

Short Report: Solana Token Rug Pull Risk Model Findings

Holders (Arkham Intelligence API)

Classic indicator on the potential of rug pull for tokens. This provides a clear read on rug-pull risk. By analyzing wallet concentration and ownership structure, we can identify structural weaknesses and pinpoint which tokens carry the highest likelihood of a future exploit or liquidation event.

Summary

This POC system uses Arkham API token-holder data to score wallet concentration risks for Solana tokens on a 0-100 scale, with risk tiers designed for semi-technical stakeholders. High-risk classifications flag tokens with extreme concentration in a few wallets, medium risk for moderate concentration or unknown entity holdings, and low risk for widely distributed tokens.

The model aligns with observed rug pull patterns in Solana projects, providing defensible, explainable insights into structural vulnerabilities. Trade-offs: Focused on wallet-level concentration rather than full liquidity metrics; API limitations constrain depth.

Design Process

1. **API Selection:** Fetched (/token/holders) for Solana tokens to capture wallet distribution, entity types (CEX, DEX, unknown), and top holder shares.
2. **Heuristics:** Chose 3 core factors: top-10 concentration, unknown/anonymous wallet share, and largest single-holder percentage. Each factor reflects a structural risk that could amplify rug potential.
3. **Normalization:** Batch min/max scaling to 0-1 for each factor (dynamic, avoids hard-coded assumptions). Composite score aggregates weighted contributions: top-10 concentration 45%, unknown holdings 30%, largest holder 25%.
4. **Tiers:** >70 High Risk, >40 Medium Risk, >15 Low Risk, else Very Low Risk.

Formulas

Components normalized to 0-1, then averaged/scaled to 0-100 composite.

1. Top-10 Wallet Concentration Score (`norm_concentration`)

Measures how much of the token supply is held by the top 10 wallets. Higher concentration → higher risk.

$$\text{norm_concentration} = \frac{\text{top_10_pct} - \min(\text{top_10_pct})}{\max(\text{top_10_pct}) - \min(\text{top_10_pct})}$$

- Values are clipped between 0 and 1.
 - **Weight in composite score:** 45%
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2. Unknown/Anonymous Wallet Score (`norm_unknown`)

Measures the portion of the supply held by wallets with unknown entity type. Higher unknown → higher risk.

$$\text{norm_unknown} = \frac{\text{unknown_concentration} - \min(\text{unknown_concentration})}{\max(\text{unknown_concentration}) - \min(\text{unknown_concentration})}$$

- Clipped to 0–1.
 - **Weight in composite score:** 30%
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3. Largest Holder Score (`norm_whale`)

Measures the single biggest holder's share. Higher percentage → higher risk.

$$\text{norm_whale} = \frac{\text{largest_holder_pct} - \min(\text{largest_holder_pct})}{\max(\text{largest_holder_pct}) - \min(\text{largest_holder_pct})}$$

- Clipped to 0–1.
 - **Weight in composite score:** 25%
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Model Design:

1. Top-10 Wallet Concentration Risk

What it measures:

How much of a token's supply is held by the top 10 wallets. A high concentration means a few wallets control a large portion of the supply.

Why it matters:

- High concentration = one or a few wallets can drastically impact price.
- These wallets can dump suddenly, triggering cascades or flash crashes.

- Low concentration = supply is more evenly distributed, making the token structurally safer.

Interpretation:

- 0–30% top-10 = generally safe
- 30–60% top-10 = moderate structural vulnerability
- 60%+ top-10 = high risk, token can be “rugged” by a few wallets

2. Anonymous/Unknown Wallet Concentration Risk

What it measures:

The proportion of the token held by wallets whose identity cannot be verified (not labeled as exchange, project, or known entity).

Why it matters:

- Unknown wallets = unpredictable actors.
- Large unknown holdings are a red flag because these wallets could dump without warning.
- Known entities (like exchanges) are generally more reliable and less likely to rug.

Interpretation:

- 0–20% unknown = low risk
- 20–50% unknown = moderate risk
- 50%+ unknown = high risk, high potential for rug or manipulation

3. Largest Holder (“Whale”) Risk

What it measures:

The single wallet that owns the largest percentage of the token supply.

Why it matters:

- One whale controlling a large portion can move the market with a single transaction.
- Can trigger cascading liquidations or price manipulation.

Interpretation:

- <5% = low whale risk

- 5–15% = moderate whale risk
- 15% = high whale risk, token is vulnerable to sudden dumps

4. Trade Off

- **Relative vs. Absolute Risk Quantification:** Using min/max normalization ranks tokens and wallets relative to the current dataset.
 - **Known vs. Unknown Wallet Assumptions:** Treating unknown wallets as inherently risky simplifies scoring but may overstate danger. Some unknown wallets may belong to legitimate long-term holders or exchanges.
 - **Aggregate vs. Individual Risk:** Composite scores for top-10, unknown, and largest-holder concentration capture structural risk but do not account for activity, intentions, or liquidity of individual wallets. High scores indicate vulnerability, not certainty of a rug.
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Why These Weights?

Weights (45% top-10 concentration, 30% unknown wallets, 25% largest holder) reflect structural vulnerability in token ownership. **Top-10 concentration** captures systemic risk from a few wallets controlling a large portion of supply. **Unknown wallets** highlight opacity and potential hidden manipulation. **Largest holder** emphasizes whale risk, as a single holder can trigger cascades. Together, they provide a defensible, composite risk view.

The reason behind this weightage and some trade-offs:

- **Top-10 concentration:** When the top wallets [hold over 30%](#) of a token's supply, coordinated dumps by whales become a major risk. High concentration often creates exit liquidity traps, leaving retail investors unable to sell during sudden crashes.
- **Unknown wallets:** Serves as a warning about the fundamentals of the token, as high unknown concentration indicates low transparency and potential hidden control. The trade-off is that some of these unknown wallets may belong to legitimate, long-term holders, so not all are inherently risky.
- **Largest holder:** A classic rug pull indicator, where the creator or a major investor holds a significant portion of tokens and could potentially dump to manipulate the market. However, this metric alone is not always conclusive; a large holder may simply be a long-term investor or treasury wallet, so context matters.

Key Findings from Sample Run

- **High Risk:** Top-10 or largest-holder dominance is extreme, unknown wallets high → structurally vulnerable token.
- **Medium Risk:** Moderate concentration and some unknown wallets → potential for manipulation or sudden dumps.
- **Low Risk:** Balanced distribution, minimal unknown exposure → structurally stable token with low rug potential.

HOLDER CONCENTRATION RISK ANALYSIS	
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-RECORD 0-----	
token_address	9jZgvgS2bWtQiYzv48GcWzY4tnkeRSANbTm8Kp1LmSyS
token_name	SHARPEI
token_symbol	shar
num_holders_shown	100
largest_holder_pct	97.98
top_10_concentration_pct	98.82
top_5_concentration_pct	98.49
cex_concentration_pct	0.0
dex_concentration_pct	98.03
unknown_concentration_pct	1.52
composite_risk_score	70.12
risk_tier	HIGH RISK
-RECORD 1-----	
token_address	JUPyiwrYJFskUPiHa7hkeR8VUtAeFoSYbKedZNsDvCN
token_name	Jupiter
token_symbol	jup
num_holders_shown	100
largest_holder_pct	25.71
top_10_concentration_pct	72.03
top_5_concentration_pct	63.08
cex_concentration_pct	6.53
dex_concentration_pct	68.81
unknown_concentration_pct	10.03
composite_risk_score	46.24
risk_tier	MEDIUM RISK
-RECORD 2-----	
token_address	9BB6NFEcjBCtnNLFko2FqVQBq8HHM13kCyYcdQbgpump
token_name	Fartcoin
token_symbol	fartcoin
num_holders_shown	100
largest_holder_pct	7.14
top_10_concentration_pct	32.83
top_5_concentration_pct	23.53
cex_concentration_pct	25.09
dex_concentration_pct	3.26
unknown_concentration_pct	35.64
composite_risk_score	45.32
risk_tier	MEDIUM RISK

Conclusion

This risk assessment framework is not intended to definitively predict a rug pull, but rather to identify structural vulnerabilities in token ownership that may increase the likelihood of market manipulation or abrupt price crashes. By normalizing and combining **top-10 wallet concentration** (capturing systemic risk from a few controlling holders), **unknown wallet proportion** (indicating opacity and potential hidden manipulation), and **largest holder size** (highlighting whale risk), the system produces a defensible, composite score for each token.

In practice, it successfully highlights tokens with highly concentrated or opaque ownership structures, while assigning lower risk to well-distributed, transparent projects. Key limitations include sensitivity to the sample of holders retrieved from the API and the relative nature of normalization- tokens outside the dataset could still carry high absolute risk. Future improvements could integrate historical wallet activity or on-chain transaction patterns to enhance predictive accuracy and provide a more holistic early-warning tool.

Perpetual Contract (Trying out Arkham exchange API)

First and foremost, why perpetual contracts?

Perpetual futures (perps) are derivative contracts that mimic spot trading without expiration, using a **funding rate mechanism** to keep perp prices aligned with the underlying spot price. If perps trade above spot (premium), longs pay shorts (positive funding); if below (discount), shorts pay longs (negative funding). This incentivizes arbitrage: traders buy spot/sell perps (or vice versa) to profit from discrepancies, driving convergence.

In short, perps lead spot prices through arbitrage and funding, especially in crypto's high-leverage environment.

Summary

This POC system uses Arkham API perp data to score rug pull risks for new Solana tokens on a 0-100 scale, with tiers for semi-technical stakeholders. High-risk classifications for low-liquidity memecoins, moderate for volatile ones , and low for established. Model aligns with 2025 rug stats ([98.6% in low-liquidity launches](#)), providing defensible, explainable output. Trade-offs: Simplicity over complexity; API limits depth.

Design Process

1. **API Selection:** Fetched Solana perps (/public/contracts) for liquidity/sentiment signals. Fetch (/token/holders) for token weightage and allocation.

2. **Heuristics:** Chose 3 factors: liquidity (OI inverse, primary rug signal per 93% "soft rugs" in low-depth pools), funding rate (extremes for traps), price gap (manipulation proxy).
3. **Normalization:** Batch min/max scales to 0-1 (dynamic, no assumptions). Composite averages for balance.
4. **Tiers:** >80 HighRisk, >60 Moderate, >40 Low Risk else Safe.

Formulas

Components normalized to 0-1, then averaged/scaled to 0-100 composite.

- **Liquidity Risk (0-1):**
 $\max(0, \min(1, 1 - \frac{OI - \min_{OI}}{\max_{OI} - \min_{OI}}))$
 (Inverse OI; low = high risk.)
- **Funding Risk (0-1):**
 $\max(0, \min(1, \frac{|\text{funding}| - \min_{funding}}{\max_{funding} - \min_{funding}}))$
 (Absolute extremes.)
- **Price Gap Risk (0-1):**
 $\max(0, \min(1, \frac{|\text{price} - \text{mark}| / (\text{mark} - \min_{gap})}{\max_{gap} - \min_{gap}}))$
 (Relative deviation.)
- **Composite Risk Score (0-100):**
 $\left(\frac{\text{liquidity} + \text{funding} + \text{gap}}{3} \right) \times 100$
 (Equal weights for simplicity—liquidity/funding emphasized in selection.)

Model Design:

1. Liquidity Risk:

Liquidity risk measures the **market's depth and its ability to resist massive price changes** when a sudden surge of selling (or buying) occurs. It shows how **fragile** the price structure is.

Liquidity = how much money is sitting in the market waiting to buy or sell.

- **High liquidity** → the market is deep, stable, and hard to crash
- **Low liquidity** → the market is thin, unstable, and easy to crash

Why Low Liquidity Is Dangerous

When the market drops, some traders get **liquidated** (forced selling).

In a **high-liquidity market**, there are plenty of buyers to absorb this selling. *Price drops slowly and stays stable.*

In a **low-liquidity market**, there are very few buyers.

Even a small amount of forced selling can smash through the order book and cause a sudden crash.

2. Funding Risk:

Funding rate is one of the **fastest early warnings** that a perp market is becoming unstable, manipulated, or at risk of a rug-style move. Here's the no-BS breakdown:

Funding rate shows where the pain is

- **Positive funding** = longs paying shorts → market biased long.
- **Negative funding** = shorts paying longs → market biased short.

When funding becomes **extremely one-sided**, it means one side is over-leveraged and vulnerable to a wipeout.

3. Price Gap Risk:

Price gaps are one of the clearest signs that a market is **illiquid, fragile, and vulnerable to sudden collapses**. Here's the straight-to-the-point breakdown:

Price gaps show the market has no “shock absorber.”

When the price jumps up or down with no trades in between, it means the order book is empty at key levels.

Why this is dangerous:

- **Thin liquidity = no buyers or sellers nearby.**
Even small market orders can cause huge jumps.
- **Liquidations hit empty order books.**
Forced selling doesn't get absorbed leads to price freefalls.
- **Stop-losses don't work properly.**
You get filled at a much worse price because the market “skipped” your level.
- **Easy to manipulate.**
Whales can push the price through empty gaps and trigger cascades.

When price gaps appear repeatedly, it means the token is structurally unsafe and can rug with very little effort.

4. Trade-Off

- **Relative vs. Absolute Risk Quantification:** The use of min/max scaling forces the output to be a **relative ranking** within the current dataset, not an **absolute measure of market danger**. The "safest" token may still be critically risky outside the context of the small sample size.
 - **Directional vs. Neutral Risk Signal:** Applying the **absolute value** to Funding and Price Gap components simplifies the risk calculation but eliminates the **actionable directional signal**. The model cannot distinguish whether the market is vulnerable to a short-squeeze or a long-squeeze, reducing predictive specificity.
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Why these Weights?

Equal weights (1/3 each) balance factors while implicitly prioritizing liquidity/funding as core rug predictors.

Each weights are equally important as it tells a different narrative on the possibility of a short term volatility.

Key Findings from Sample Run

- **High Risk:** Driven by 100% liquidity/gap, matches low-depth rugs.
- **Moderate Risk:** Balanced risks; watch for funding spikes.
- **Low Risk:** Strong liquidity, no gaps, safe utility token

...	baseSymbol	openInterestUSD	usdVolume24h	fundingRate	price	markPrice	liquidity_risk	funding_risk	price_gap_risk	composite_risk_score	risk_tier
PUMP.P	5530.7813	6582.439279	-0.00003	0.002692	0.002734	94.9	100.0	100.0	98.3	HIGH RISK	
PENGU.P	6.0144086	382.1371473	-0.000028	0.010267	0.010358	99.9	92.86	100.0	97.59	HIGH RISK	
PYTH.P	193.2964352	319.993558	-0.000024	0.07216	0.07293	96.3	78.57	100.0	91.62	HIGH RISK	
BONK.P	1768.23624672	36407.83796539	-0.000014	0.0000864	0.0000867	99.7	42.86	100.0	88.85	HIGH RISK	
FARTCOIN.P	0.88404	347.18889	0.000005	0.2101	0.21	100.0	18.71	100.0	70.24	MODERATE RISK	
POPCAT.P	1.42432	370.97893	-0.000004	0.88902	0.88958	100.0	7.14	100.0	69.05	MODERATE RISK	
GRASS.P	1.95518	202.97898	0.000003	0.3371	0.3417	99.9	3.57	100.0	67.82	MODERATE RISK	
WIF.P	17170.032225	30165.106897	0.000003	0.3182	0.3193	96.5	3.57	100.0	66.69	MODERATE RISK	
JUP.P	20016.9736	6889.55584	-0.000003	0.2392	0.239	82.3	3.57	100.0	61.96	MODERATE RISK	
JTO.P	934.96184	292.30815	-0.000002	0.4646	0.4651	80.5	0.0	100.0	68.17	MODERATE RISK	
TRUMP.P	5788.324165	12084.610604	-0.000013	6.385	6.334	97.1	39.29	41.76	59.38	LOW RISK	
RENDER.P	39952.2732	4226.56728	-0.000012	1.671	1.681	42.4	35.71	100.0	59.37	LOW RISK	
SOL.P	147577.630844315	296850.46225	-0.000017	127.47	127.93	97.0	53.57	0.0	50.19	LOW RISK	
MELANIA.P	20755.4249553	1264.1979427	-0.000002	0.1217	0.1223	0.0	0.0	100.0	33.33	SAFE	

Conclusion

This risk assessment model is not designed to predict with certainty that a rug pull will occur, but rather to detect suspicious patterns in perpetual contract metrics that may indicate upcoming volatility or manipulative activity. By normalizing and combining liquidity risk (from low open interest, signaling thin market depth and easy dumps), funding risk (extremes suggesting retail traps or squeezes), and price gap risk (deviations hinting at inefficiencies), the system provides an early warning for high-risk tokens.

In the sample run, it effectively flagged newer memecoins like PUMP while classifying established ones like SOL appropriately

Key limitations include reliance on perp data alone (no on-chain holder analysis) and batch normalization (sensitive to sample size). Future enhancements could incorporate more API endpoints (e.g., order book depth) or integrate time-series trends for better volatility forecasting, turning this POC into a robust monitoring tool.