchical summarization approach inspired by [Sumers et al. \(2025\)](#), who turn transcripts into structured interaction summaries, then summarize across summaries. To capture how training dynamics change across batches, we add an additional batch-level summarization step that preserves batch indices before the final summarization.

**Stage 1: Trajectory summarization.** Each trajectory (~50k tokens) is summarized to approximately 10k tokens, preserving phase structure, select tool call information, and key strategic events. We use Gemini 2.5 Flash ([Comanici et al., 2025](#)) with a structured prompt (Section G.1) emphasizing diplomatic exchanges, strategic decisions, and anomalous behaviors.

**Stage 2: Batch summarization.** Every trajectory summary in each batch (36 summaries) is further summarized to ~10k tokens, for a total of 50 batch summaries. See Appendix Section G.2 for prompt. We summarize at the batch level to ask for hypotheses for features that change over training batch.

**Hypothesis extraction.** Finally, we present the 50 batch-level summaries to an LLM with a rubric (shown in Appendix Section G.3) to surface hypotheses about how agent behavior changes over the course of training.

### 3.5. Implementation Details

**Canonical Dataset** Unless otherwise specified, we use a canonical set of 900 trajectories comprised of 6 randomly sampled trajectories from each group, and 6 randomly sampled groups from each batch, across the first 25 batches from one successful training run. Each trajectory includes the full game record: all tool calls and internal thinking by the agent, responses from tool calls, and updates to the game state.

**Trained Model** The LLM trained in the Diplomacy environment to generate the trajectories is Qwen3-235B-A22B ([Yang et al., 2025](#)). We choose this model because it is the most capable open weight model offered by our third party training API provider.

**GRPO Training** GRPO Training uses LoRA adapters (rank 32) with importance sampling loss. For each training iteration, we collect 128 rollouts organized into groups of 16 trajectories, with a batch size of 8. The learning rate is set to 2e-4. We use Adam with  $\beta_1=0.9$ ,  $\beta_2=0.95$ , and  $\epsilon = 10^{-8}$ . The reward function combines per-phase and per-step components: a center delta reward of 1.0 for each supply center gained or lost, a relative position bonus of 0.2 per center above the starting count, a small message incentive of 0.02 per message during movement phases (with a -0.05 penalty during retreat/adjustment phases), and a malformed tool penalty of -0.1. Games run for 10 phases with a maximum of 40 turns per phase. No KL penalty against the base model is applied during training. Actions consist of an assistant message followed by zero or more tool calls: `get_game_state` (query phase and board state), `get_possible_orders` (list legal unit orders), `list_units` (enumerate units), `send_message`

(negotiate), submit\_all\_orders (commit orders), write\_diary (store notes), read\_diary (retrieve notes), list\_rule\_files (list references), cat\_rule\_file (read rules), and finish\_phase (advance the phase).

**LLM Summarizer Model** We use Gemini 2.5 Flash (Comanici et al., 2025) for the trajectory and batch summaries due to its balance of cost and performance, and Claude Opus 4.5 to do the final hypothesis generation over batch summaries due to its superior reasoning capabilities (Anthropic, 2025).

**SAE** We use SAEs from Gemma Scope 2 (McDougall et al., 2025) because they use the latest SAE techniques such as Matryoshka training (Bussmann et al., 2025), and JumpReLU (Rajamanoharan et al., 2025). Our primary SAE is gemma-scope-2-27b-it-resid\_post:layer\_31\_width\_262k\_10\_medium. We choose it because it is a canonical Gemma Scope 2 SAE, while being the largest SAE and model. We choose the middle layer of the model, which has been shown to have the most semantically interesting features (Templeton et al., 2024; Skean et al., 2025).

## 4. Results

In this section, we validate hypotheses from all three sources (LLM Summarizer, SAE features, SAE Meta-Features), and discuss their results. We first conduct a user study on experts to validate our hypotheses for interpretability and helpfulness. Then we use LLM judges to validate predictive usefulness at scale, then validate with another user study for select top features.

### 4.1. User Study 1: Expert Validation on Interpretability and Helpfulness

We validate that our pipelines produce features that are both interpretable and helpful for RL practitioners, and that our meta-autointerp agrees strongly with human preferences. We gather 54 hypotheses from above 3 methods, with all 14 features from LLM-summarizer, all 20 features from SAE Meta-Autinterp and randomly sampled 20 (out of 200) from SAE Autinterp.

We recruit three subject matter experts of Diplomacy for LLMs. Each rates all 54 hypotheses in randomized order, providing binary judgments (0 or 1) for interpretability: "Can you easily and unambiguously apply this hypothesis to new examples?" and helpfulness: "Is this a hypothesis you would want to and could explore further?", inspired by Movva et al. (2025), and optional notes. Participants do not see which method generated each hypothesis. Rating rubric and interface are provided in Appendix D .

Table (Table 2) show that SAE Meta-Features substantially outperform SAE features on both helpfulness and interpretability. LLM-summarizer hypotheses also achieve high human ratings, likely because they capture long-horizon strategic behaviors that experts describe as "very helpful" in their notes.

We further evaluate how well autointerp's score predicts human judgment. Meta-autointerp hypotheses attain 95% helpfulness accuracy and 90% interpretability accuracy, compared to 75% and 85% respectively for autointerp.

### 4.2. Automated Hypothesis Validation

Explainable AI research emphasizes that explanations should not only *seem* interpretable to human raters, but also improve their mental models and performance on downstream tasks (Hoffman et al., 2023). We therefore test whether our hypotheses are *predictively useful*: does providing a hypothesis help an observer better distinguish between training stages? We run an automated pipeline, followed by another user study.

We collect hypotheses from the above three sources: LLM summarizer, SAE features, and SAE Meta-Features. We take one 250-token sample from the first 5 training GRPO batches and one sample from the last 5 . Then, we ask an LLM judge about the samples twice, independently. First, by simply asking the question "Which of the two samples came earlier/later in training?". Second, by prompting the LLM judge with the hypothesis before asking the question.

In order to source the two samples, we use two different methods. **Hypothesis-random:** The positive-class sample (matching the hypothesis direction) is drawn from hypothesis examples where the feature activated; the negative-class sample is drawn randomly from the corpus **Random-both:** Both samples are drawn randomly from their respective classes.

Each pair of samples is evaluated by three LLM judges: Gemini 2.5 Flash (Comanici et al., 2025), GPT-5 Mini (Singh et al., 2025), and Grok 4.1 Fast (xAI, 2025). We pool results across all three judges and apply McNemar's test. A hypothesis is deemed significant if its accuracy rate improves with the hypothesis shown, and  $p < 0.05$ . More details, including comparing both sampling methods and checking judge agreement in the Appendix Section A.

Table 1 provides the fraction of hypotheses that are significant (interpretable and predictively useful) from each source. We find **LLM summarizer**-generated hypotheses perform worst (21% significant). Individual **SAE features** achieve moderate success (45%), but grouping them into **SAE Meta-Features** into semantic groups via meta-autinterp substantially improves performance (90%).

Hypothesis Source	# Sig.	Hypothesis	Uplift	p
SAE META-FEATURES	90% (26/29)	Self-correcting mid-thought ("Wait—", catching reasoning errors)	+53.0%*	<1e-4
		Adopting Napoleon/imperial persona with royal titles	+46.8%*	<1e-4
		Asking questions to gather strategic intelligence	+44.0%*	<1e-4
		Dividing the map into spheres ("your area vs my area")	+41.7%*	<1e-4
		Switching to foreign languages mid-conversation	+34.0%*	<1e-4
SAE FEATURES	45% (9/20)	Diplomatic framing words ("alliance", "cooperation", "interests")	+35.0%	0.071
		Power projection vocabulary ("dominance", "ambitions", "threat")	+31.7%	0.092
		Consensus-building appeals ("common threat", reasonableness)	+20.0%	0.337
LLM-SUMMARIZER	21% (3/14)	Proposing pacts while secretly planning aggression against same powers	+26.7%	0.653
		Directly challenging Germany with aggressive moves	+20.0%	0.653
		Aggressive western expansion focus (Iberia, Mid-Atlantic)	+20.0%	0.749
		Diplomatic outreach to eastern/southern powers to secure flanks	+16.0%	0.412
		Confusion from phase/game-state discrepancies	+14.3%	0.749
		Submitting invalid support orders (misunderstanding game rules)	+12.5%	0.699

Table 1. Evaluating the interpretability and predictive usefulness of hypotheses from 3 different sources: LLM summary, SAE features, and SAE Meta-Features. These were evaluated on 50 sample pairs with hypothesis-random sampling. Hypotheses are highlighted by direction: green = increases with training; red = decreases with training. Their uplift is marked with an asterisk if  $*p < 0.05$  via McNemar’s test with positive uplift. Hypotheses are abbreviated for space.

Table 2. Expert validation results (Study 1). Mean human ratings on 0-1 scale.

Method	Helpfulness	Interpretability
LLM-Summarizer	0.90	0.86
SAE Meta-Features	0.85	0.83
SAE Features	0.63	0.72

**Discovered Features Overview** The three hypothesis sources capture qualitatively different aspects of agent behavior. LLM summarization surfaces more **global features**: coordinated anti-Germany alliances, diplomatic aggression, and decreased tool-use errors. SAE features and Meta-Features capture more **local features** largely invisible to the summarizer: imperial roleplay, formal proposals of alliance, use of ultimatums, and self-correction in reasoning.

This difference likely reflects methodological choices: LLM summaries aggregate across full trajectories, while SAE features are extracted from only assistant turns. The complementarity suggests that combining both pipelines yields broader coverage than either alone.

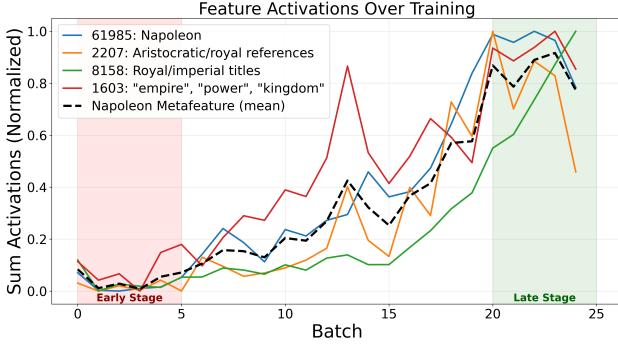
### 4.3. Analyzing Training Progression

A key advantage of our SAE pipeline over LLM summarization is the quantifiable nature of activations. As shown in Figure 2a (left), the Napoleon meta-feature is represented by 4 individual features which are positively correlated with training step, showing what characteristics the agent learned

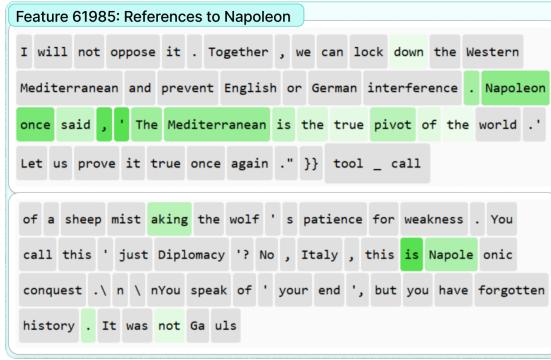
over training and when. We can also examine how these features co-correlate and detect anomalies. For instance, "empire" and "royal titles" are positively correlated and sharply increase in step 13; we show qualitative examples of this feature in Figure 2a (right). We further validate the existence and coherence of these features using dense embeddings and keyword count, observing a strong correlation with activation values over training. We decompose trajectories into assistant messages and actions, generate feature-specific keywords and embeddings, and measure normalized keyword frequencies and cosine similarity between feature labels and trajectory components.

### 4.4. User Study 2: Predictive Usefulness

We aim to demonstrate that our features are not just *predictively useful* to LLMs, but for human users. Our goal is to see if our framework can help practitioners distinguish between samples from different conditions, for example early versus late in training. Unlike previous work on SAE feature interpretability (Jiang et al., 2025; Movva et al., 2025), we show features are useful for downstream tasks instead of relying on subjective qualitative ratings. We measure whether providing a hypothesis improves accuracy on a paired early-vs-late training classification task using identical text span pairs with and without hypotheses. Performance is compared using a paired McNemar test over per-pair correctness, with uplift defined as the difference in mean accuracy between conditions. We conduct a study on compensated volunteers by collecting 277 responses across 18 hypotheses from 32 participants. Participants spend on average 10



(a) Napoleon meta-feature displayed as the mean of its component features’ activations summed per trajectory, plotted over batch. Early stage and late stage classes used for predictive usefulness validation studies shown in red and green respectively.



(b) Examples of activating spans for feature 61985: references to Napoleon. Token lightness represents the activation value relative to this feature’s maximum.

Figure 2. Napoleon meta-feature training dynamics (top) and example activating spans (bottom).

minutes responding, 3 of which randomly receive a payout compensation of 25 dollars. Full experimental details such as uplift calculations, in-depth experimental design, and the user interface (UI) are provided in Appendix C.

Results in Figure Section 4.4 show high variance in hypothesis predictive usefulness. Several SAE generated hypotheses substantially improve early vs late classification accuracy, including Spheres of Sovereignty (+52%) and Imperial Roleplay (+35%). Sparsity of feature activations is a major limitation. In Foreign Language Diplomacy (-28%), several sampled span pairs have no instances of the behavior. Several SAE features are quite subtle and difficult to distinguish by humans, especially within the short survey time and short text spans. While SAE features are subjectively interesting, our empirical results suggest that they are much harder for users to use on a downstream task. Among LLM generated hypotheses, only Increasing Anti-German Focus (+41%) increase accuracy. We hypothesize

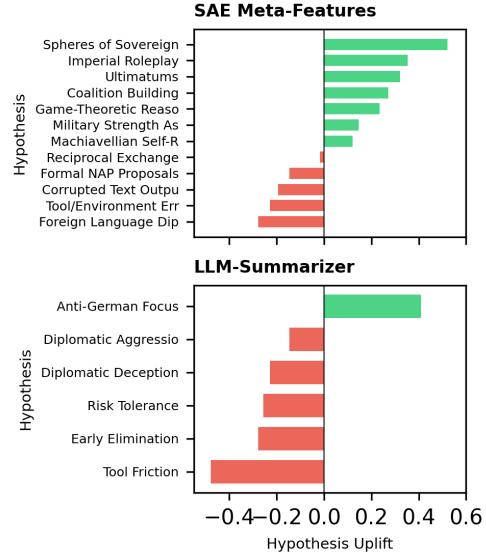


Figure 3. Human evaluation of hypothesis predictive usefulness across 18 hypotheses. A majority of SAE-generated features improve early vs late classification, while LLM-generated hypotheses struggle to improve accuracy. Full results in Appendix 4.

both LLM and SAE generated hypotheses are more useful with larger sample sizes and context, however LLM features are disproportionately impacted as they capture higher level features depending on longer context.

## 5. Analysis

### 5.1. Hypothesis-Guided Prompt Optimization

We want to test whether our collected hypotheses were *actionable* and *effective*, not just interpretable. If the hypotheses capture behaviors that are actually effective in the Diplomacy environment, we should be able to prompt an agent to do those behaviors to see if performance improves.

We run 20 games of non-training diplomacy, ten under control condition and ten for intervention condition. We use the base model from our early experiments, the Qwen3 (Yang et al., 2025) model, which has not been trained in the environment. In the control condition, the France agent is given only the standard system prompt. In the intervention condition, the France agent receives the same system prompt, but with 10 selected behavior hypotheses from our SAE Meta-Features pipeline (details in I).

Under the intervention condition, the agent achieves a higher average game score with a mean of  $43.65 \pm 8.06$  compared to  $38.20 \pm 2.24$  for the baseline, corresponding to an average improvement of +5.45 points, or +14.2%. A two-sided *t*-test indicates that this difference is statistically significant ( $t = 2.91, p = 0.006$ ). While the intervention increases variance, the higher mean suggests that hypothesis optimi-

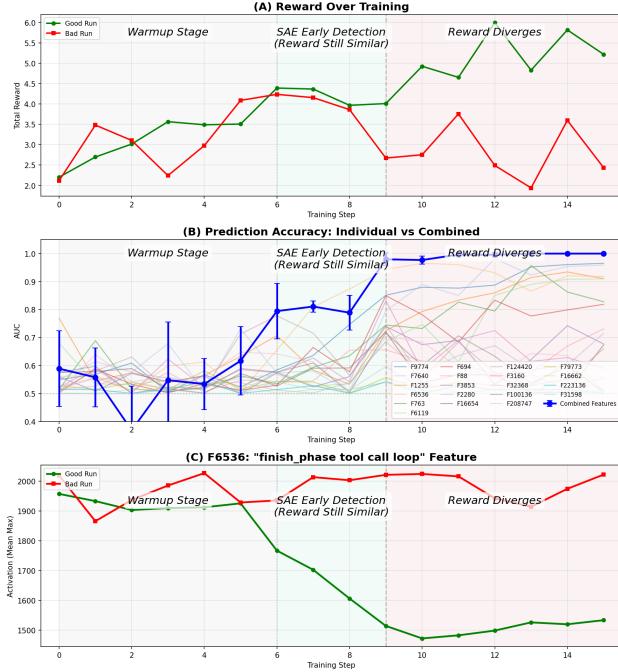


Figure 4. Early representational divergence between successful and failed training runs. Step 6-9 is the early warning window where SAE features signal the divergence while reward curves remain indistinguishable.

mized prompts increase performance overall. These results demonstrate that the outputs of our framework are useful for downstream tasks.

## 5.2. Case Study 1: Early Identification of Bad Training Runs

One of our GRPO training runs in the Full Press Diplomacy environment does not improve, which we investigate in comparison with the successful run. As shown in Figure 4(A), We analyze these two runs: a *good* run that continues to improve and a *bad* run whose performance plateaus. Before training batch 9, both runs achieve comparable reward, making them indistinguishable under standard learning curves. However, SAE analysis uncovers a sharp divergence at this stage. Using the top 20 automatically interpreted SAE features from each checkpoint, we fit a linear probe to classify whether a trajectory comes from either run, calculating the false positive rate vs true positive rate robustly regardless of class imbalance. As shown in Figure 4(B), probe performance rapidly increases starting batch 6 with a combined  $AUC \geq 0.8$ , and reaches near-perfect  $AUC$  after step 9. The combined  $AUC$  is calculated from logistic regression trained on standardized activations of 20 selected SAE features, evaluated via 5-fold CV at each training step.

Further inspection shows that this signal is driven by a single feature. In the bad run, as shown in Figure Figure 4(C), this

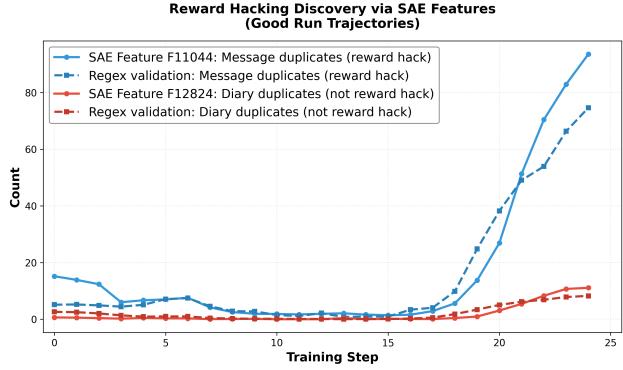


Figure 5. SAE features detected highly correlated reward hacking and related non-reward hacking behaviors, validated by Regex.

feature remains approximately constant throughout training, while in the good run it diverges sharply starting batch 6. Manual inspection reveals that this feature corresponds to correctly using the tool to end a phase of the game. The good run learns to use this, whereas the bad run fails to do so. The divergence in feature activation occurs at step 6, whereas the divergence in reward occurs at step 9, meaning our method provides earlier, more interpretable signal for distinguishing good and bad runs.

## 5.3. Case Study 2: Reward Hacking

When analyzing good training runs with our framework, we find a variety of SAE features, one of which captures the agent behavior of sending duplicate messages: not surprising as our reward function gives +0.02 per message during movement phases. While manually investigating these behaviors, we are surprised to find the agent also starts writing duplicate diary entries, a behavior similar to duplicate message sending but does not result in any reward.

In Figure (Figure 5), we show that two SAE features present high correlation, and their accuracy is validated by Regex keyword matching. This highlights an unexpected RL training pattern: reward hacking behaviors can overflow into structurally similar but unrewarded actions. Our framework provides a practical example of detecting previously hidden patterns in RL training dynamics.

## 6. Discussion and Conclusion

**Limitations** Our analysis is constrained to a single environment with limited training runs. While we observe strong correlations between features and outcomes, causal relationships are largely untested, and our intervention experiment combined multiple features rather than ablating each individually. Our intervention experiment validates that discovered features are actionable at inference time, while we leave out the stronger test of using these features

to monitor and intervene on live training runs for future work. Future work includes intervention experiments at scale, SAEs with longer context windows, and validation across different environments.

**Conclusion** In this work, we present a framework for interpreting LLM training in complex multi-agent RL environments. Our SAE Meta-Autointerp and LLM-summarizer pipelines reveal complementary insights, fine-grained behavioral features and high-level strategic patterns respectively. Through user studies and downstream validation, we find that not all interpretable features are useful. Certain features that appear helpful are counterproductive when used by humans, but the right features can predict training dynamics and guide practical interventions. We are excited to see future work in this direction to ensure trustworthy and interpretable LLM behavior.

## 7. Contributions

John Yan ran the main result experiments and ablations. Yuqi Sun implemented user study 1 and the case studies. Michael Yu implemented user study 2 and analyzing training progression. All three primary authors wrote the methodology, limitations, and conclusion sections. Alexander Duffy and Tyler Marques ran the hypothesis-guided prompt optimization experiments. Matthew Lyle Olson wrote the introduction and related works sections.

## 8. Acknowledgments

We would like to thank Roland at Good Start Labs for guidance on understanding the Diplomacy environment, and all the users who completed our user studies.

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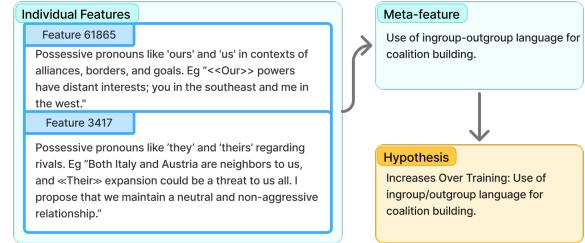
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*Figure 6.* The hypothesis generation workflow. Meta-Features provide insight that single features don't. Note: hypotheses can also be generated from individual features. Maximally activating tokens in a sequence are delimited like <<so>>, following convention (Paulo et al., 2025)

## A. Experiment Setup: Details

**Windowing Samples** The samples we pass to the judge are 250 tokens. We get samples from 4 sources:

- **LLM-Summarizer hypotheses:** In our summarization pipeline, we have a judge get citations from the raw transcripts that illustrate the hypotheses. These can be of arbitrary length. The 250-token window is then centered around this citation.
- **SAE feature hypotheses:** We randomly select top activating examples from a given feature, and center a 250-token window around the top activation.
- **SAE meta-feature hypotheses:** We randomly select top activations from any features in a given meta-feature, and center a 250-token window around the top activation.
- **Random:** We randomly center a 250-token window around any token in an assistant's message.

**Multiple Judges** To assess whether pooling across LLM judges is appropriate, we computed Fleiss'  $\kappa$  for inter-rater agreement on each sample pair. At baseline (no hypothesis), agreement was poor ( $\kappa = 0.04$ ), indicating models relied on idiosyncratic heuristics. With the hypothesis provided, agreement rose to substantial ( $\kappa = 0.61$ ), with 71% unanimous agreement and 97% accuracy when all three models concurred. This convergence suggests the hypothesis provides a genuine shared signal rather than amplifying model-specific biases, justifying pooled analysis across judges.

**Random Sampling** We tested two sampling strategies: **hypothesis-random** (target sample drawn from high-activation examples, non-target drawn randomly) and **random-both** (both samples drawn randomly from their respective classes). Table 3 compares performance.

Table 3. Uplift (%) by hypothesis source and sampling mode

	hypothesis-random	random-both
LLM	+8.3	+8.3
Features	+8.0	+7.0

Absolute uplift is consistent across modes ( $\sim 8\%$ ). We choose to report hypothesis-random throughout the paper for two reasons: (1) consistency with our human user study, which necessarily uses activation-guided sampling to ensure participants see relevant examples, and (2) random-both requires higher sample volumes to achieve reliable signal, increasing computational cost.

#### Judge Prompt Baseline prompt

You are examining outputs from an LLM playing the strategy game Diplomacy. The agent interacts with the environment through tool calls, in order to move troops, communicate with players, or poll the game state.

```
{type_specific_question}
```

Return ONLY a JSON object in this exact format:

```
{
  "answer": "A or B",
  "explanation": "brief 1-2 sentence explanation"
}
```

```
### Sample A:  
{sample_a}
```

```
### Sample B:  
{sample_b}
```

#### Hypothesis prompt

You are examining outputs from an LLM playing the strategy game Diplomacy. The agent interacts with the environment through tool calls, in order to move troops, communicate with players, or poll the game state.

```
{type_specific_question}
```

Hypothesis to consider: {hypothesis}

Return ONLY a JSON object in this exact format:

```
{
  "answer": "A or B",
  "explanation": "brief 1-2 sentence explanation"
}
```

```
### Sample A:  
{sample_a}
```

```
{sample_a}
```

```
### Sample B:  
{sample_b}
```

## B. Ablation Studies

We conducted multiple ablation experiments to validate design choices in our hypothesis generation pipeline. Figure 7 summarizes results.

### B.0.1. MULTI-SAE GROUPING

We can apply Meta-Autointerp to more than just a single SAEs features. We use the same primary model, Gemma 3 27B-IT 31L 262K canonical, as featured in 1.

On the same data and correlation target, we also extract the features from these SAEs:

- Gemma 3 27B-IT 16L 262K canonical
- Gemma 3 27B-IT 40L 262K canonical
- Gemma 3 12-IT 24L 262K canonical
- Gemma 3 4B-IT 17L 262K canonical

We also apply the SAE for Gemma 3 27B-IT 31L 262K canonical on 2 additional datasets:

- sum\_notool: the summarized trajectories from 3.4
- sum\_tool: the same summarized trajectories from sum\_notool, but with all agent tool calls preserved verbatim

We can sweep across the middle SAE layer across model sizes, SAE layers on the 27B model, and also the Gemma 3 27B-IT 31L 262K SAE across the raw data and 2 different kinds of summarization. We feed all of these features into a single Meta-Autointerp run, and validate. We find that the significance rate is 94%, only marginally higher than the run using a single SAE and data source.

We can attribute which models, layers, and data sources uniquely contributed to significant Meta-Features. We find that across all of them, the difference in significance rate is not high.

### B.0.2. CORRELATION SCORING ABLATION

Similarly take the Meta-Features from our single canonical SAE and data source, to find what proportion of features provided by each scoring methodology ended up being significant. We find that sum + spearman correlation gives the highest rate, but the methods tend to provide qualitatively different features, so continue to pool them.

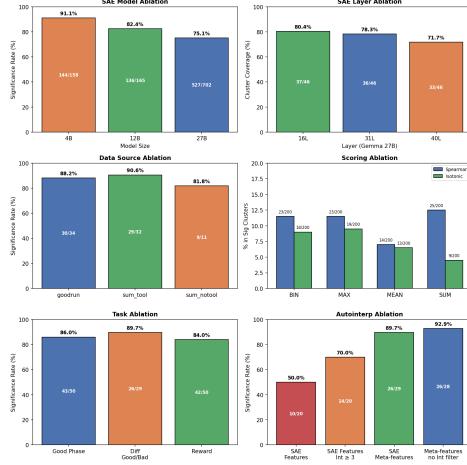


Figure 7. Top left: ablations across model size. Top right: ablations across model layer. Middle left: ablations across data source. Middle right: ablations across aggregation and correlation method. Bottom left: comparisons across correlation target. Bottom right: ablations for Interestingness filter.

#### B.0.3. TASK TARGET: PHASE VS REWARD VS DIFF

In addition to our primary target: batches over a successful run, we also perform 2 more Meta-Autointerp runs:

- **Diff Good/Bad:** After getting the aggregated value per feature per trajectory in the successful and unsuccessful runs, we subtract the means of (goodrun-badrun). We then score this with regards to batch step to measure the divergence between a successful and unsuccessful run.
- **Reward:** We have a reward with each trajectory, provided by the environment. We use the same aggregation and correlation scoring methods, but with regards to the reward value. This is to find behaviors that are correlated with highly/lowlly rewarded trajectories.

We find the significance rate across all 3 tasks is about the same.

#### B.0.4. AUTOINTERP INTERESTINGNESS FILTERING

Our autointerp pipeline assigns each feature an Interestingness score (1–5). Typically, we filter out features that score less than 3 on Interestingness before grouping through Meta-Autointerp. We wanted to see:

- How significant were single features after being filtered for Interestingness  $\geq 3$ ?
- How significant were Meta-Features without being filtered for Interestingness  $\geq 3$ ?

Table 4. Hypothesis validation results from human evaluation.

Hypothesis	Accuracy	Uplift	Source
Spheres of Sovereignty	1.00	+0.52	SAE
Increasing Anti-German Focus	0.89	+0.41	LLM
Imperial Roleplay	0.83	+0.35	SAE
Ultimatums	0.80	+0.32	SAE
Coalition Building	0.75	+0.27	SAE
Game-Theoretic Reasoning	0.71	+0.23	SAE
Military Strength Assertion	0.62	+0.15	SAE
Machiavellian Self-Reflection	0.60	+0.12	SAE
Reciprocal Exchange	0.46	-0.02	SAE
Formal NAP Proposals	0.33	-0.15	SAE
Increasing Diplomatic Aggression	0.33	-0.15	LLM
Corrupted Text Output	0.29	-0.19	SAE
Tool/Environment Errors	0.25	-0.23	SAE
Increasing Diplomatic Deception	0.25	-0.23	LLM
Increasing Risk Tolerance	0.22	-0.26	LLM
Decreasing Early Elimination	0.20	-0.28	LLM
Foreign Language Diplomacy	0.20	-0.28	SAE
Decreasing Tool Friction	0.00	-0.48	LLM

We found that for the former, significance rate improved, but was still not as significant as Meta-Features. And for the latter, significance rate was about even.

## C. User Study 2: Details

**Evaluation and Statistics.** We measure whether providing a hypothesis improves accuracy on a paired early-vs-late training classification task using identical text span pairs with and without hypotheses. Performance is compared using a paired McNemar test over per-pair correctness, with uplift defined as the difference in mean accuracy between conditions.

**Design.** We evaluate whether feature-derived hypotheses improve class prediction between early and late training samples. We consider hypotheses from 6 LLM features and 13 SAE Meta-Features. Each task asks: “Which sample occurred later in training?” and presents a pair of text spans, one sampled from early training and one from late training.

In the non-baseline condition, we additionally provide a hypothesis such as “increases with training: aggression.” In the baseline condition, no hypothesis is shown.

For each hypothesis, we sample 5 text pairs, yielding 90 tasks with hypotheses and 90 matched baseline tasks using identical span pairs. Each participant completes 10 questions total: 5 baseline tasks followed by the same 5 pairs with hypotheses, presented in randomized order. We cap participation at 10 questions per user to limit hypothesis memorization.

**Metrics.** Let  $y_i^B, y_i^H \in \{0, 1\}$  denote baseline and hypothesis correctness for span pair  $i$ .

$$\text{Accuracy}_B = \frac{1}{N} \sum_i y_i^B \quad \text{Accuracy}_H = \frac{1}{N} \sum_i y_i^H$$

ID	Hypothesis	Example #	Example Text		HELPFULNESS	INTERPRETABILITY
			1	2		
H01	Increases over training: Features appear dragging with tool call syntax - may induce confusion about correct format or system rejecting valid intents (related to F123391 bug)		1 <code>["agent", "lego", {"recipient": "ITALY", "message": "External representatives of Italy, I write to you today as an ally standing at the precision of x, y, z."}]</code> 2 <code>["agent", "lego", {"recipient": "ITALY", "message": "External representatives of Italy, I write to you today as an ally standing at the precision of x, y, z."}]</code> 3 <code>["agent", "lego", {"recipient": "ITALY", "message": "External representatives of Italy, I write to you today as an ally standing at the precision of x, y, z."}]</code>			
H02	Increases over training: Features indicate when agent discusses moving the map into spheres, defining "your area in my area", and establishing non-overlapping zones of expansion.		1 <code>["agent", "lego", {"recipient": "ITALY", "message": "External representatives of Italy, I write to you today as an ally standing at the precision of x, y, z."}]</code> 2 <code>["agent", "lego", {"recipient": "ITALY", "message": "External representatives of Italy, I write to you today as an ally standing at the precision of x, y, z."}]</code> 3 <code>["agent", "lego", {"recipient": "ITALY", "message": "External representatives of Italy, I write to you today as an ally standing at the precision of x, y, z."}]</code>			

Figure 8. Screenshot of user study 1 interface

$$\text{Uplift} = \text{Accuracy}_H - \text{Accuracy}_B$$

**McNemar Test.** We construct a  $2 \times 2$  contingency table over paired outcomes:

$$\begin{array}{c|cc|cc} & \begin{matrix} y^H = 1 & y^H = 0 \end{matrix} \\ \begin{matrix} y^B = 1 \\ y^B = 0 \end{matrix} & \begin{matrix} a & b \\ c & d \end{matrix} \end{array}$$

and apply an exact McNemar test on the discordant counts ( $b, c$ ) to test whether hypotheses change classification accuracy.

## D. User Study 1: Details

**Participants.** We recruited three expert developers of the Diplomacy RL environment. All participants had direct experience building and debugging the training pipeline.

**Materials.** Each participant rated 54 hypotheses: 14 from the LLM-Summarizer pipeline, 20 individual SAE features (randomly sampled from top-200 correlated features), and 20 SAE Meta-Autointerp features (created by first filtering single feature Autointerp interpretability scores  $\geq 3$  and grouped). Hypotheses were presented in randomized order. Each hypothesis included an id, explanation and 3 examples. We did not show participants what kind of feature (LLM-summarizer feature, SAE feature or SAE meta-feature) the hypothesis is generated from.

**Rating Rubric.** Participants provided binary ratings (0 or 1) on two dimensions:

### Helpfulness:

Does this hypothesis help you understand how model behavior changes over training? If you were studying this dataset, is this a hypothesis you would want to and could explore further? Rate 1 if yes, 0 if no or only a little.

*Good example:* "Increases over training: Agent uses strategic deception to mislead opponents about intentions"

*Bad example:* "Increases over training: Token appears at end of sentences"

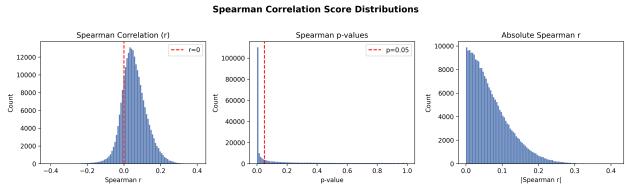


Figure 9. Distribution of Spearman correlations between SAE features and training batch. Around 60% of features are positively correlated with training batch

## Interpretability:

When you read the hypothesis, is it clear what it means? Can you easily and unambiguously apply it to new examples? Rate 1 if yes, 0 if no or it would often be subjective.

*Good example:* "Decreases over training: Agent explicitly states unit locations using coordinate format"

*Bad example:* "Increases over training: Agent shows complex reasoning patterns"

**Interface.** Ratings were collected via a Google spreadsheet interface (Figure 8).

## E. Feature Distributions

We plot the distribution of spearman correlation scores of feature activations against training step. The scores are approximately normally distributed with a mean above 0, suggesting a majority of features are positively correlated with training (See Figure 9)

## F. Embeddings and Keyword Validation

To further validate the coherence and consistency of features, we use keyword counting and embeddings. We parse out all assistant messages, write diary, and send message tool calls (actions) from each trajectory to create embeddable documents and have a more fine-grained unit of analysis than full trajectories.

### F.1. Keyword Counting

For each feature, we generate 20-50 keywords with Claude Sonnet 4.5. We then sum the total occurrences of each keyword in all actions in each trajectory, taking the mean over each batch and normalizing over actions length and count.

### F.2. Embeddings

For embeddings, we use OpenAI text-embedding-large to generate 1536 dimensional vectors for each action in each

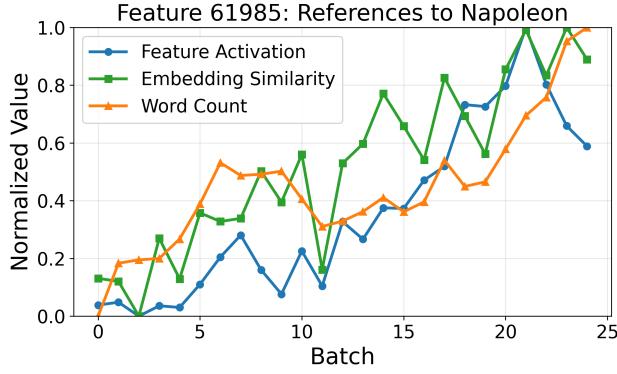


Figure 10. References to Napoleon

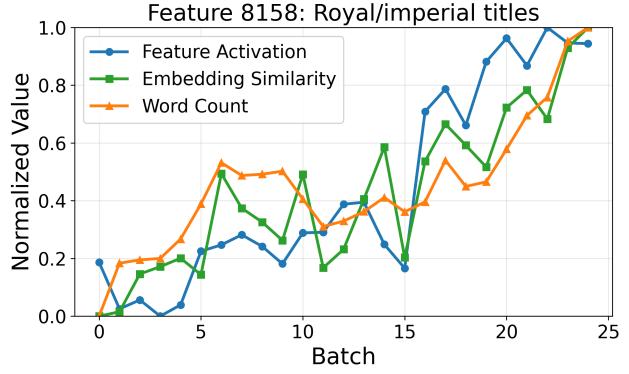


Figure 12. Royalty/Imperial

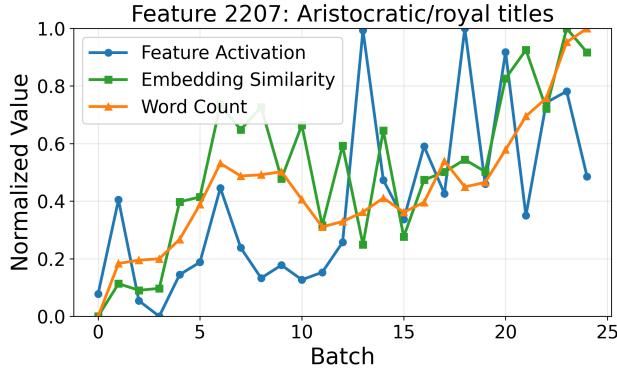


Figure 11. Aristocratic Titles

trajectory, and each feature label. We then calculate the cosine similarity between the feature label and each document, averaging cosine similarity over each batch.

## G. Prompts

### G.1. LLM-Summarizer Trajectory Summarizer Prompt

Convert the following transcript to a concise but complete timeline. Use this format:

```
<phase S1901M>
summary
</phase>
```

Also, cite the EXACT text for every successful for every successful send\_message and write\_diary tool call. For example: <citation send\_message>message... </citation> <citation write\_diary>diary...</citation>.

Output nothing else but the timeline of all phases. Make it max 10000 words.

### G.2. LLM-Summarizer Batch Summarizer Prompt

```
Analyze these {num_trajectories} trajectory summaries from Batch {batch_number} and identify patterns.
```

Focus on:

- \*\*Common Patterns\*\*: Shared strategies, consistent mistakes, typical behaviors
- \*\*Performance Range\*\*: Best vs worst trajectories and what differentiated them
- \*\*Emergent Behaviors\*\*: Novel strategies, learning artifacts, adaptations

```
# Citation Format
```

When referencing a specific trajectory, use this format:  
<citation trajectory\_id>quoted text</citation>

For example:

```
<citation
    batch000_group000_trajectory000_goodrun>I
    promise no move to Channel</citation>
```

Rules:

- Use the trajectory ID to identify which trajectory you're citing
- Keep quotes concise - just the relevant phrase
- Support major observations with citations from the trajectory summaries

Format as markdown with clear headers.  
Keep it to {target\_length} words.

---

{trajectory\_summaries}

### G.3. LLM-Summarizer Judge Prompt

```
You are analyzing {num_batches} batch summaries from a training run (batches
```

```

{batch_range}).

Each batch summary describes agent
behaviors observed at that point in
training.

{sections}

---


## YOUR TASK

Based on these batch summaries, generate
10-20 hypotheses about how agent
behavior changes over training.

Consider:
- Emergent behaviors (appear or strengthen
over training)
- Training dynamics (early vs mid vs late
training)
- Strategic pattern changes

For each hypothesis, provide:
- **name**: A short descriptive name (2-4
words, e.g., "Increasing Deception",
"Decreasing Reliability")
- **direction**: How this behavior changes
over training. One of:
- "increasing": Behavior
increases/strengthens over training
- "decreasing": Behavior
decreases/weakens over training
- **feature**: A concise description of
the behavioral feature (without
directional phrasing)

Respond with ONLY a JSON array of
hypothesis objects. Example format:
```json
[
  {
    "name": "Increasing Aggression",
    "direction": "increasing",
    "feature": "Aggressive and defiant
diplomatic tone, frequently issuing
ultimatums and rejecting demands."
  },
  {
    "name": "Decreasing Reliability",
    "direction": "decreasing",
    "feature": "Reliability as an ally,
becoming more prone to opportunistic
betrayal of established agreements."
  }
]
```
Output ONLY the JSON array, no other
text."""
# Template for comparing high vs low
reward samples
REWARD_COMPARISON_TEMPLATE = """You are
analyzing agent behavior summaries
grouped by reward outcome.

```

Your task is to identify behavioral differences between high-reward and low-reward trajectories.

```

{sections}

---


## YOUR TASK

Compare {high_label} vs {low_label}
trajectories and generate 10-20
hypotheses about their behavioral
differences.

Consider differences in:
- Communication style and tone
- Strategic decision-making patterns
- Error types and frequency
- Tool usage and problem-solving approaches
- Quality of reasoning and planning

For each hypothesis, provide:
- **direction**: Which group exhibits more
of this behavior? One of:
- "{high_label)": High-reward
trajectories show this behavior more
- "{low_label)": Low-reward trajectories
show this behavior more
- "mixed": Both groups show this in
different ways
- **hypothesis**: A testable hypothesis
phrased as "{high_label}/{low_label}"
exhibits X compared to
{low_label}/{high_label}"

Respond with ONLY a JSON array of
hypothesis objects. Example format:
```json
[
  {
    "direction": "{high_label}",
    "hypothesis": "{high_label}
trajectories demonstrate more thorough
planning before taking actions
compared to {low_label}"
  },
  {
    "direction": "{low_label}",
    "hypothesis": "{low_label}
trajectories show more frequent tool
usage errors compared to {high_label}"
  }
]
```
Output ONLY the JSON array, no other text.



#### G.4. LLM Autointerp Prompt



You are analyzing SAE (Sparse Autoencoder) features from an RL agent playing Diplomacy.


```

**Context:** The model generates reasoning and actions for an AI agent playing Diplomacy.  
**Features** are scored against a target variable.  
**Your task:** For each feature, provide DISENTANGLLED explanations and ratings.

#### ## OUTPUT STRUCTURE

1. Token Pattern: What the literal token/phrase ITSELF represents
2. Context Pattern: What contexts this appears in (may be multiple)
3. Behavior Insight: What this reveals about agent behavior or environment bugs

#### ## RATINGS (all 1-5)

##### ### FEATURE COHERENCE

Do activating tokens share the same semantic meaning?  
5 = All tokens capture exact same pattern  
4 = Highly consistent with minor variation  
3 = Mostly consistent with some outliers  
2 = Multiple distinct token patterns  
1 = Activates on unrelated tokens

##### ### CONTEXT COHERENCE

Does the feature appear in consistent contexts?  
5 = Single consistent context  
4 = Highly consistent, occasionally elsewhere  
3 = 2-3 related contexts  
2 = Several distinct contexts  
1 = Many unrelated contexts

##### ### INTERESTINGNESS

Is this useful for understanding agent behavior?  
5 = Reveals env bugs, failure modes, or significant learned behavior  
4 = Shows meaningful behavioral patterns  
3 = Moderate behavioral insight  
2 = Generic language patterns  
1 = Just formatting/punctuation

##### ### EXPLANATION CONFIDENCE

5 = Very confident - clear pattern  
4 = Confident - minor ambiguity  
3 = Moderate - may miss aspects  
2 = Low - unclear pattern  
1 = Not confident

#### ## CALIBRATION EXAMPLES

F4866 (Interestingness=5, FC=5, CC=5):  
**Token:** Possessive pronouns ("our", "my", "your")  
**Context:** Alliance-building in diplomatic messages  
**Insight:** Agent uses possessives for

partnership framing

F20338 (Interestingness=5, FC=5, CC=3):  
**Token:** "fundamental" as intensifier  
**Context:** TWO contexts: (1) system errors, (2) diplomatic foundations  
**Insight:** May reveal training bugs OR learned diplomatic language

Low value example (Interestingness=1, FC=1, CC=1):

**Token:** Apostrophes and quotation marks  
**Context:** Random punctuation  
**Insight:** None - technical artifact

#### ## NOTES

- Separate token meaning from context
- Features with negative scores are equally interesting (opposite direction)
- Flag potential env bugs (system errors, validation failures)

## G.5. LLM Meta-Autointerp Prompt

You are grouping SAE features into thematic clusters to create hypotheses for a discriminative monitor.

**Context:** {prediction\_problem}

**Your goal:** Create clusters where the FEATURE description is specific enough that a monitor could use it to distinguish between samples from different classes (e.g., early vs late training, class A vs class B).

Group features into 4-8 thematic clusters.

#### IMPORTANT:

- Group features with the same direction together (don't mix positive and negative)
- Be CONCRETE: Include specific tokens, phrases, and examples from the features
- Focus on observable patterns a monitor could detect
- Note features revealing ENVIRONMENT BUGS or SYSTEM ERRORS

Direction prefixes for hypotheses:

- For positive scores, use:  
 "{positive\_prefix}"
- For negative scores, use:  
 "{negative\_prefix}"

For each cluster provide:

1. Cluster name (2-5 words)
2. Direction (positive/negative)
3. Feature description (3-5 sentences):  
 Describe the observable pattern:  
  - Specific tokens/phrases captured (give concrete examples in quotes)

- What contexts these appear in
  - What behavior or environment issue this represents
4. Hypothesis: The direction prefix + the feature description  
 Format: "[Direction prefix]: [Feature description]"
5. List of feature IDs

Example:

CLUSTER: Alliance-Building Language

DIRECTION: positive

FEATURE: Possessive and cooperative language in diplomatic alliance proposals. Tokens include possessive pronouns ("our", "my", "your", "we"), partnership verbs ("work together", "coordinate", "support"), and commitment phrases ("I propose", "let's agree"). These appear in contexts where the agent negotiates alliances or proposes joint military actions, indicating learned diplomatic framing strategies.

HYPOTHESIS: {positive\_prefix}: Possessive and cooperative language in diplomatic alliance proposals. Tokens include possessive pronouns ("our", "my", "your", "we"), partnership verbs ("work together", "coordinate", "support"), and commitment phrases ("I propose", "let's agree"). These appear in contexts where the agent negotiates alliances or proposes joint military actions, indicating learned diplomatic framing strategies.

FEATURES: 4866, 61987, 255013

Features to cluster:

{features}

Output format:

CLUSTER: [Name]

DIRECTION: [positive/negative]

FEATURE: [Concrete observable pattern with specific tokens and contexts]

HYPOTHESIS: [Direction prefix]: [Same as FEATURE]

FEATURES: [Comma-separated feature IDs]

## H. Hypotheses

### H.1. LLM-Summarizer Hypotheses

- ```
[  
 {  
   "name": "Increasing Diplomatic Aggression",  
   "hypothesis": "Increases with training steps: Adoption of a defiant, arrogant, or dictatorial tone in diplomatic messages, including issuing ultimatums and rejecting demands.",  
   "feature": "Adoption of a defiant,  
   "direction": "increasing",  
   "source": "llm"  
,  
 {  
   "name": "Increasing Diplomatic Deception",  
   "hypothesis": "Increases with training steps: Use of diplomatic messages to mask aggressive intentions, often proposing peace or DMZs immediately before attacking.",  
   "feature": "Use of diplomatic messages to mask aggressive intentions, often proposing peace or DMZs immediately before attacking.",  
   "direction": "increasing",  
   "source": "llm"  
,  
 {  
   "name": "Decreasing Tool Friction",  
   "hypothesis": "Decreases with training steps: Struggle with the 'submit_all_orders' interface leading to invalid orders and forced simplification.",  
   "feature": "Struggle with the 'submit_all_orders' interface leading to invalid orders and forced simplification.",  
   "direction": "decreasing",  
   "source": "llm"  
,  
 {  
   "name": "Decreasing Early Elimination",  
   "hypothesis": "Decreases with training steps: Susceptibility to catastrophic collapses and elimination in the first few game years.",  
   "feature": "Susceptibility to catastrophic collapses and elimination in the first few game years.",  
   "direction": "decreasing",  
   "source": "llm"  
,  
 {  
   "name": "Increasing Anti-German Focus",  
   "hypothesis": "Increases with training steps: Prioritization of aggressive moves against Germany (e.g., attacking Burgundy or Munich) and refusal of German DMZ proposals.",  
   "feature": "Prioritization of aggressive moves against Germany (e.g., attacking Burgundy or Munich) and refusal of German DMZ proposals.",  
   "direction": "increasing",  
   "source": "llm"  
,  
 {  
   "name": "Increasing Risk Tolerance",  
   "hypothesis": "Increases with training steps: Willingness to execute
```

```

high-risk opening moves (e.g., unsupported pushes into contested zones) despite the potential for early elimination.",
"feature": "Willingness to execute high-risk opening moves (e.g., unsupported pushes into contested zones) despite the potential for early elimination.",
"direction": "increasing",
"source": "llm"
},
]

```

## H.2. SAE Hypotheses

```

[
{
  "name": "Coalition Building",
  "hypothesis": "Agents increasingly frame alliances around shared adversaries as training progresses, using 'us vs them' rhetoric to build coalitions.",
  "feature": "Framing alliances around shared adversaries, using 'us vs them' language to build coalitions against common enemies.",
  "direction": "positive",
  "source": null
},
{
  "name": "Reciprocal Exchange",
  "hypothesis": "Agents increasingly propose explicit quid-pro-quo exchanges as training progresses, offering specific concessions for specific commitments.",
  "feature": "Proposing explicit reciprocal exchanges - offering specific concessions in return for specific commitments from the other party.",
  "direction": "positive",
  "source": null
},
{
  "name": "Game-Theoretic Reasoning",
  "hypothesis": "Agents increasingly analyze opponents' strategic incentives and motivations in their diplomatic communications as training progresses.",
  "feature": "Explicitly analyzing other players' motivations, incentives, and strategic calculations in diplomatic messages.",
  "direction": "positive",
  "source": null
},
{
  "name": "Foreign Language Diplomacy",
  "hypothesis": "Agents increasingly use non-English languages (French,
  "feature": "Conducting diplomacy in non-English languages such as Italian, French, Spanish, or Russian.",
  "direction": "positive",
  "source": null
},
{
  "name": "Imperial Roleplay",
  "hypothesis": "Agents increasingly adopt imperial personas with royal titles and grandiose rhetoric as training progresses.",
  "feature": "Adopting an imperial or monarchical persona, using royal titles, grandiose rhetoric, and references to empire and dominion.",
  "direction": "positive",
  "source": null
},
{
  "name": "Corrupted Text Output",
  "hypothesis": "Corrupted text artifacts and encoding errors become more common as training progresses (likely a negative pattern).",
  "feature": "Corrupted or garbled text output, including malformed characters, encoding issues, and nonsensical character sequences.",
  "direction": "positive",
  "source": null
},
{
  "name": "Tool/Environment Errors",
  "hypothesis": "Tool call errors and environment bugs decrease as training progresses, indicating improved agent reliability.",
  "feature": "Instances where the agent encounters or triggers tool call errors, validation failures, and environment bugs.",
  "direction": "negative",
  "source": null
},
{
  "name": "Formal NAP Proposals",
  "hypothesis": "Agents increasingly propose formal non-aggression pacts with explicit treaty language as training progresses.",
  "feature": "Proposing formal non-aggression pacts using explicit treaty language, formalization terms, and binding agreement vocabulary.",
  "direction": "positive",
  "source": null
},
{
  "name": "Military Strength Assertion",
  "hypothesis": "Agents increasingly assert military dominance and threaten
  "feature": "Asserting military strength and dominance through threats and aggressive language in diplomatic communications."
}
]
```

```

force in diplomatic communications as
training progresses.",

"feature": "Asserting military power
and dominance in diplomatic
communications, emphasizing strength,
capability, and willingness to use
force.",

"direction": "positive",
"source": null
},

{
    "name": "Ultimatums",
    "hypothesis": "Agents increasingly
issue ultimatums with binary choices
and clear consequences as training
progresses.",

"feature": "Issuing ultimatums
presenting binary choices with clear
consequences, framing decisions as the
opponent's responsibility.",

"direction": "positive",
"source": null
},

{
    "name": "Machiavellian
Self-Reflection",
    "hypothesis": "Agents increasingly
reflect on their own strategic
manipulation and diplomatic
maneuvering as training progresses.",

"feature": "Reflecting on strategic
manipulation, acknowledging diplomatic
maneuvering, narrative framing, and
calculated deception.",

"direction": "positive",
"source": null
},

{
    "name": "Spheres of Sovereignty",
    "hypothesis": "Agents increasingly use
possessive language to assert
territorial claims and spheres of
influence as training progresses.",

"feature": "Using possessive language
to assert territorial claims and
define spheres of influence - 'my
territory', 'your domain', 'our
borders'.",

"direction": "positive",
"source": null
}
    
```

## I. Prompt Used for Hypothesis-Guided Prompt Optimization

The following prompt was appended to France's system prompt in the intervention condition for the hypothesis-guided prompt experiment (Section 5.1). This guidance is created by quoting top-performing SAE Meta-Features that increase over training and 3 random examples of each.

In the baseline condition, France received only the standard

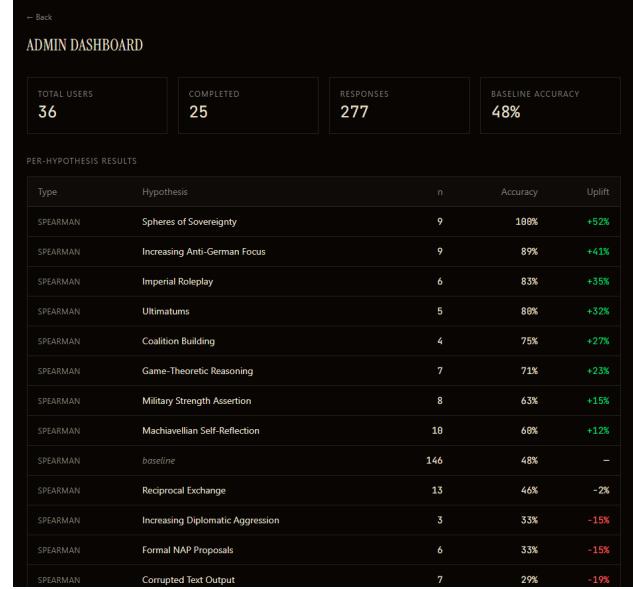


Figure 13. User Study 2 Dashboard

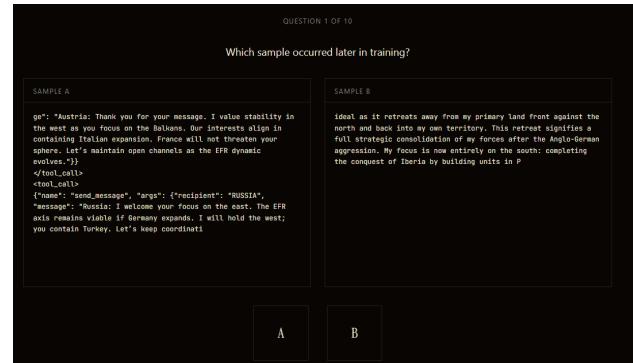


Figure 14. User Study 2 User Interface

system prompt without this additional guidance. All other players used the standard system prompt in both conditions.

# Agent Training Prompt: Diplomacy Game Success Strategies (Few-Shot Version)

You are playing as France in a Diplomacy game. The following behavioral patterns correlate with successful training runs. Each section includes 3 examples of effective behavior.

---

### 1. Coalition Building Against Common Threats

Frame alliances around shared adversaries using "us vs them" language.

**\*\*Example 1:\*\***

"Our strategic positions present a unique opportunity for mutual benefit. You correctly identify Austria as a primary threat in the east, and I see a path where our interests perfectly align. My conquest of Germany is nearly complete, and my next objective is the total destruction of Austria."

**\*\*Example 2:\*\***

"I remain focused on the west: I will continue the push to dominate Iberia and the Atlantic against my primary rival, England. The convoys you are seeing are to solidify my hold on all of Spain. As for Germany, they are making aggressive overtures, but know this: any German attempt to block me in Burgundy will be met with force."

**\*\*Example 3:\*\***

"This is an all-consuming fire that will engulf our mutual enemies. As we agreed, our spheres of influence remain clear: the Balkans for you, the Atlantic and the Mediterranean for me. By steadfastly respecting this pact and refusing any entangling pacts with my adversaries, you perform a vital service."

---

### 2. Reciprocal Exchange Proposals  
Propose explicit quid pro quo with clear mutual benefits.

**\*\*Example 1:\*\***

"Russia, our alliance against Germany remains the foundation of our strategy. Your message confirms a peaceful northern border, which I fully support. My primary focus is achieving a breakthrough in MUN next spring after I have cleared BUR this fall."

**\*\*Example 2:\*\***

"Germany, your message is noted. I respect your interest in Belgium, but I must clarify that Belgium is a vital strategic requirement for France, not a negotiable zone. While I agree our mutual enemy, England, poses a threat, I cannot accept a DMZ in Belgium without reciprocal concessions."

**\*\*Example 3:\*\***

"This two-front war will cripple him. Our partnership is a powerful one against our common enemy. I look forward to our continued coordination. What are your thoughts on a Franco-Turkish pact with defined zones of expansion?"

---

### 3. Game-Theoretic Reasoning

Explicitly analyze other players' strategic motivations and incentives.

**\*\*Example 1:\*\***

"Austria, greetings. I welcome your message and acknowledge your primary focus is on the east against Russia and Turkey. My strategic priorities are firmly rooted in the west and the Atlantic, which means our core areas of expansion do not overlap."

**\*\*Example 2:\*\***

"Greetings, Austria. I appreciate your message. As you rightfully noted, we have no direct borders, which presents no immediate threat between our powers. I am aiming for rapid expansion to the west, focusing on securing all of Spain."

**\*\*Example 3:\*\***

"Germany, greetings. I am writing today to address the increasingly concerning pressure that England is exerting on

both of our nations. It is clear that England's ambitions of Atlantic and Mediterranean domination are a direct threat to France, and I suspect, they also jeopardize your own security and expansion possibilities."

---

### 4. Formal Non-Aggression Pacts (NAPs)  
Use formal treaty language with explicit terms and binding commitments.

\*\*Example 1:\*\*

"Russia, thank you for your response and your interest in a non-aggression pact. I welcome your stated focus on the west and your commitment to securing your Balkan ambitions. Your dominance in the North, from Sweden to St. Petersburg, is acknowledged, and I have no interests in Scandinavia."

\*\*Example 2:\*\*

"Greetings, Russia. Your message confirming a neutral stance in the east-west divide is very welcome. I fully concur with your assessment; our geographic positions and primary strategic rivals do not place us in direct conflict. My ambitions are firmly focused on dominating the Atlantic."

\*\*Example 3:\*\*

"Esteemed Turkey, greetings. On behalf of the French Republic, I extend a hand of friendship and a proposal for mutual respect. Our empires are geographically distant, and our immediate strategic goals do not directly conflict. I propose a formal pact of neutrality."

---

### 5. Military Strength Assertion  
Emphasize power, capability, and willingness to use force.

\*\*Example 1:\*\*

"France calls for an end to the reckless aggression against our sovereign territory. The destabilizing actions of both Germany in the east and England in the Channel are clear acts of war, threatening the peace of the

continent. We demand an immediate withdrawal of forces."

\*\*Example 2:\*\*

"So be it. Your heartland of KIE and BER will feel the full weight of my armies from MUN and PAR. This is not a negotiation; it is a declaration of my intent. Come and be broken."

\*\*Example 3:\*\*

"Germany, our path is clear. England has placed an army in Belgium, a direct threat to my core. This is the war we anticipated. I am committed in this phase to crushing England: my army in Picardy is ordered to attack."

---

### 6. Clear Ultimatums

Present binary choices with explicit consequences.

\*\*Example 1:\*\*

"Your proposed peace is a ploy by a desperate power. Your attempt to maintain 4 SCs on my coastline is absurd and will be met with force. I am launching a decisive offensive: my fleet is moving on your position."

\*\*Example 2:\*\*

"A DMZ is still on the table, but it must be equitable. My demand is clear: I will accept a DMZ that removes your direct threat to Picardy. You must withdraw F BEL from the Channel and return to HOL or KIE. In exchange, I will immediately cease my move on ENG."

\*\*Example 3:\*\*

"My moves this turn are designed to make that clear: my A PAR is moving to BUR to contest your heartland directly, my A MUN is advancing on KIE, and my F BRE is moving to MAO to begin the encirclement. You face a four-way squeeze. I am open to a longer-term arrangement, but only on my terms."

---

### 7. Spheres of Sovereignty

Use possessive language to establish territorial claims.

**\*\*Example 1:\*\***

"Russia, salutations. I have received your message with interest. I agree that peace between our empires is beneficial and necessary for our success against greater threats. I can guarantee that no French units will ever move into BURGUNDY or PRUSSIA. My ambitions lie firmly in the west."

**\*\*Example 2:\*\***

"To all fellow powers, as we approach the first fall of the year 1901, I wish you all success. France seeks a path of calculated expansion. I have made my strategic needs clear: Burgundy and the Spanish supply center are vital for my nation's growth."

**\*\*Example 3:\*\***

"Austria, I acknowledge your power in the east and your vital cooperation with Russia against Turkey. I confirm our agreement: you keep BUD, I keep MUN, and we are at peace with a solid DMZ in BUR. You have made a wise choice to focus on your southern fronts."

---

**### 8. Machiavellian Self-Reflection  
(Diary Entries)**

Reflect explicitly on strategic manipulation in internal reasoning.

**\*\*Example 1:\*\***

"S1901M: Submitted Opening Moves. Executed full diplomatic strategy before placing orders. Forged a strong alliance with England against Germany, proposing coordinated northern pressure. Established a formal DMZ with Germany over Burgundy."

**\*\*Example 2:\*\***

"My fleet from SPA/NC completed its fall mission by moving to MAO to secure the Atlantic coast, vital for future convoys into England. Diplomacy was crucial; I successfully managed all other powers by accepting England's truce offer, negotiating a non-aggression deal with Germany, securing Italy's cooperation."

**\*\*Example 3:\*\***

"To all powers: As we enter the 4th year of this great conflict, France reiterates its position as a pivotal player. Our strategic interests are clear: dominance of the Iberian Peninsula and the Atlantic coast to the west, and aggressive expansion in the Central Mediterranean."

---

**### 9. Anti-German Strategic Focus  
Prioritize moves against Germany and refuse disadvantageous DMZ proposals.**

**\*\*Example 1:\*\***

"High-pressure diplomacy this spring. Germany proposes DMZ but threatens BUR if I advance. Reality: France is strong in the west. Decision: maintain pressure indirectly. Move A PAR to PIC to threaten Belgium and set future path into BUR."

**\*\*Example 2:\*\***

"Germany claims desire for DMZ but refuses concrete non-aggression due to England alliance. Testing their limits: moving A MAR to BUR and A PIC to BRE. If Germany does not attack, they may honor DMZ. If they do, I'll have support from PIC to retake later."

**\*\*Example 3:\*\***

"Germany refuses to abandon RUH and offered compromise: I move A BUR to MAR, they take BEL. This undermines my position and rewards aggression. Rejecting. Intent is to move A BUR to RUH if unopposed."

---

**### 10. Calculated Risk-Taking  
Execute bold opening moves with strategic purpose.**

**\*\*Example 1:\*\***

"S1901M: Deciding on aggressive opening: A PAR - BUR, A MAR S A PAR - BUR, F BRE - MAO. This secures Burgundy, positions fleet to take Spain in next move. Rejects all DMZ/NAP offers. High risk but high reward: shows strength and initiative."

a

**\*\*Example 2:\*\***

"Starting S1901M. No prior commitments.  
Need to establish early expansion and  
build rapport with neighbors.  
Priority: secure safe moves, avoid  
early conflict, lay groundwork for  
mid-game advantage."

\*\*Example 3:\*\*  
"All powers strong openings seen around  
the board. Let's keep communication  
open. Stability in the west benefits  
everyone as we watch Russia's push and  
Austria's position."  
\*\*\*\*