



GitHub

Simulation of Multi-deck BlackJack

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Abstract:

We develop a reproducible Monte Carlo pipeline to quantify player expected value (EV) in blackjack across deck sizes and house rules. The single-file Python implementation covers dataset generation (decision-point EVs), analysis (EV by dealer upcard, hard/soft action heatmaps, hit-threshold curves), and full-round simulation with two policies: a table-driven Basic Strategy (pairs/soft/hard with splits and doubles) and a Naive baseline. We evaluate rule sensitivities including S17 vs H17, 3:2 vs 6:5 payouts, Double-After-Split, hit-after-split-Aces, and doubling constraints, reporting EV per initial hand with 95% confidence intervals.

Introduction:

We model blackjack as a finite-horizon stochastic control problem.

A state $s = (t, \text{soft}, u, k_split, d_ok)$ encodes the player total t , softness flag, dealer upcard u , splits used, and doubling availability.

Actions $a \in \{H, S, D, P\}$ cause a transition $s' \sim T_\theta(s' | s, a)$, where θ are the house rules (decks, S17/H17, blackjack payout $p \in \{1.5, 1.2\}$, DAS, etc.).

The round reward $R \in \{-1, 0, +1, +p\}$ is measured per initial hand (splits/doubles change stake and are netted at the round level).

Given a policy π (Basic or Naive), the target is the expected value.

$$V^\pi(\theta) = \mathbb{E}_\pi[R | \theta].$$

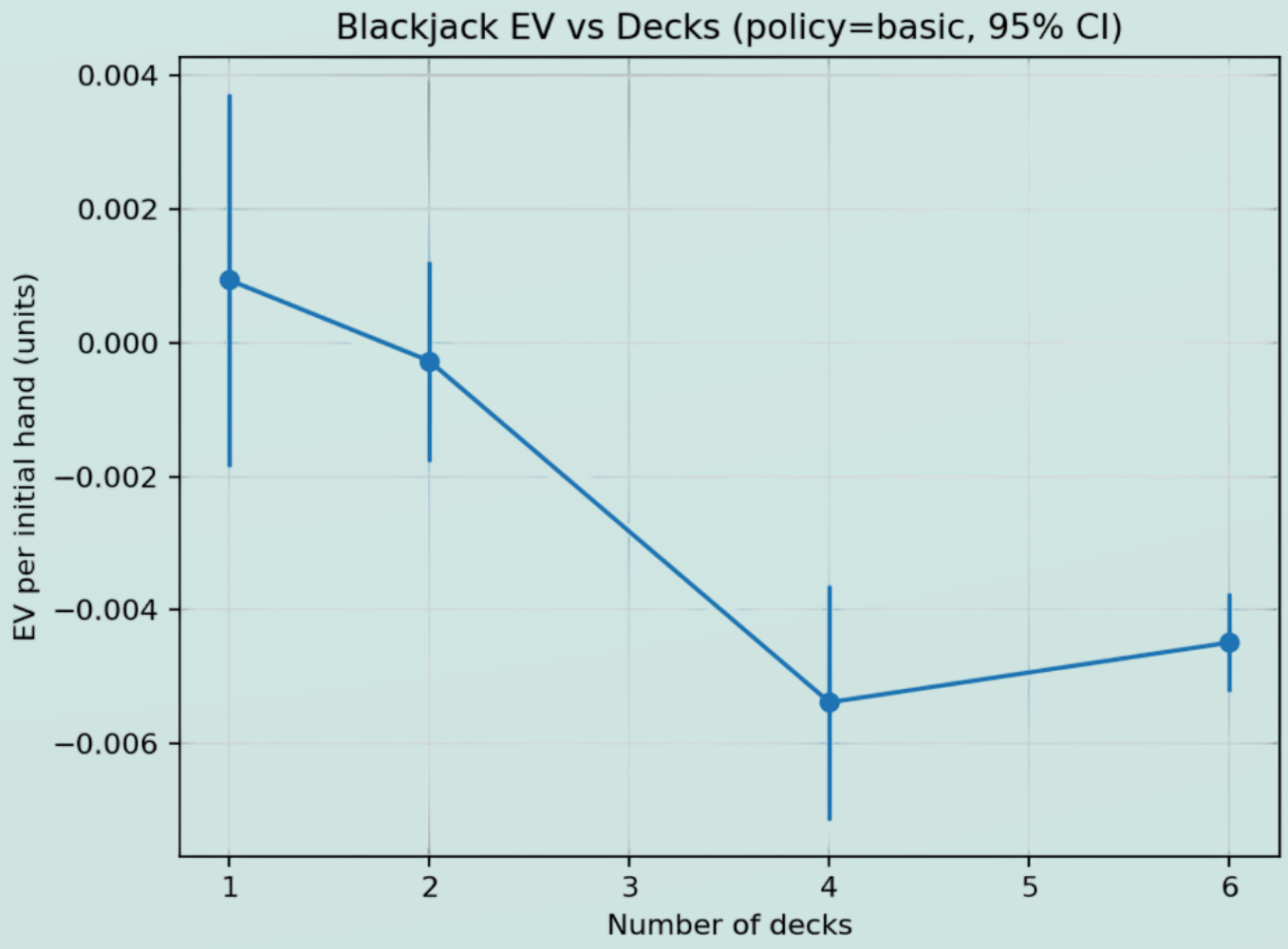
We estimate V^π by Monte Carlo over N rounds from a finite shoe (without replacement):

$$\bar{V} = \frac{1}{N} \sum_{i=1}^N R_i, \quad CI_{95\%} = \bar{V} \pm 1.96 \frac{s}{\sqrt{N}},$$

Where s is the sample standard deviation.

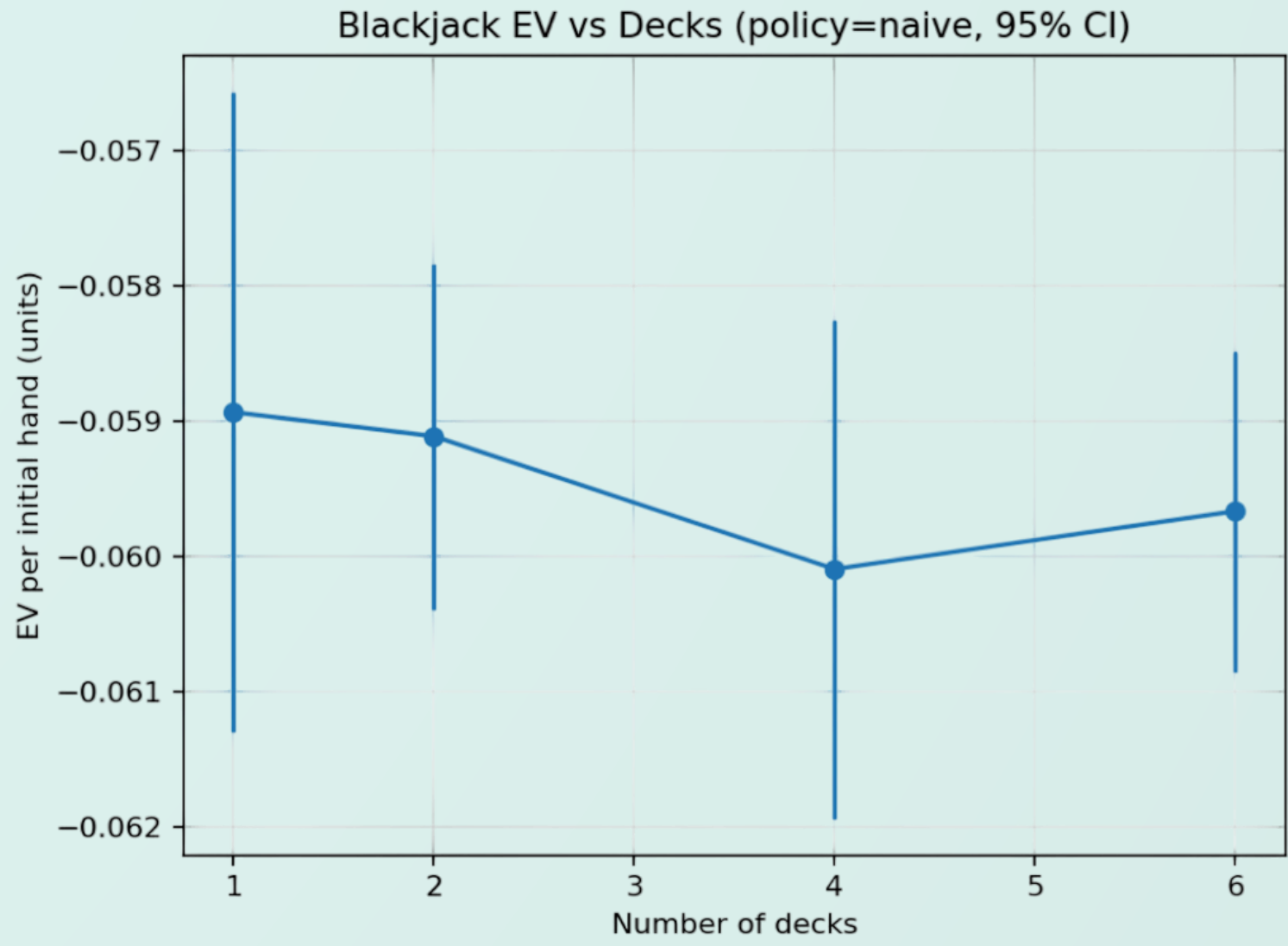
We also approximate one-step action values $Q(s, a)$ via stand/hit rollouts to visualize decision structure (hard/soft heatmaps) and report EV vs. decks with 95% CIs to quantify rule impacts.

Results:



- Deck effect: EV drops as decks increase. Under Basic Strategy, 1–2 decks \approx break-even (CIs overlap 0), by 4–6 decks EV is negative.
- Statistical note: 95% CI bars show uncertainty; the 4-deck point is below zero even with CI, confirming a real deck penalty.
- Interpretation: EV of $-0.005 \approx -0.5\%$ house edge per hand (per 1-unit bet).

Context: Results are for the listed rules (3:2 payout, dealer soft-17 rule as configured, DAS on, double any two)

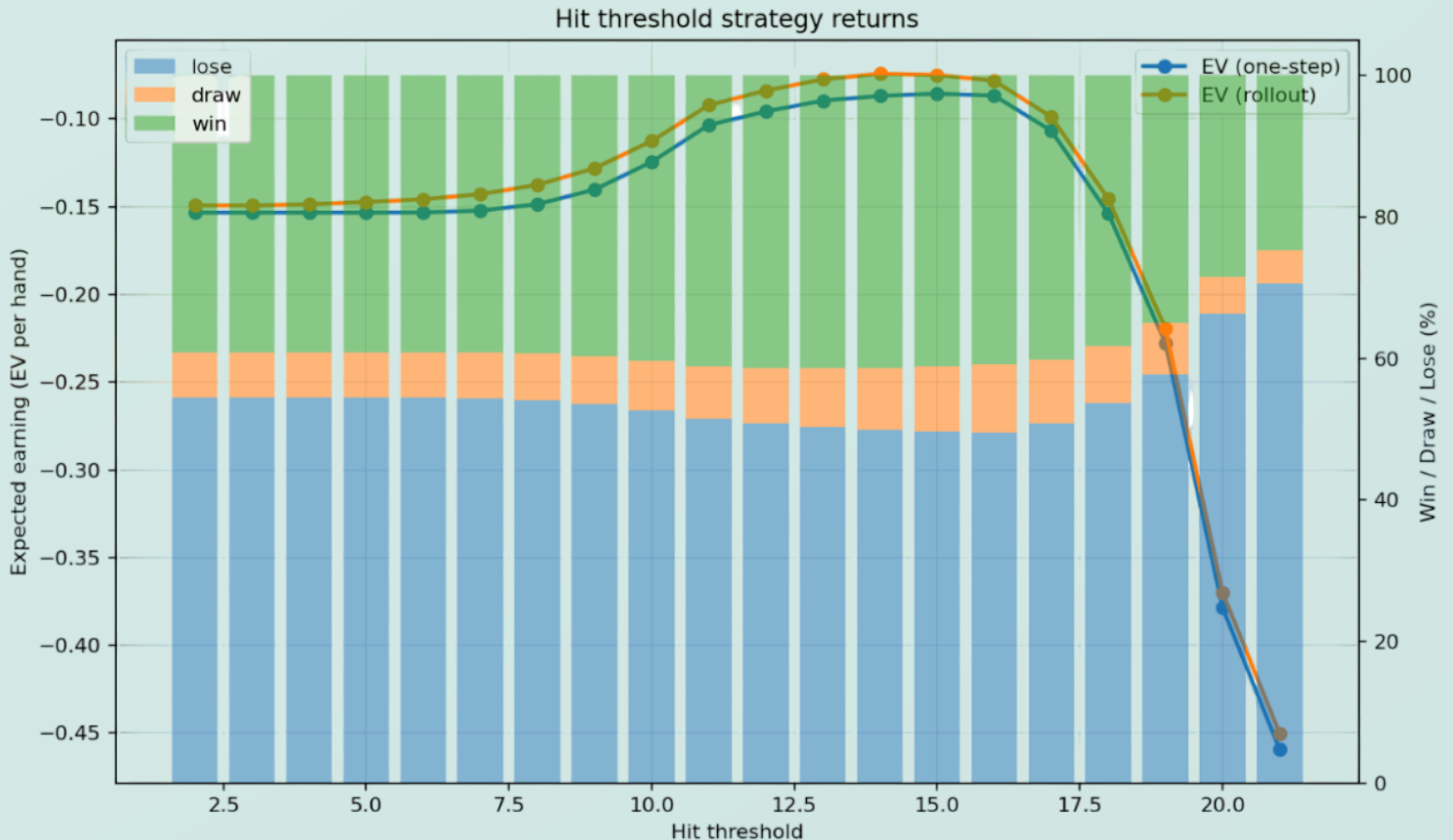


- Large, stable loss: $EV \approx -0.059$ across all decks \rightarrow about a -5.9% house edge per hand (1-unit bet).
- Deck count barely matters here: the 95% CIs overlap, differences between 1–6 decks are not statistically significant under this policy.
- Why it’s so bad: the naive rule ignores the dealer upcard and soft/hard context, causing too many bad hits/stands (and missed doubles).
- Context: Switching to Basic Strategy is near break-even under fair rules, rule changes (e.g., S17 $\approx +0.2$ pp, 6:5 ≈ -1.3 – 1.5 pp) affect EV far more than deck count with a naive policy.

Rule-by-Rule EV Comparison (6 Decks):

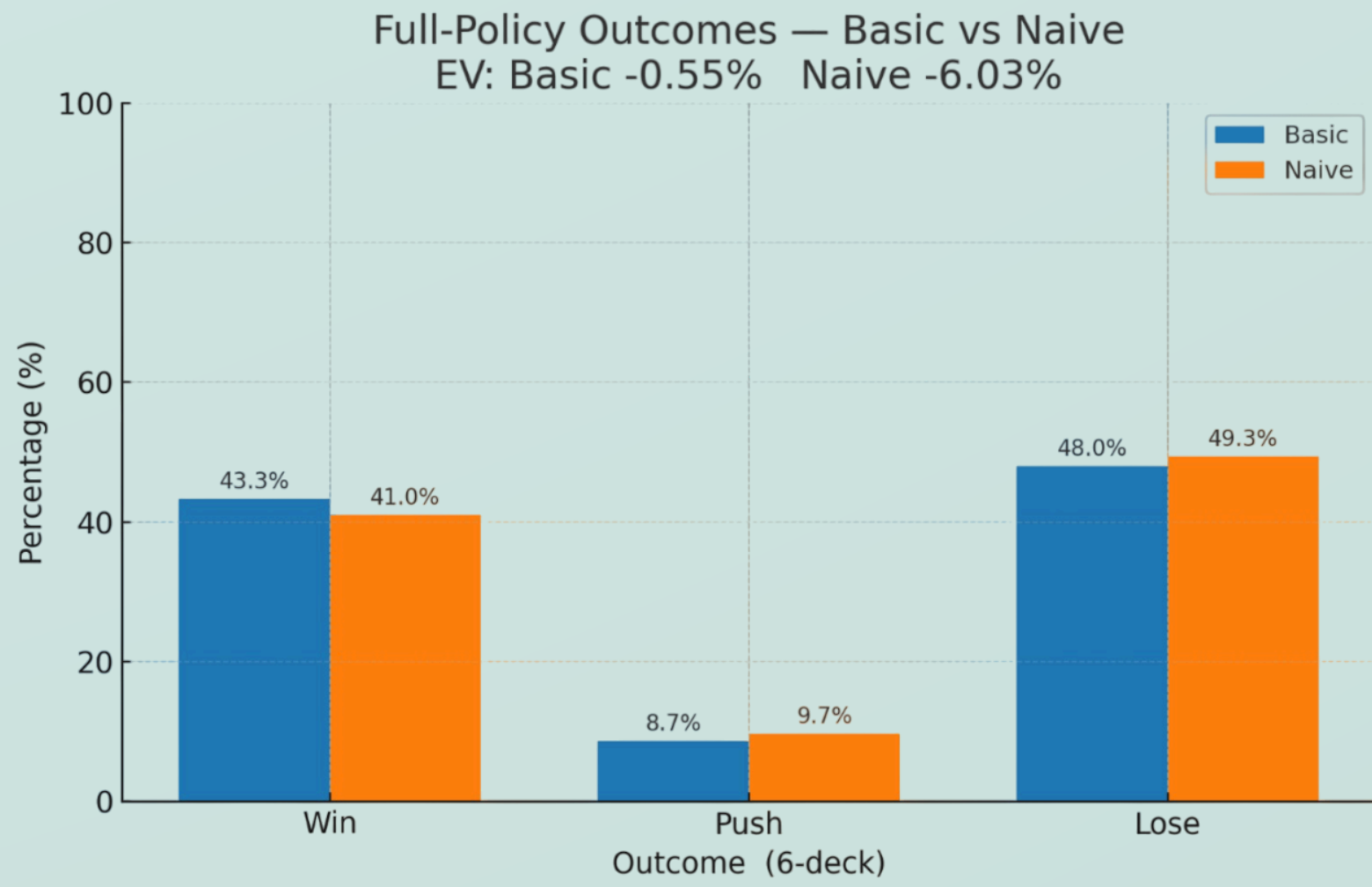
Rule	Policy	EV	Replicates	Win%	Draw%	Lose%	EV-Base(pp)
Base	Basic	-0.00581	5	43.2708	8.6733	48.0559	
6:5 Payout	Basic	-0.01944	5	43.2708	8.6733	48.0559	-1.36312
Double on hard	Basic	-0.00739	5	43.2674	8.6833	48.0493	-0.15767
Hit_split_aces	Basic	-0.00474	5	43.3047	8.6469	48.0484	0.10703
2 Maxsplit	Basic	-0.00576	5	43.2728	8.6736	48.0536	0.00550
No double after split	Basic	-0.00750	5	43.2033	8.7481	48.0486	-0.16890
Soft 17	Basic	-0.00334	5	43.3655	8.7295	47.9050	0.24740

Hit threshold



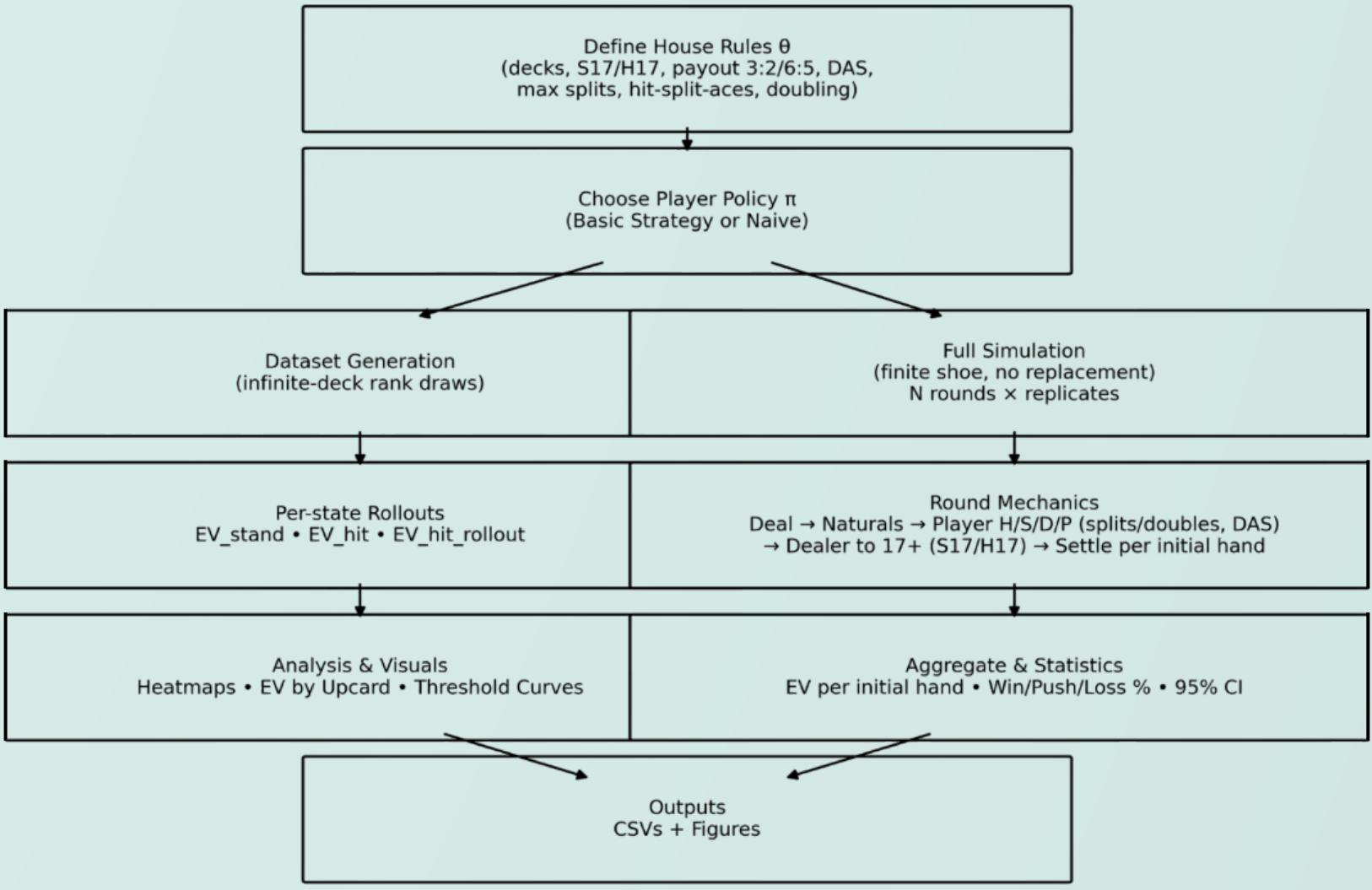
$Hit \leq T$, else Stand: EV (line) peaks around $T \approx 15$ – 16 (soft-only ≈ 17 – 18). Early increases in T reduce premature stands,beyond ~ 16 , busts rise and EV falls.
Bars = outcome mix: as T rises to the peak, Win% Increases and Loss% decreases; after the peak, Loss climbs.
Even at the best T , EV stays negative because this rule ignores dealer upcard and softness, showing why full Basic Strategy performs better.

Outcome:



Basic: Win/Push/Lose $\approx 43.28\% / 8.68\% / 48.04\%$ (EV -0.55%).
Naive: $41.03\% / 9.66\% / 49.32\%$ (EV -6.03%).
Basic wins more and loses less; Naive misses profitable doubles and makes sub-optimal hit/stand choices, raising busts (slightly higher Push% from more middling totals).

Methodology:



Inputs: Choose house rules (decks, S17/H17, payout, DAS, splits, doubling) and a player policy (Basic or Naive).
Branch A – Dataset/Analysis: Infinite-deck state sampling \rightarrow compute, rollout EV \rightarrow visualize decision structure (hard/soft heatmaps, threshold curves).
Branch B – Full Simulation: Finite shoe, no replacement \rightarrow per round: deal, check naturals, play H/S/D/P (incl. splits & doubles), dealer to 17+ (S17/H17), settle per initial hand.
Outputs: Aggregate over rounds \times replicates \rightarrow EV per initial hand, Win/Push/Loss %, 95% CI. Compare rule variants by changing only.

Discussion:

- Policy impact: Basic vs Naive improves the edge by $\sim +5.5$ pp ($-0.55\% \rightarrow -6.03\%$), with Increase in Win% and Decrease in Lose% from better doubles/splits and fewer marginal hits/stands.
- Threshold insight: Blind “ $Hit \leq T$ ” peaks near $T \approx 15$ – 16 yet stays negative—dealer upcard and softness are essential.
- Practical takeaway: Prefer 3:2, S17, DAS tables; avoid 6:5; play Basic to cut losses by ~ 5 – 6 units per 100 hands at a 1-unit stake.
- Next steps: Add surrender/insurance, configurable penetration, and card counting + bet spread.

References:

[1] Baldwin, R. R., Cantey, W. E., Maisel, H., & McDermott, J. P. (1956). The Optimum Strategy in Blackjack. Journal of the American Statistical Association, 51(275), 429–439. JSTOR
[2] Griffin, P. A. (1999). The Theory of Blackjack: The Compleat Card Counter’s Guide to the Casino Game of 21 (6th ed.). Huntington Press. Huntington Press
[3] Schlesinger, D. (2008). Blackjack Attack: Playing the Pros’ Way (3rd ed.). Huntington Press.
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Software: Python (numpy, pandas, matplotlib, scipy).