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Tutorial on Explainable Reinforcement Learning (XRL)

Explaining black-box trading models

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Why XRL in finance?

- Finance demands trust and transparency
- Black-box models (RL, deep nets) hard to interpret
- Regulators and risk managers require explainability
- Goal: bridge performance and interpretability

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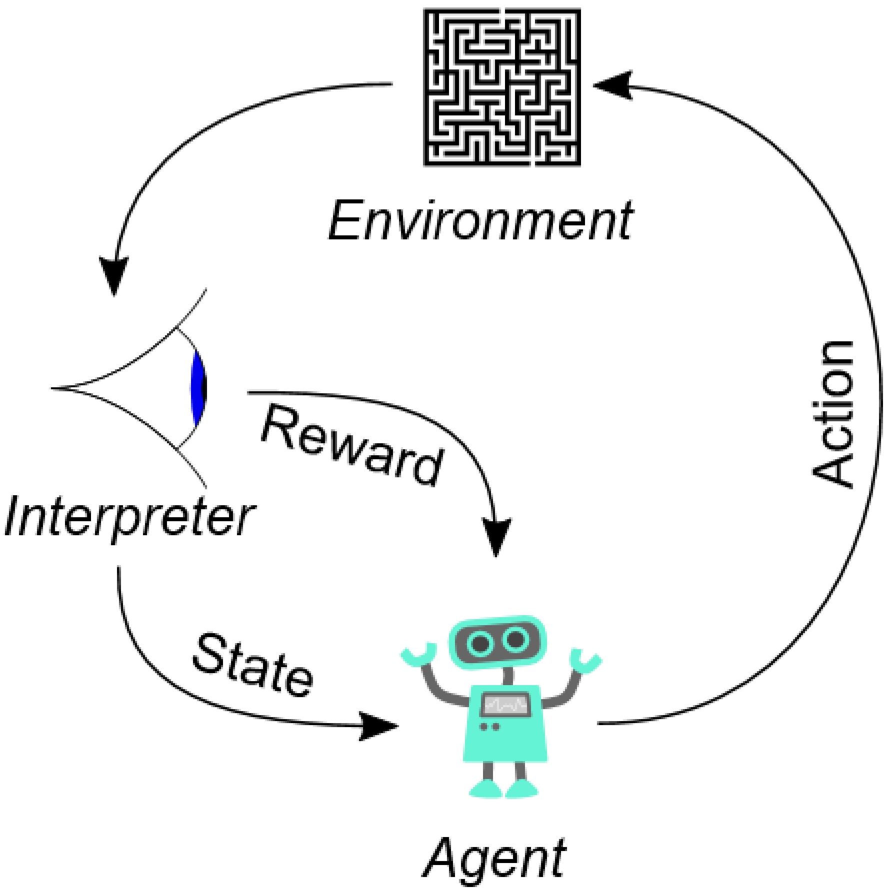
Recap: Reinforcement Learning



- Framework for sequential decision making
- Agent interacts with environment
- Observes **state** S, chooses **action** a, receives **reward** $R(s,a)$
- Learns **policy** π to maximize expected long-term reward

- **Value-based methods**: capture expected long-term reward in value function $V(s')$
- **Policy-based methods**: directly adjust policy π_θ parameterized by θ

- Example in finance: portfolio allocation, trading strategies, market making

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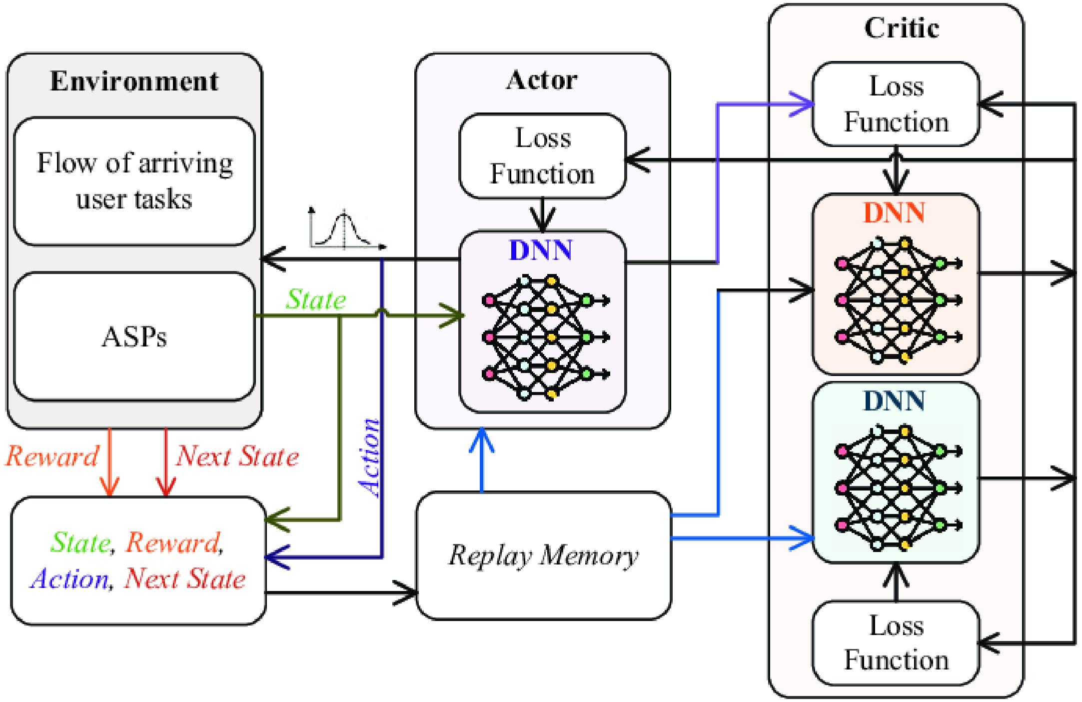
Soft Actor Critic (SAC) algorithm

- State-of-the-art RL algorithm
  - In family of deep deterministic policy gradient algorithms
  - Differentiates updates through the critic
- Learns stochastic policy with entropy regularization
- Balances exploration and exploitation
  - Relatively high degree of exploration due to entropy bonus, suitable for environments with much uncertainty
- Strong benchmark for continuous finance tasks



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The Explainability Gap

- RL policies are black-box neural networks
  - SAC has opaque architecture with multiple neural networks
  - Complex interplay between policy, (long-term) rewards and state trajectory
- Hard to understand 'why' actions are chosen
  - Reward signal may not be directly observable
  - Decision made based on complex latent representations
  - Environment itself is noisy and nonstationary
- In finance: unacceptable for risk oversight
  - Need human-readable explanations

Decision Trees as Surrogate Explainers

- Train a decision tree on (state, action) pairs generated by the agent
- Tree outputs simple if–then rules that approximate policy
- Useful for quick audits and communicating strategy to non-technical stakeholders

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How to Read Decision Trees

1. Pick a leaf — follow splits from root to leaf → yields an if–then rule
2. Translate numeric thresholds to readable statements (e.g., 'volatility > 0.02')
3. Check how many samples follow this rule (support) and the surrogate's fidelity there
    - **Support:** the subset of data over which the explanation is valid.
    - **Fidelity:** how accurately the explanation matches the original model’s predictions.

- Use example states to validate ('show me a trade where this rule triggers')

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Example of Decision Tree Output

```
|--- GLD_mom_20 <= 0.00
|   |--- GLD_mom_20 <= -0.03
|   |   |--- GLD_mom_20 <= -0.05
|   |   |   |--- value: [0.11, 0.48, 0.19]
|   |   |--- GLD_mom_20 >  -0.05
|   |   |   |--- value: [0.12, 0.45, 0.21]
|   |--- GLD_mom_20 >  -0.03
|   |   |--- SPY_dd_60 <= -0.05
|   |   |   |--- value: [0.17, 0.39, 0.24]
|   |   |--- SPY_dd_60 >  -0.05
|   |   |   |--- value: [0.14, 0.43, 0.23]
|--- GLD_mom_20 >  0.00
|   |--- SPY_vol_20 <= 0.02
|   |   |--- GLD_dd_60 <= -0.04
|   |   |   |--- value: [0.17, 0.39, 0.24]
|   |   |--- GLD_dd_60 >  -0.04
|   |   |   |--- value: [0.20, 0.36, 0.24]
|   |--- SPY_vol_20 >  0.02
|   |   |--- SPY_vol_20 <= 0.03
|   |   |   |--- value: [0.16, 0.44, 0.19]
|   |   |--- SPY_vol_20 >  0.03
|   |   |   |--- value: [0.11, 0.51, 0.16]
```

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SHAP: Local & Global Feature Attribution

- SHAP assigns additive contributions of features to a prediction
- Local explanations: why this single decision was made at time t
  - Useful in nonstationary environments, possible to show evolution over time
- Global explanations: which features matter across many decisions
  - Long-term perspective on explainable decisions

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SHAP in Practice — Options

- If surrogate is a tree: use shap.TreeExplainer (fast, exact for many tree models)
  - **TreeExplainer:** fast, exact feature attributions for tree-based models (e.g., XGBoost, Random Forest).
- If explaining the NN policy directly: use shap.KernelExplainer or DeepExplainer (slower)
  - **KernelExplainer:** model-agnostic, perturbs inputs to estimate feature contributions, slower.
  - **DeepExplainer:** uses NN structure for faster, accurate feature attributions, NN-only.

- Typical workflow: collect states → choose model → compute SHAP → show summary & force plots

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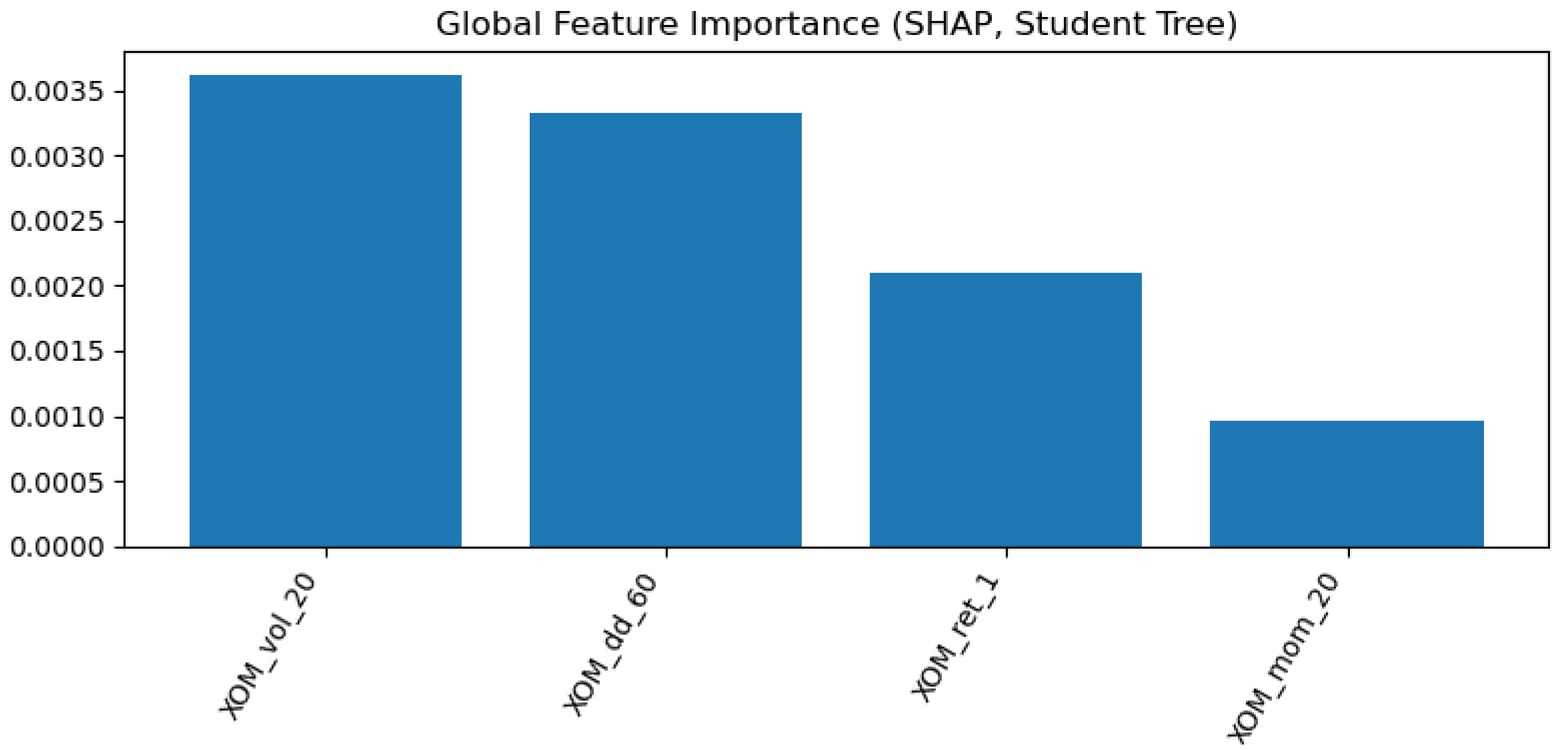
SHAP values (global average)



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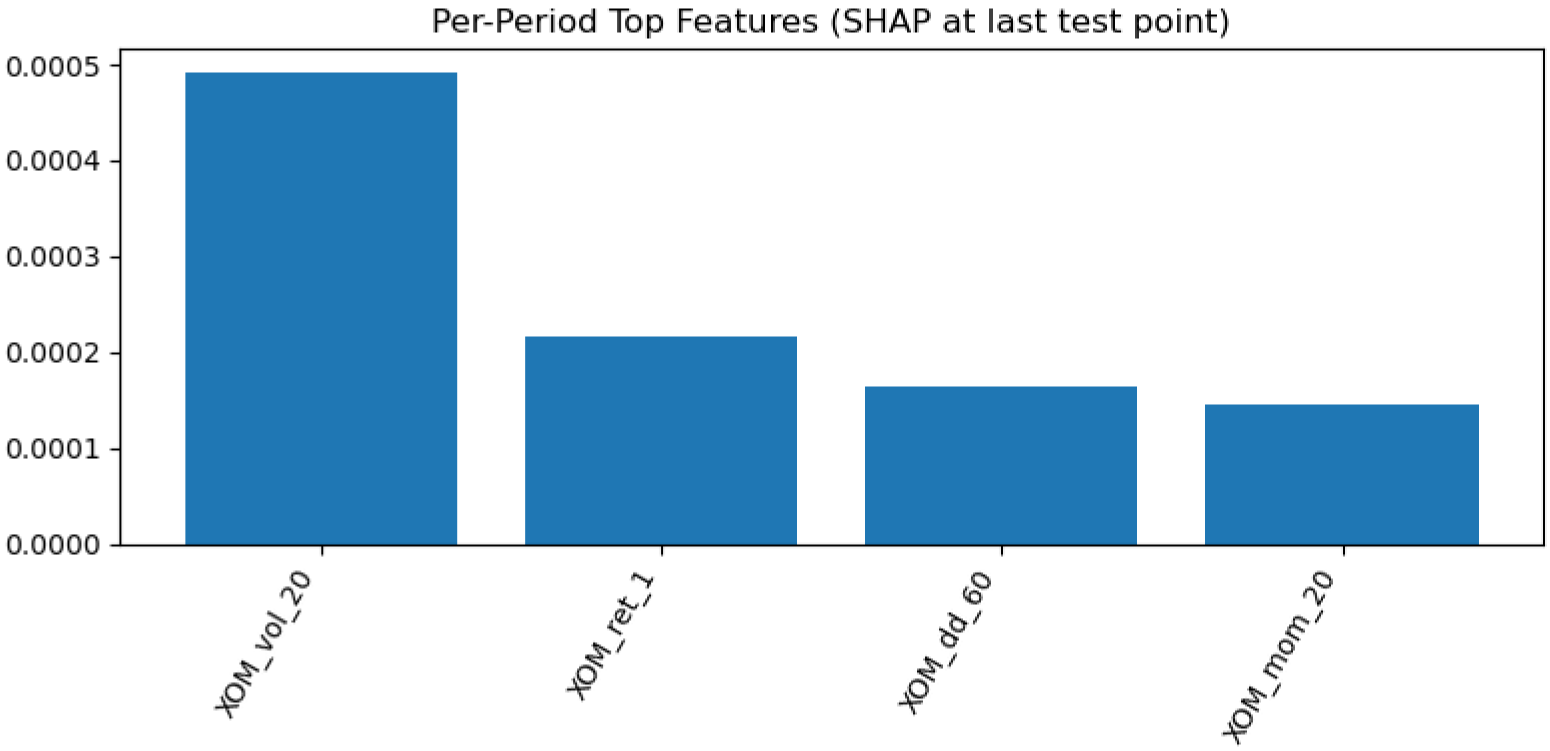
SHAP values (local at time t)



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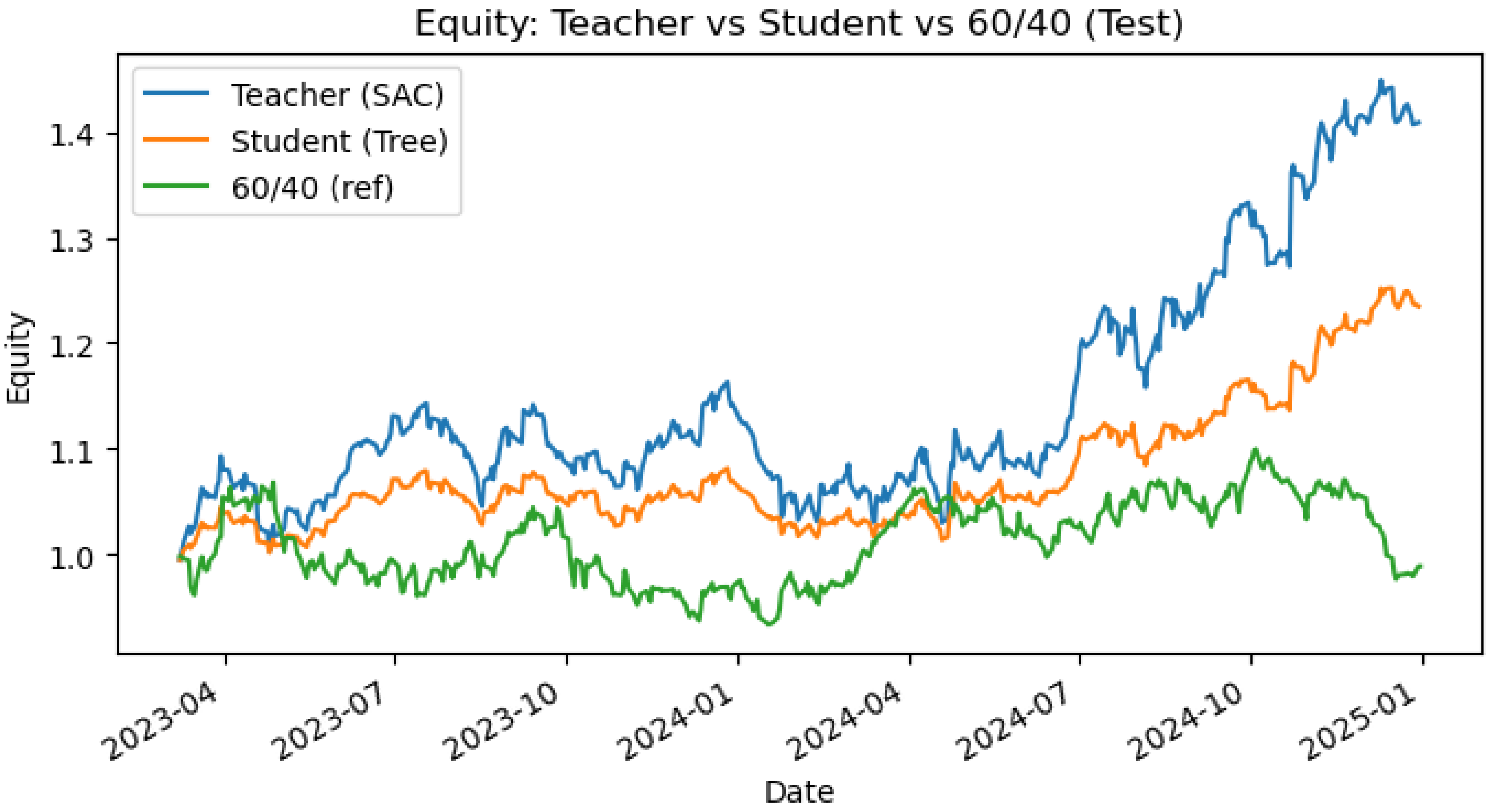
Example performance



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Demo Walkthrough — Notebook Steps

1. Load environment and train SAC agent
2. Generate rollouts → collect (state, action) pairs
3. Fit decision tree surrogate (report fidelity metrics)
4. Compute SHAP values for surrogate (or for NN with KernelExplainer)
5. Visualize: tree plot, SHAP summary, local force plot, action trace vs rule triggers

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Key Takeaways

- Surrogate trees simplify, measure fidelity and be honest about gaps
- SHAP helps both local and global interpretation but has limits (correlated features, runtime)
- Explainability is a communication tool, not a proof of correctness

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