Robust (Decentralized) Oracle Design

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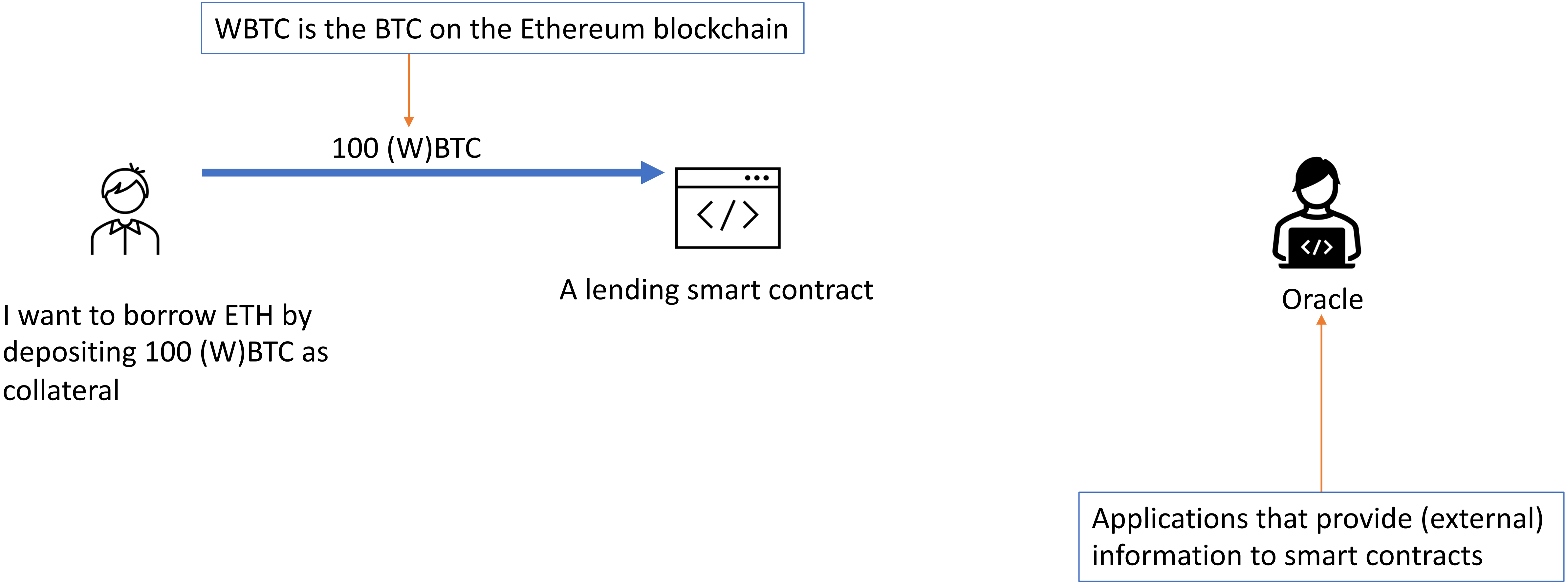
Oracle and its problem



WBTC is the BTC on the Ethereum blockchain

100 (W)BTC

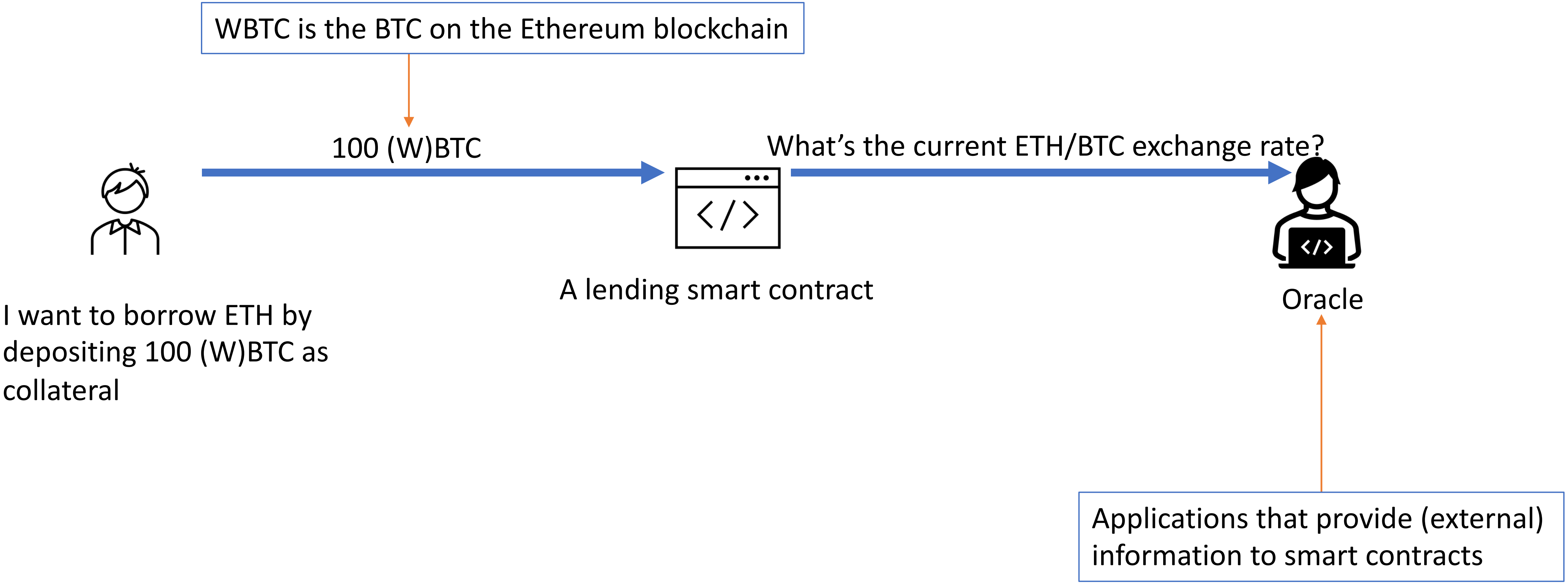
I want to borrow ETH by depositing 100 (W)BTC as collateral

A lending smart contract

Oracle

Applications that provide (external) information to smart contracts

Oracle and its problem



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What’s the current ETH/BTC exchange rate?

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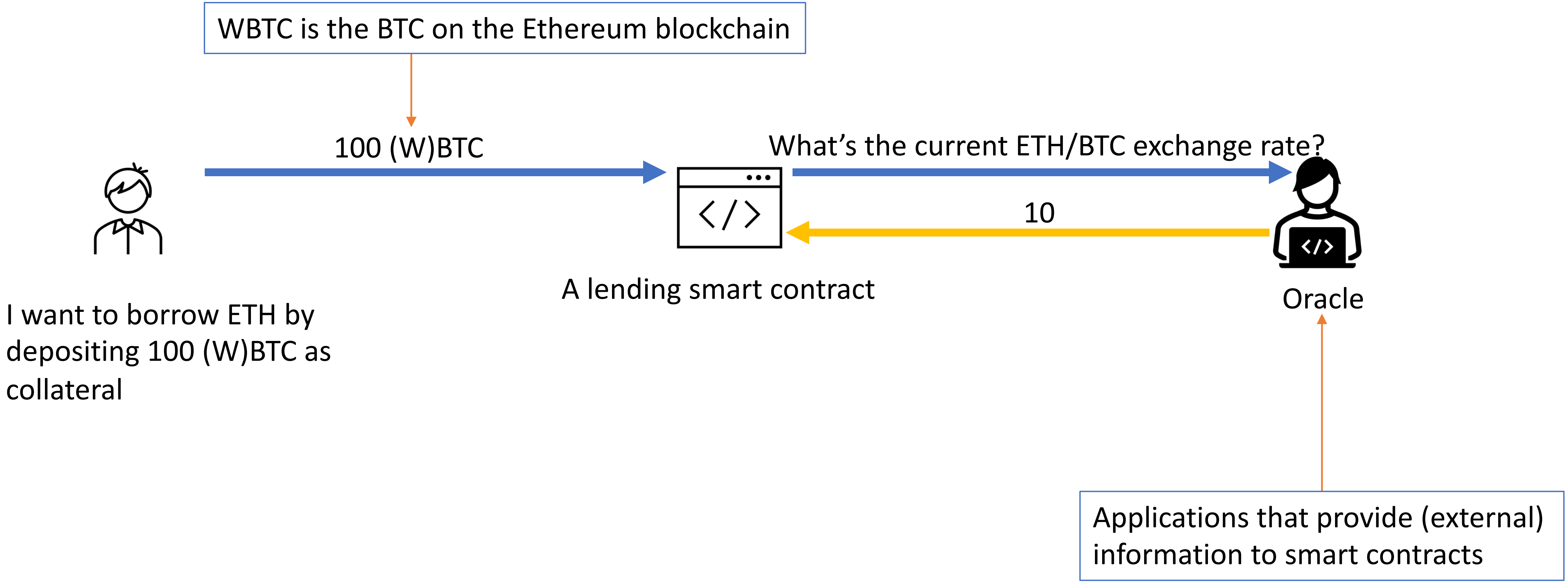

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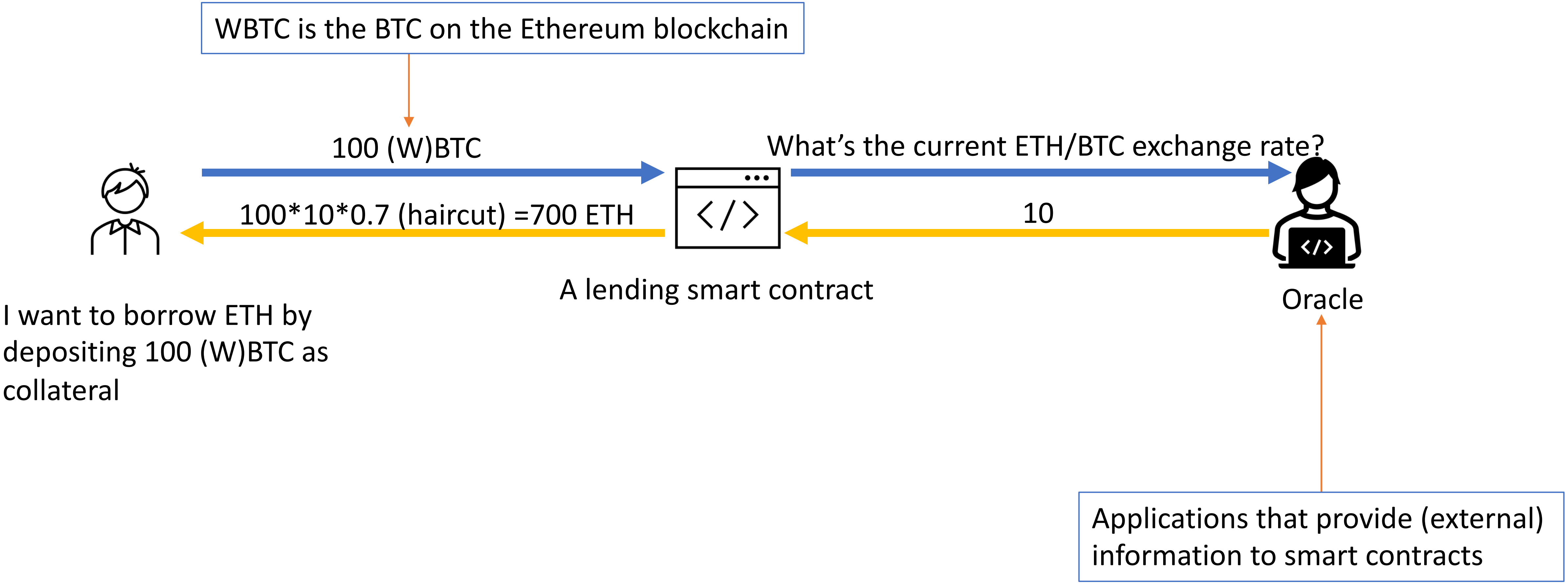

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100*10*0.7 (haircut) =700 ETH

What’s the current ETH/BTC exchange rate?

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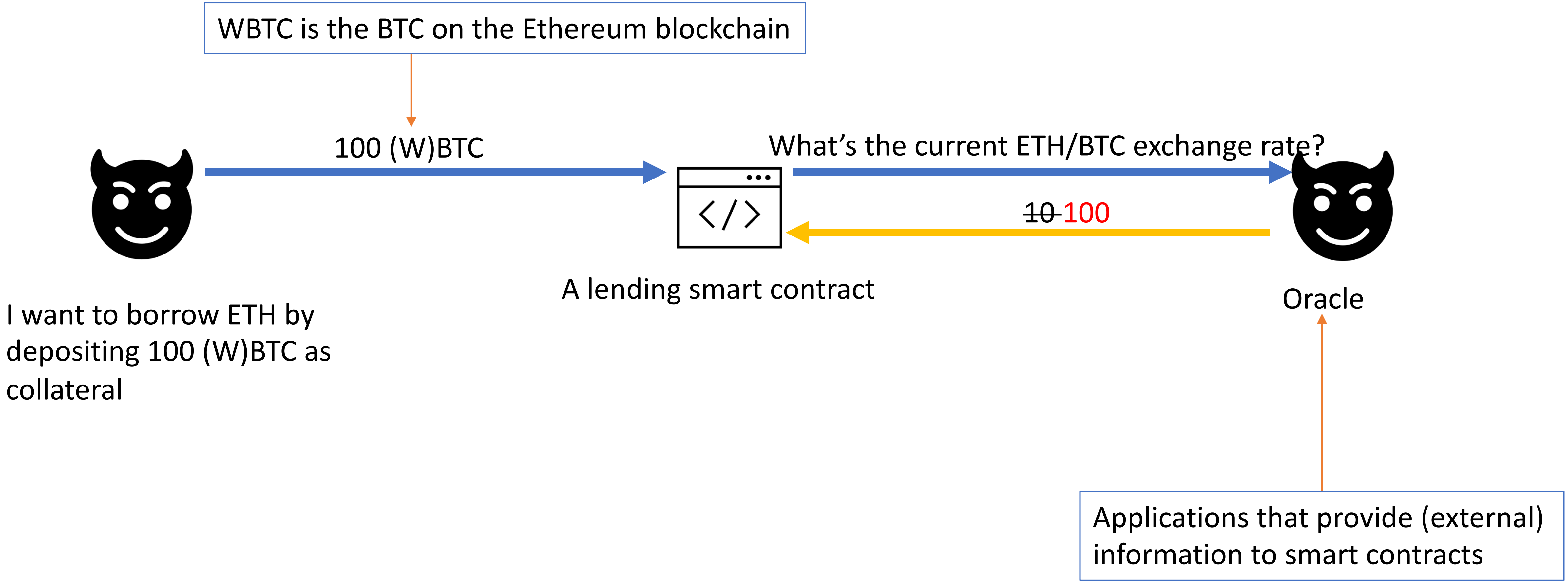

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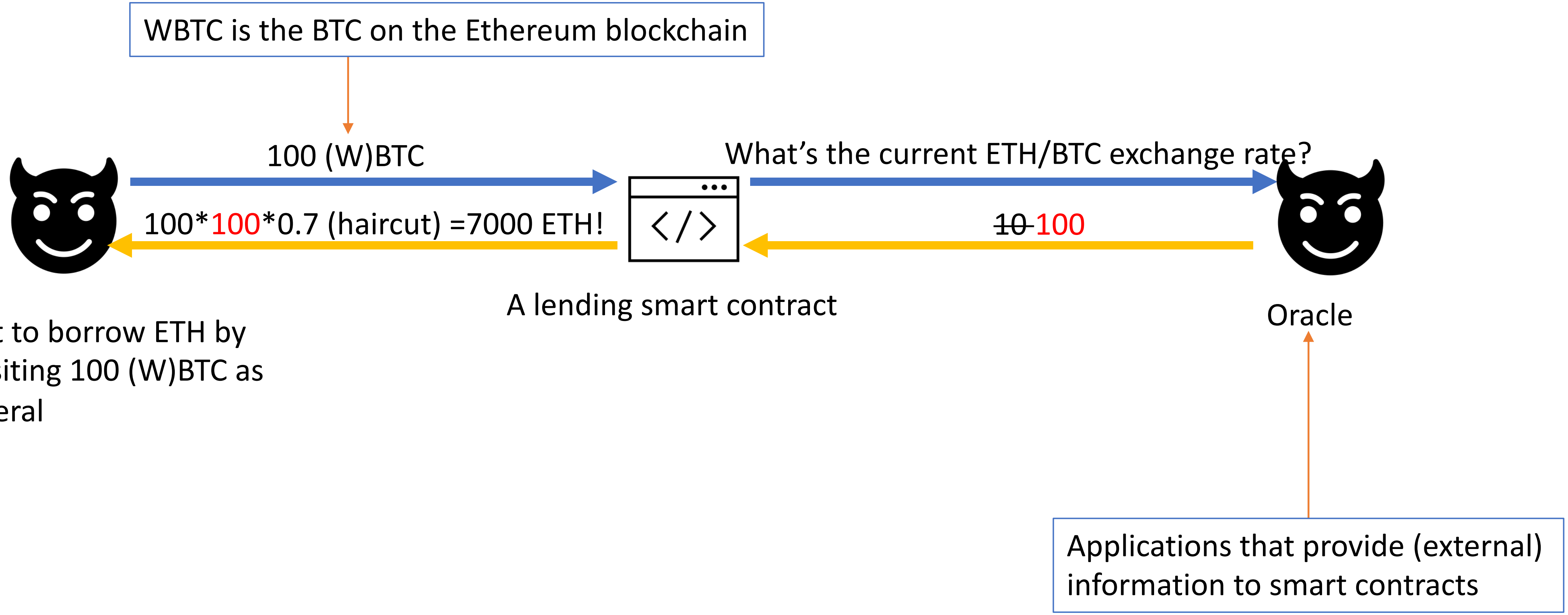

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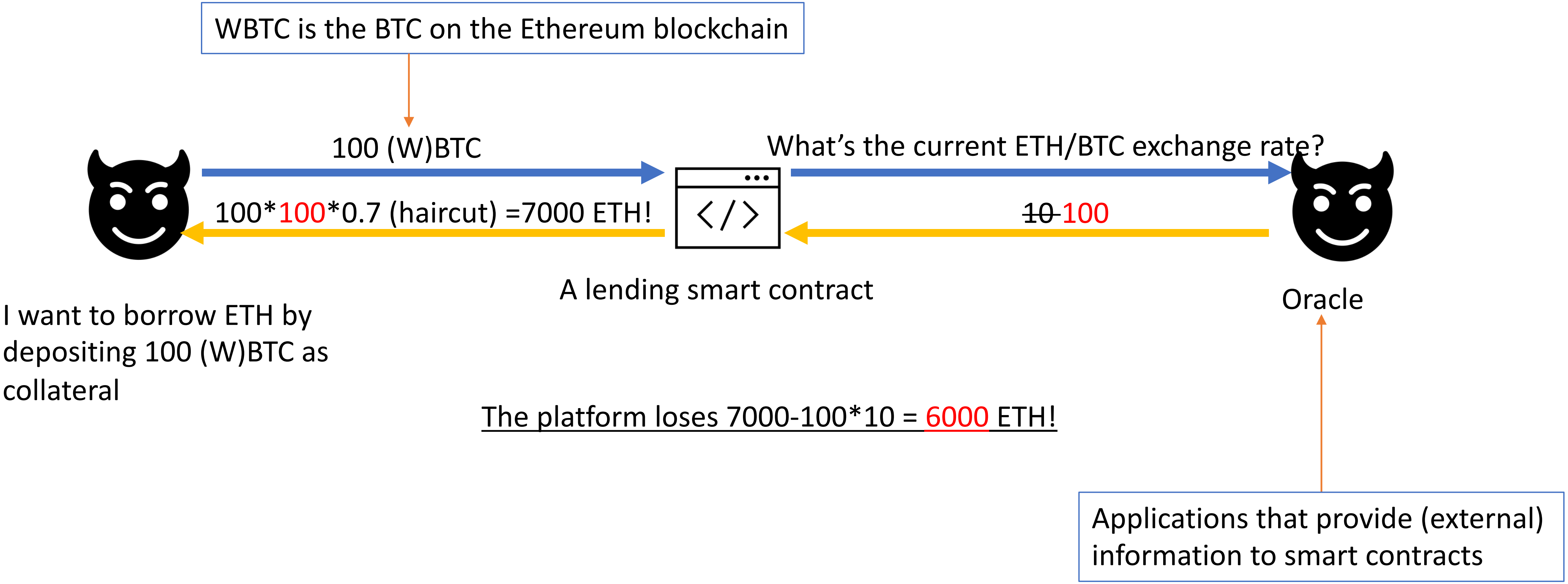

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What’s the current ETH/BTC exchange rate?

100*100*0.7 (haircut) =7000 ETH!

~~10~~ 100

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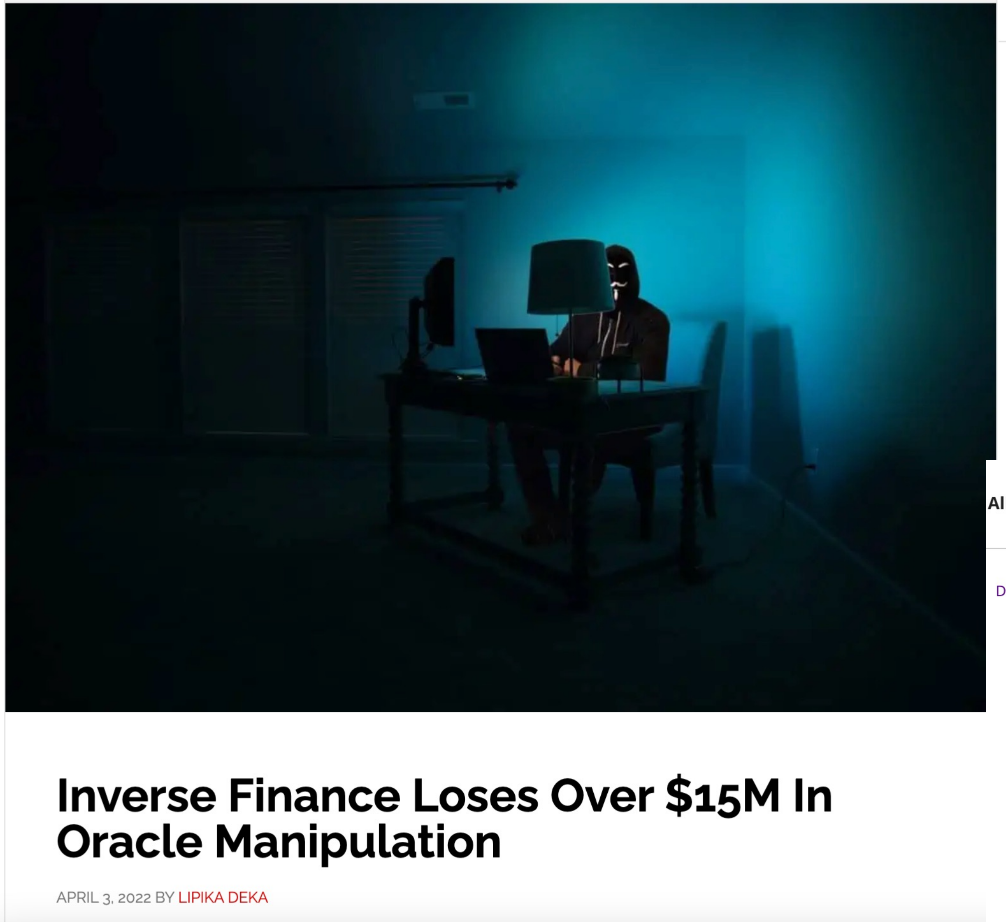
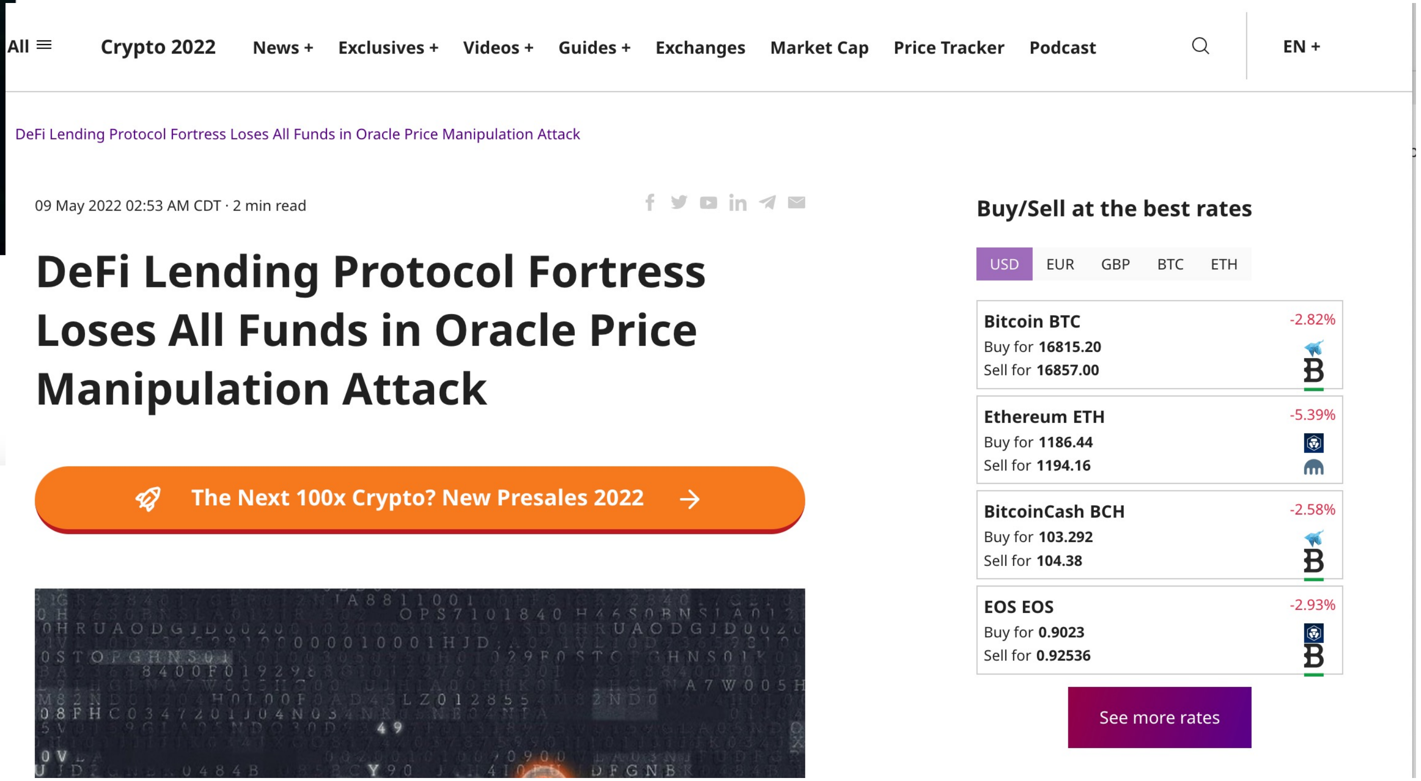
The platform loses 7000-100*10 = 6000 ETH!

Applications that provide (external) information to smart contracts



Inverse Finance Loses Over $15M In Oracle Manipulation

APRIL 3, 2022 BY LIPIKA DEKA



DeFi Lending Protocol Fortress Loses All Funds in Oracle Price Manipulation Attack

09 May 2022 02:53 AM CDT · 2 min read

DeFi Lending Protocol Fortress Loses All Funds in Oracle Price Manipulation Attack

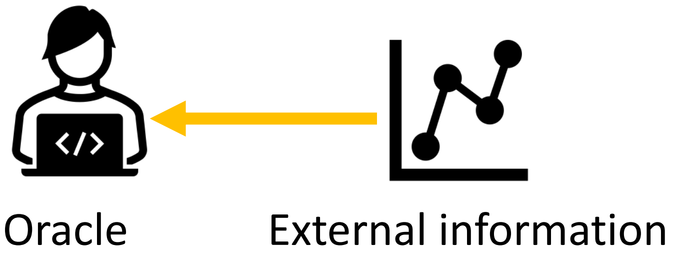
Buy/Sell at the best rates

Bitcoin BTC	Buy for 16815.20 Sell for 16857.00	-2.82%
Ethereum ETH	Buy for 1186.44 Sell for 1194.16	-5.39%
BitcoinCash BCH	Buy for 103.292 Sell for 104.38	-2.58%
EOS EOS	Buy for 0.9023 Sell for 0.92536	-2.93%

Sources: https://www.tronweekly.com/inverse-finance-loses-15m-oracle-manipulation/
https://cryptonews.com/news/defi-lending-protocol-fortress-loses-all-funds-oracle-price-manipulation-attack.htm

The importance of oracles

- Oracles are the cornerstone of DeFi
  - Decentralized lending platforms
  - Prediction markets
  - Insurance contracts
  - NFT games
  - (Many) stablecoins
  - …



The oracle problem

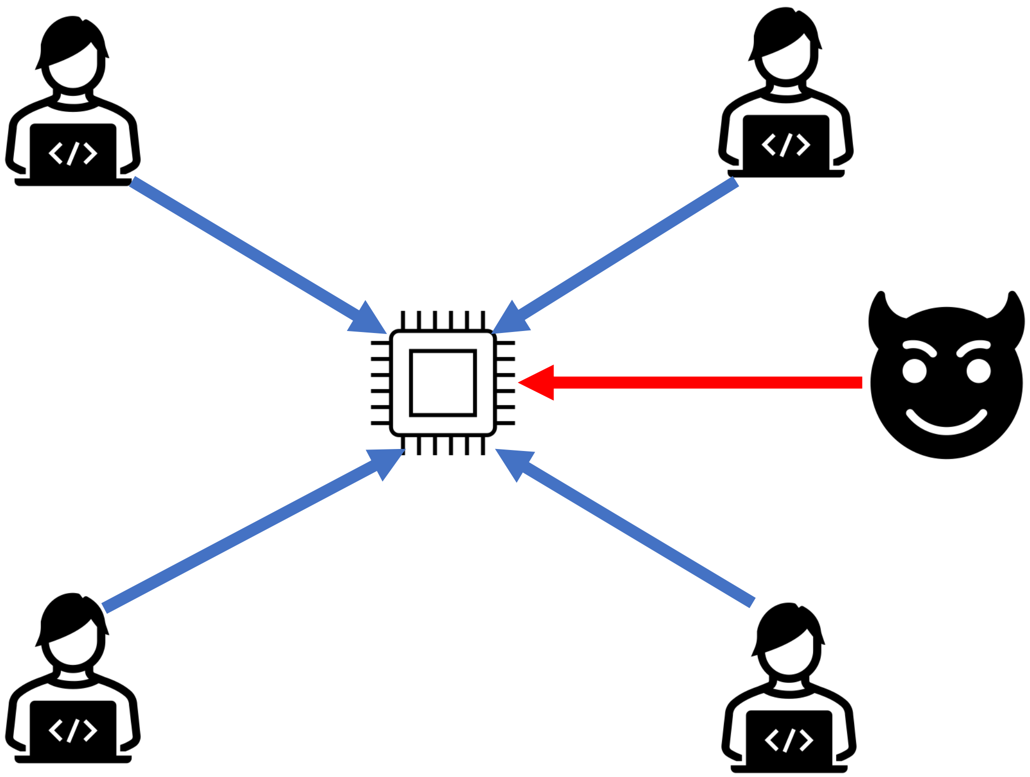
- How can we ensure the information provided by oracles is accurate?

The oracle problem

- How can we ensure the information provided by oracles is accurate?
- Single source → single point of failure

The oracle problem

- How can we ensure the information provided by oracles is accurate?
- Single source → single point of failure → decentralization!



Research question 1

- Q: Can we find a robust compensation mechanism?

Definition

A compensation mechanism is robust if, under that mechanism, there is an equilibrium in which truthful reporting is the unique optimal response for strategic nodes regardless of the adversary's strategy.

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Definition
A compensation mechanism is robust if, under that mechanism, there is an equilibrium in which truthful reporting is the unique optimal response for strategic nodes regardless of the adversary's strategy.

- A: Without identifying an honest node, generally no
- Takeaway: "A" limit of decentralization

Research question 2

- Q: What is the optimal way to aggregate information under the worst-case scenario?

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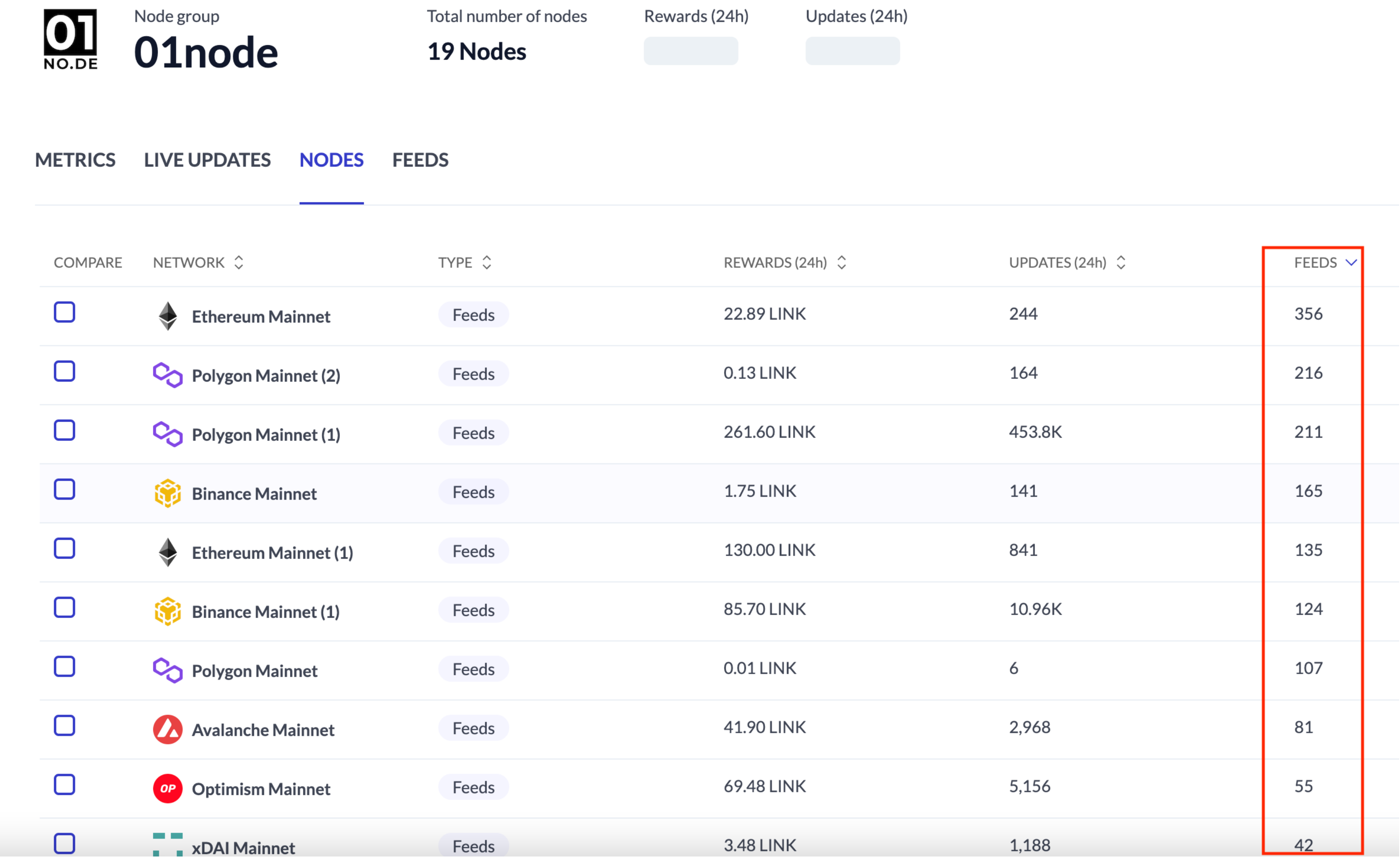
- Key observations:
  1. Obtaining consensus = unsupervised learning with contaminated data
  2. The popular aggregating method ignores the multi-dimensional structure of decentralized oracles---each node usually covers many cryptocurrencies

The multi-dimensional structure



Node group

01node

Total number of nodes

19 Nodes

Rewards (24h)

Updates (24h)

COMPARE	NETWORK	TYPE	REWARDS (24h)	UPDATES (24h)	FEEDS
□	Ethereum Mainnet	Feeds	22.89 LINK	244	356
□	Polygon Mainnet (2)	Feeds	0.13 LINK	164	216
□	Polygon Mainnet (1)	Feeds	261.60 LINK	453.8K	211
□	Binance Mainnet	Feeds	1.75 LINK	141	165
□	Ethereum Mainnet (1)	Feeds	130.00 LINK	841	135
□	Binance Mainnet (1)	Feeds	85.70 LINK	10.96K	124
□	Polygon Mainnet	Feeds	0.01 LINK	6	107
□	Avalanche Mainnet	Feeds	41.90 LINK	2,968	81
□	Optimism Mainnet	Feeds	69.48 LINK	5,156	55
□	xDAI Mainnet	Feeds	3.48 LINK	1,188	42

Source: https://market.link/nodes/568cedcc-46f3-49e4-84c7-a9d7d5e23a0d/nodes

Research question 2

- Q: What is the optimal way to aggregate information under the worst-case scenario?

- A: A filtering algorithm can dramatically improve the consensus by utilizing this multi-dimensional structure
  - Adversarial nodes which look “normal” in every single dimension could be detected from a “global” view
  - Approaching the theoretical limit

Related literature

- Oracle design
  - F. Zhang et al. (2016), F. Zhang et al. (2020), Breidenbach et al. (2021)
  - Contribution: 1) “A” limit of decentralization; 2) connecting machine learning to oracle design

- Information elicitation
  - McCarthy (1956), Savage (1971), Prelec (2004), Miller et al. (2005), P. Zhang and Chen (2014), Lambert (2019), Gao et al. (2019)
  - Contribution: Getting an impossible result under the adversarial environments

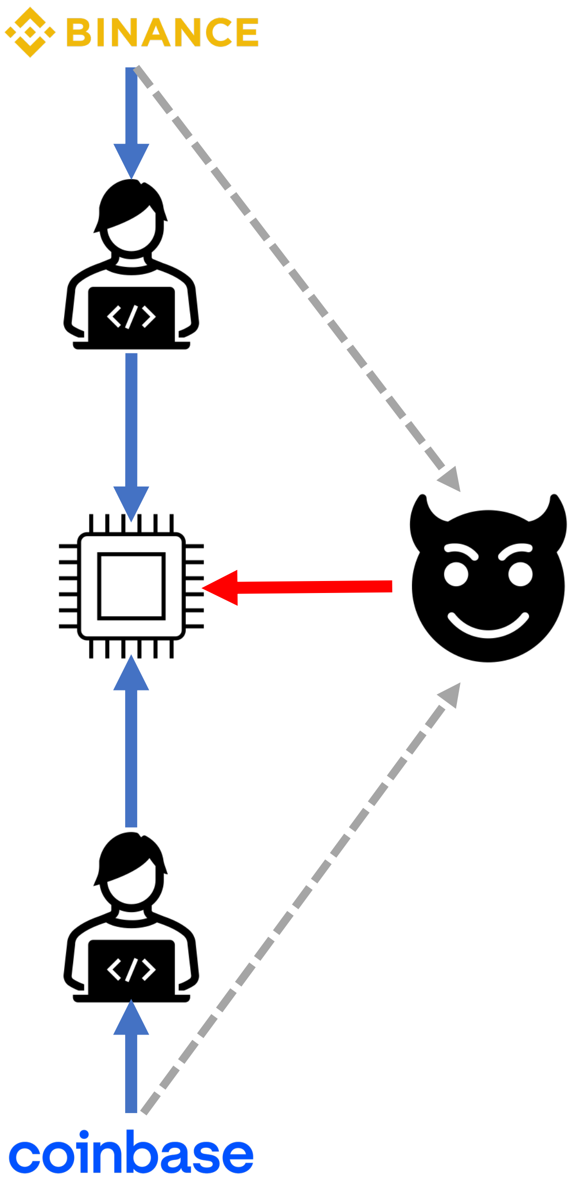
- Manipulation in traditional capital markets
  - Gandhi et al. (2019), A. Zhang (2022)
  - Contribution: Shedding light on designing replacements for the London Inter-Bank Offered Rate (LIBOR)

- Byzantine fault tolerance
  - Lamport et al. (1982), Amoussou-Guenou et al. (2021), Halaburda et al. (2021)

- Machine learning
  - Lai et al. (2016), Diakonikolas et al. (2016, 2017, 2019), Charikar et al. (2017), Zhu et al. (2022)

Setting

- n (a large number of) nodes; εn nodes are controlled by an adversary
- The rest nodes are risk-neutral and strategic: Maximizing the expected payoffs given by the designer
- Ground truth $\mathbf{X} \sim U(\mathbb{R}^d)$
- Each strategic node has a private signal
$$\mathbf{s}_i = \mathbf{X} + \mathbf{e}_i$$
  - $\mathbb{E}[\mathbf{e}_i] = \mathbf{0}$ and $\mathbf{e}_i$ has a bounded covariance matrix
- Key assumption: The adversary observes strategic nodes' private signals



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Timing:

1. The designer announces a compensation mechanism
2. Each node submits a report
3. The designer pays each node and outputs a consensus

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Goals:

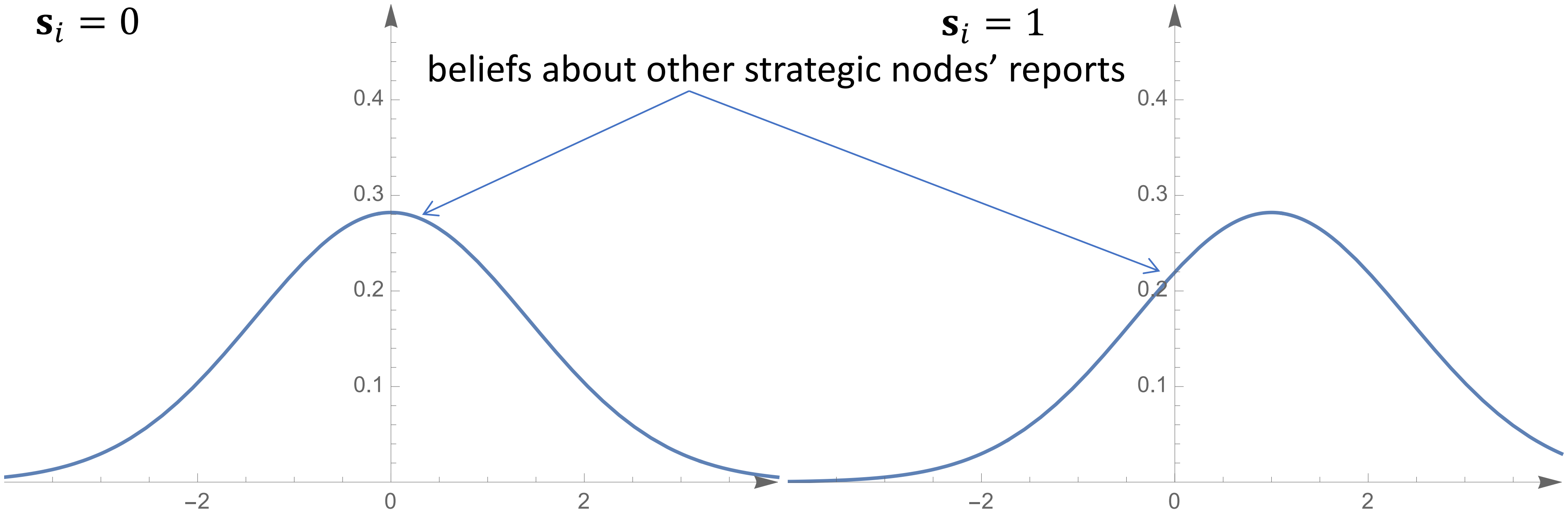
1. Find a robust compensation mechanism
2. Find a robust consensus $\widehat{\mathbf{X}}$ that is close to $\mathbf{X}$

robust = good given the adversary's any strategy

Part 1: (No) Robust compensation mechanism

No robust compensation mechanism

- Suppose $\mathbf{s}_i = \mathbf{X} + \mathcal{N}(0,1)$ and consider node i's decision problem



$\mathbf{s}_i = 0$

$\mathbf{s}_i = 1$

beliefs about other strategic nodes' reports

No robust compensation mechanism

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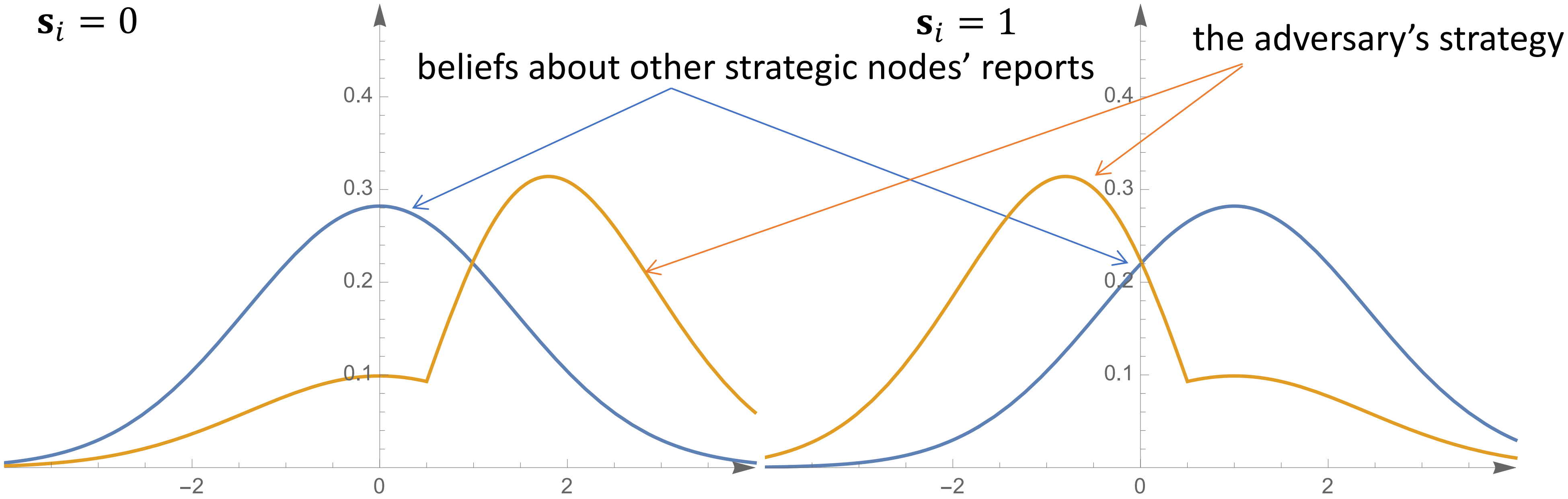
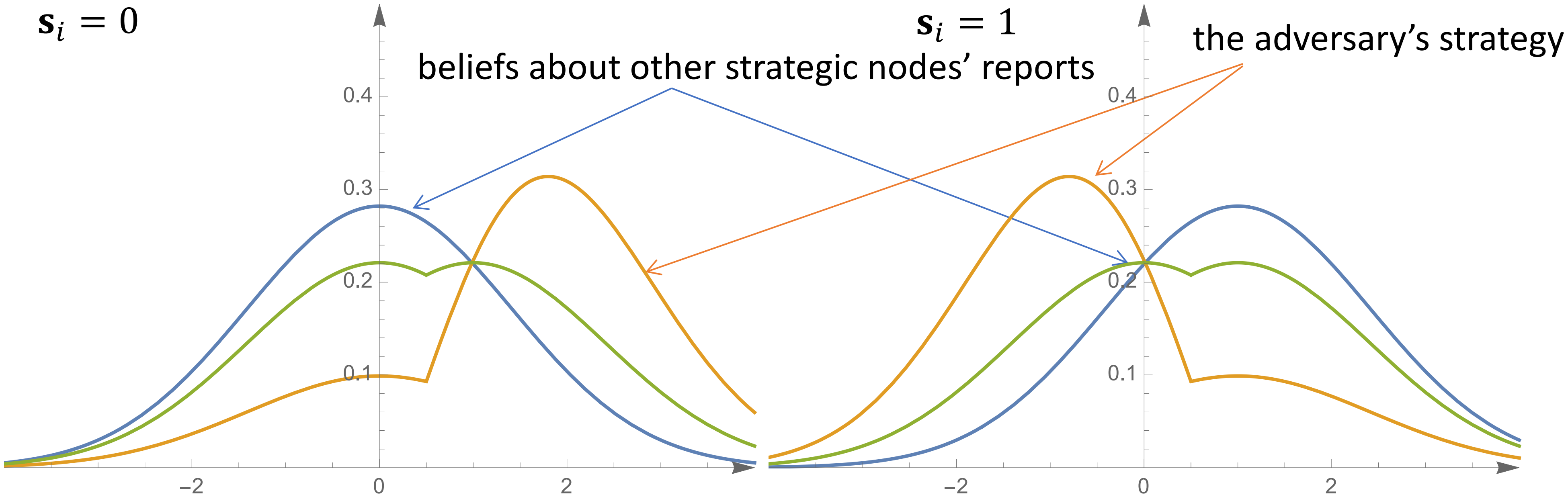


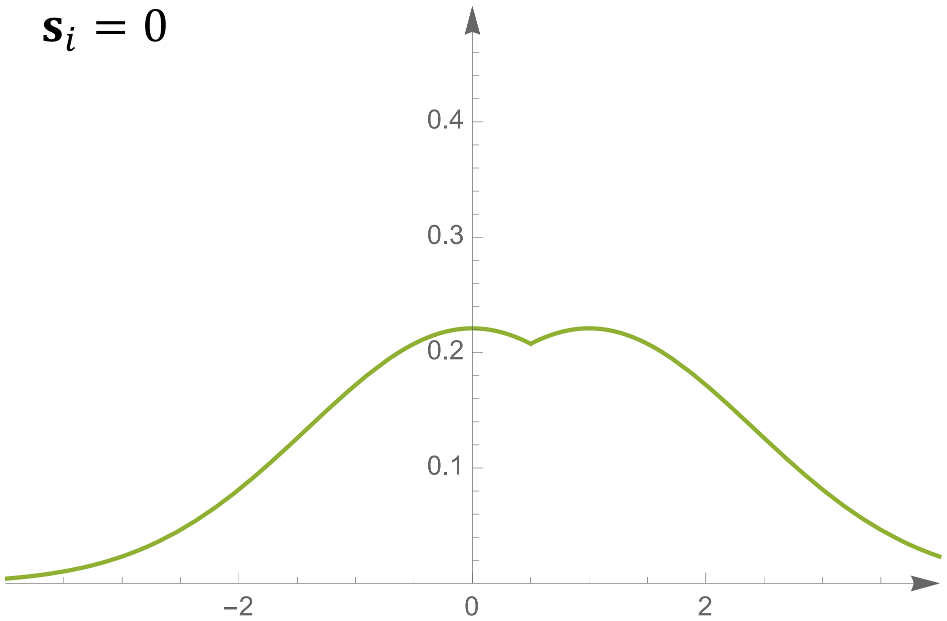
No robust compensation mechanism

- Suppose $\mathbf{s}_i = \mathbf{X} + \mathcal{N}(0,1)$ and consider node i's decision problem
- Greenline $= (1-\varepsilon) *$ Blueline + $\varepsilon *$ Orangeline
- Node i's beliefs about other nodes' reports



No robust compensation mechanism

Lemma [implied by an observation in robust statistics]
Under a mild sufficient condition, the adversary has a reporting strategy such that even if node i may have different private information, node i's beliefs about other nodes' reports are unchanged.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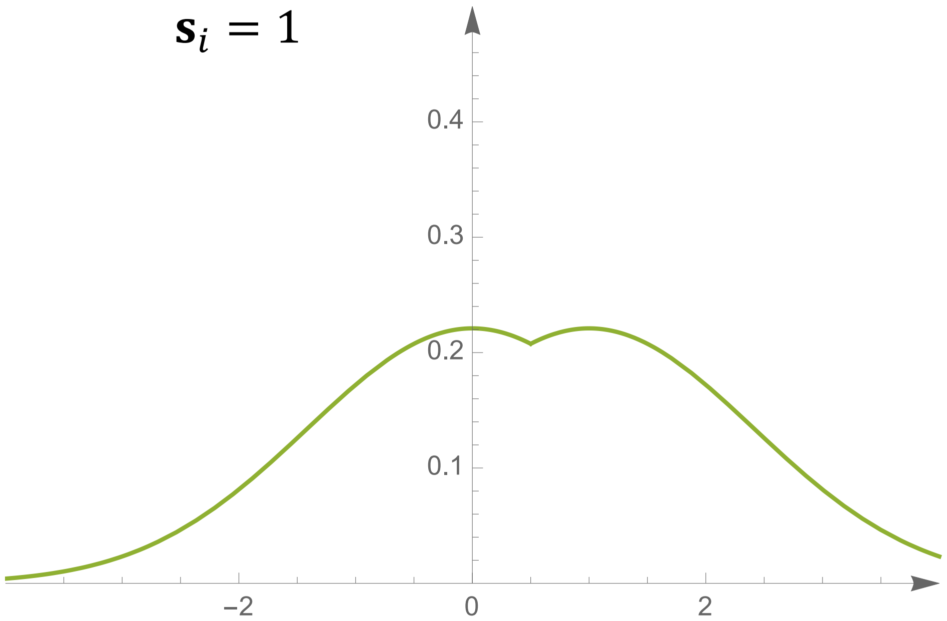
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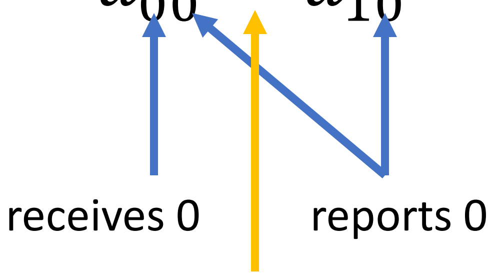
No robust compensation mechanism

- $u_{00} = u_{10}$



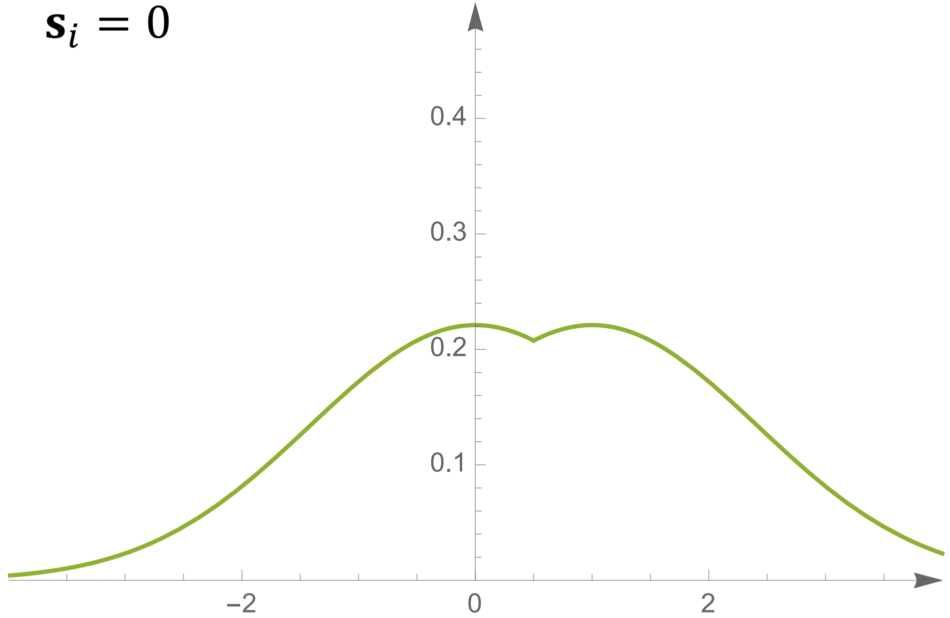
receives 0

reports 0

other nodes' reports are the same (the two green lines)

		Report $\mathbf{r}_i$	
		0	1
Private signal $\mathbf{s}_i$	0	u_{00}	u_{01}
	1	u_{10}	u_{11}

$\mathbf{s}_i = 0$



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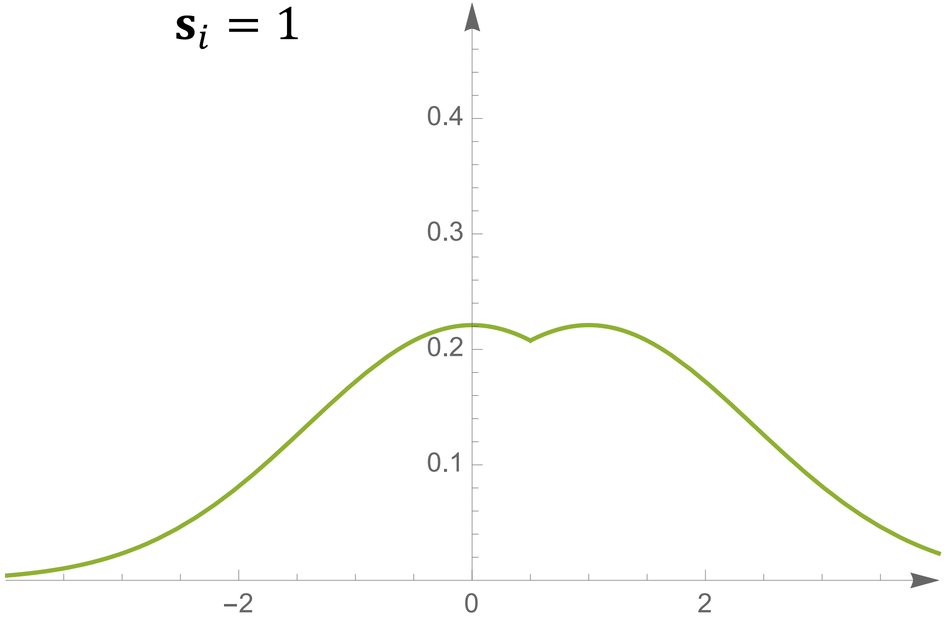
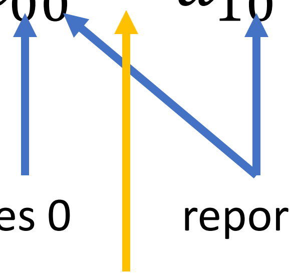


No robust compensation mechanism

- $u_{00} = u_{10} < u_{11}$



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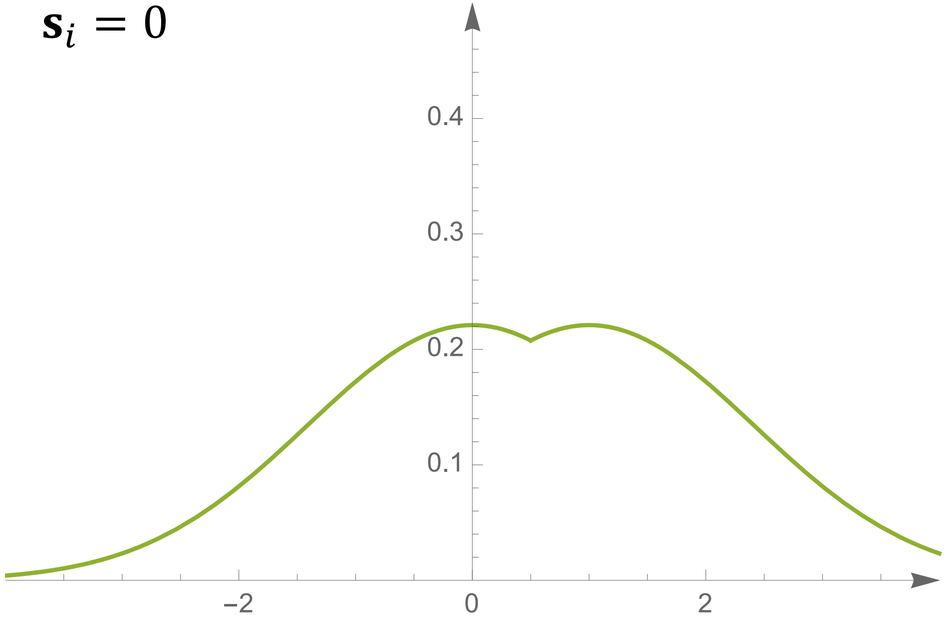

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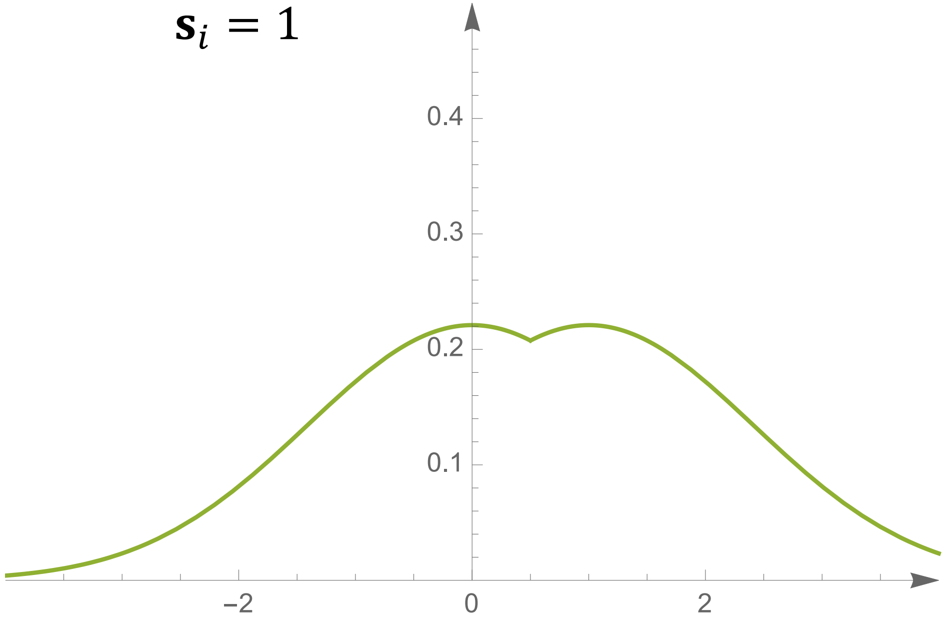

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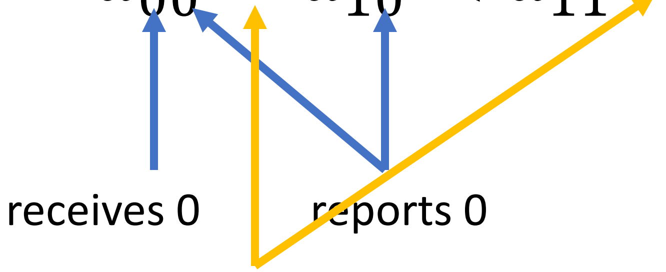

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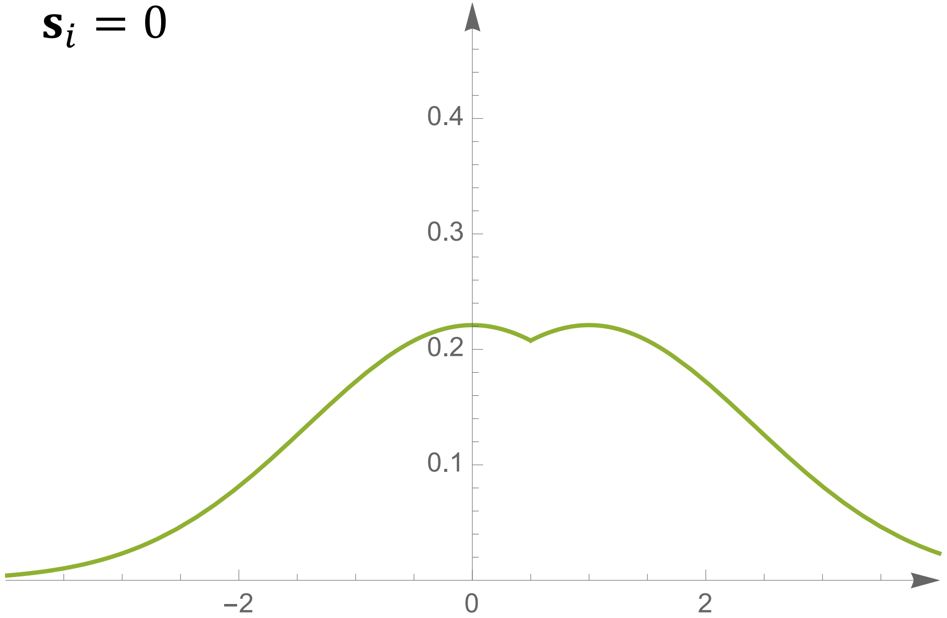

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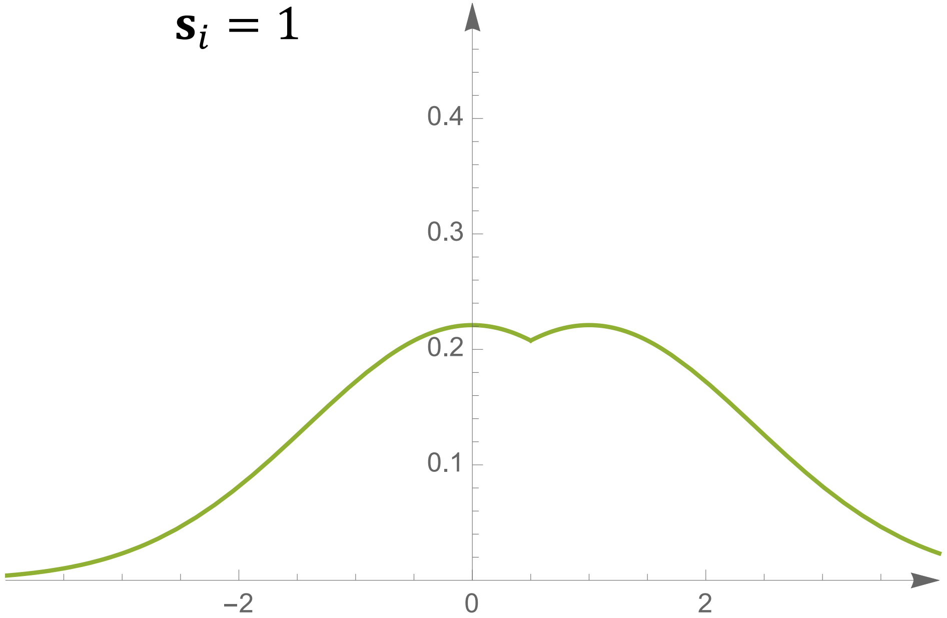
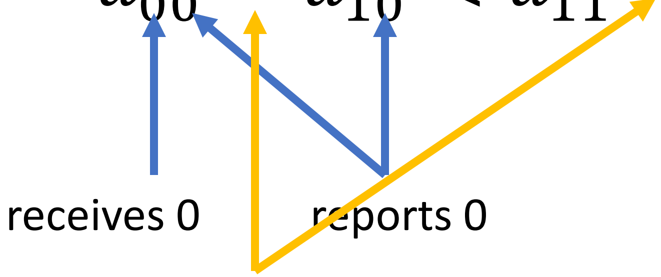


No robust compensation mechanism

- $u_{00} = u_{10} < u_{11} = u_{01} < u_{00}$



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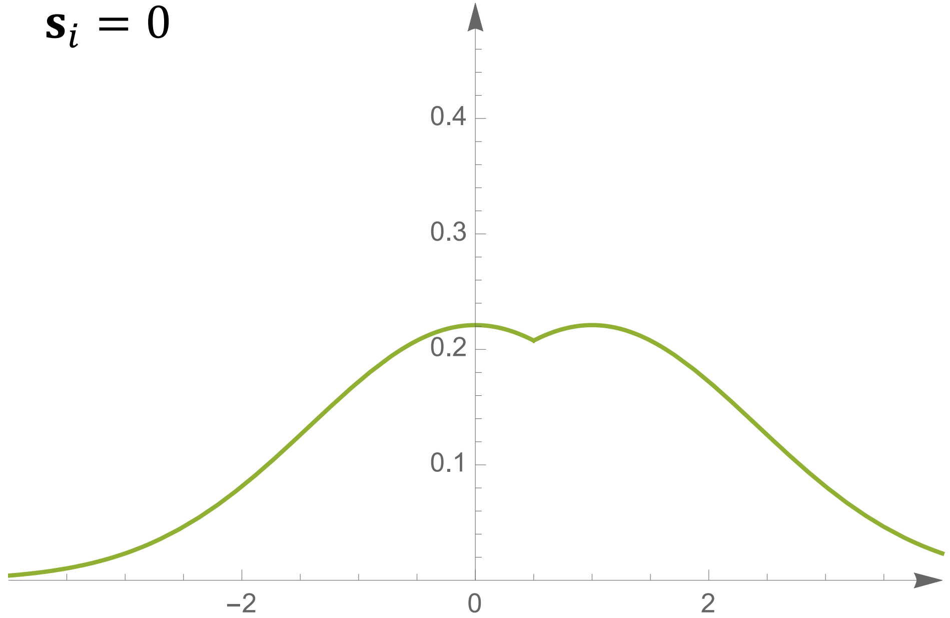

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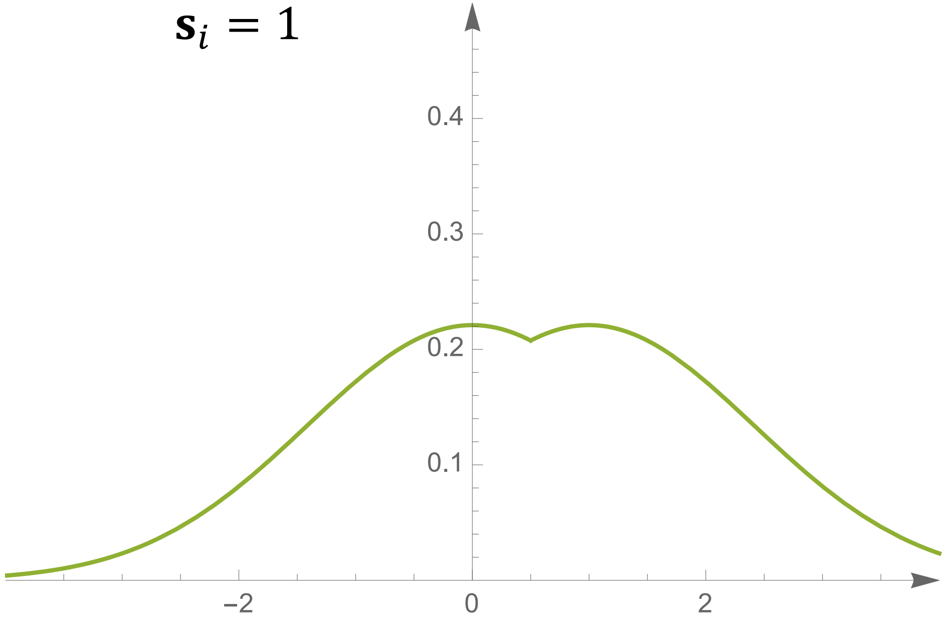

No robust compensation mechanism

- Let $Q(\cdot;\mathbf{s})$ be a strategic node's posterior belief about another strategic node's private signal after observing $\mathbf{s}$
- Let d_{TV} denotes the total variation distance

$$d_{\mathrm{TV}}(P,P') \coloneqq \sup_{E\in\mathfrak{B}}[P(E)-P'(E)]$$

- Let $\mathcal{D}$ be the dataset of all reports

Theorem

If there are are two different signal realizations, $\mathbf{s}$ and $\mathbf{s}'$, such that

$$d_{\mathrm{TV}}\big(Q(\cdot;\mathbf{s}),Q(\cdot;\mathbf{s}')\big) \le \frac{\varepsilon}{1-\varepsilon},$$

then for any compensation mechanism $\mathcal{M}$ as a function of $\mathcal{D}$, $\mathcal{M}$ cannot be robust.

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the private signal's precision

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then for any compensation mechanism $\mathcal{M}$ as a function of $\mathcal{D}$, $\mathcal{M}$ cannot be robust.

the adversary's power

No robust compensation mechanism

- Economic intuition: Has to reward truth-telling and/or punish misreporting; but no way to check whether node i misreports or not given the adversary’s strategy

- Mathematical “intuition”: Data contamination breaks the stochastic relevance condition [which is the necessary condition to have a strict truth-telling eqm (P. Zhang and Chen, 2014)] 😎

Part 2: Robust consensus

Robust consensus: Overview

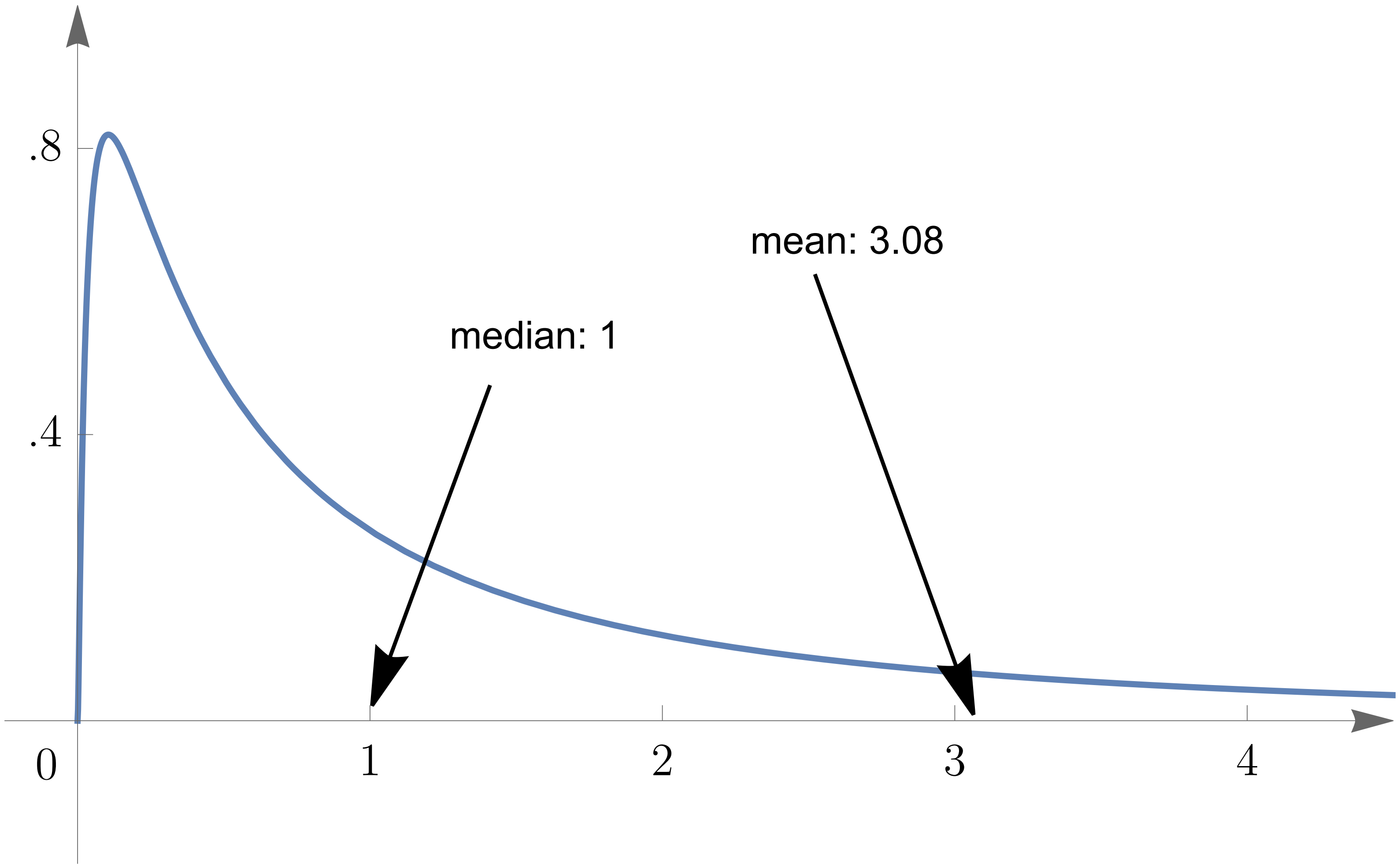
- The most popular consensus mechanism:

  Taking the (coordinate-wise) median

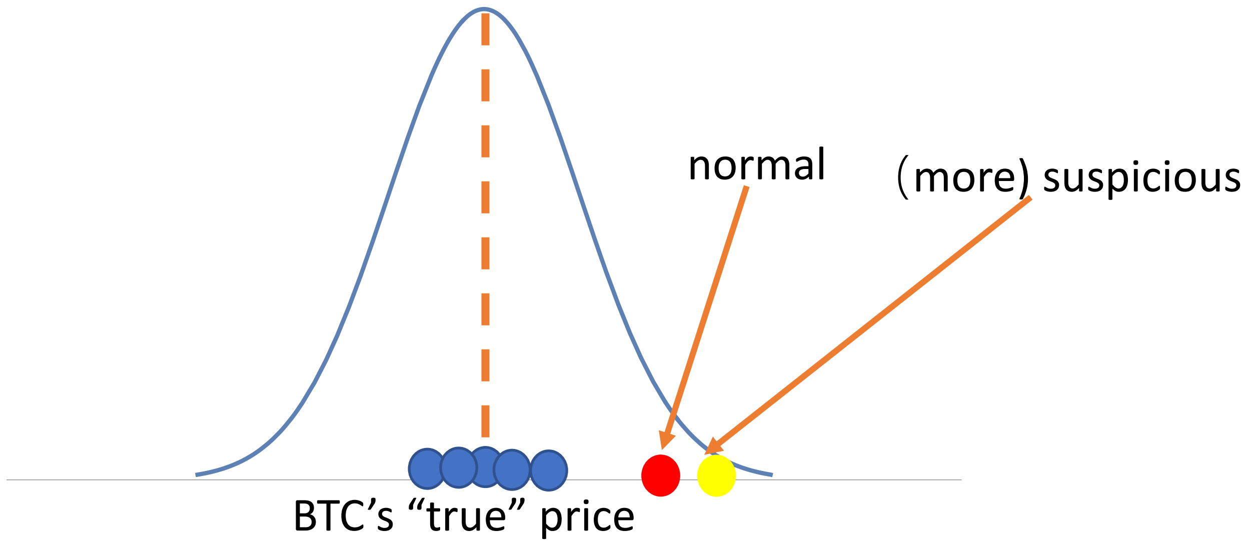
  - Bad if the noise term is asymmetric even without an adversary!
  - Not a bad estimator if symmetric; but is far from optimal under a multi-dimensional environment!
    - Even the best 1-d estimator can yield a L^2-norm error $\geq C\sqrt{\varepsilon d}$ (Folklore)

- Recent machine learning algorithms---unsupervised learning with contaminated datasets--- could yield a consensus that nearly achieves the error's theoretical lower bound without assuming symmetry!

The current method may fail



Robust consensus ($\varepsilon < 1/2$)



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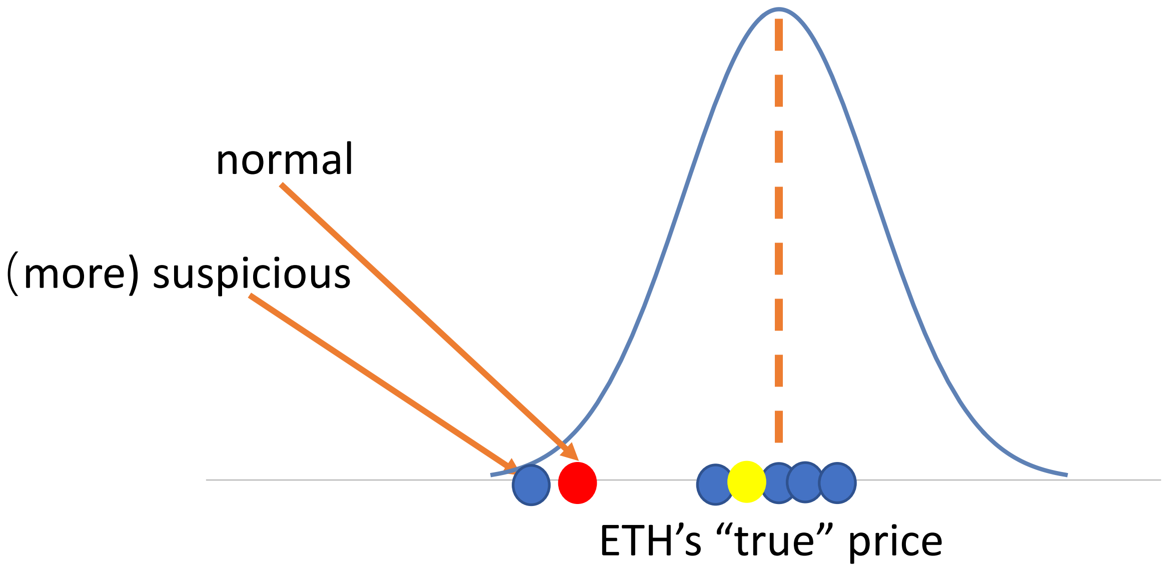

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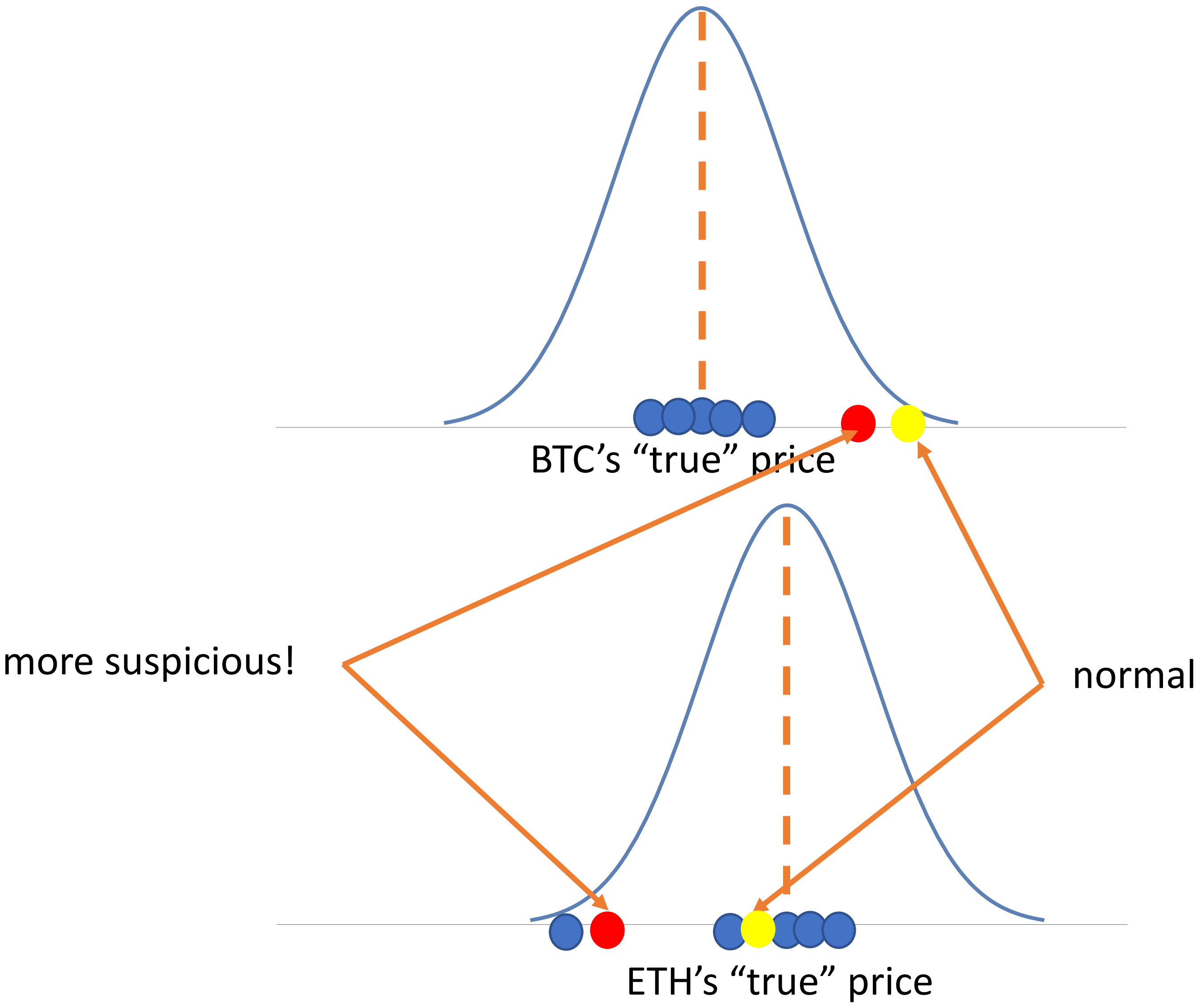

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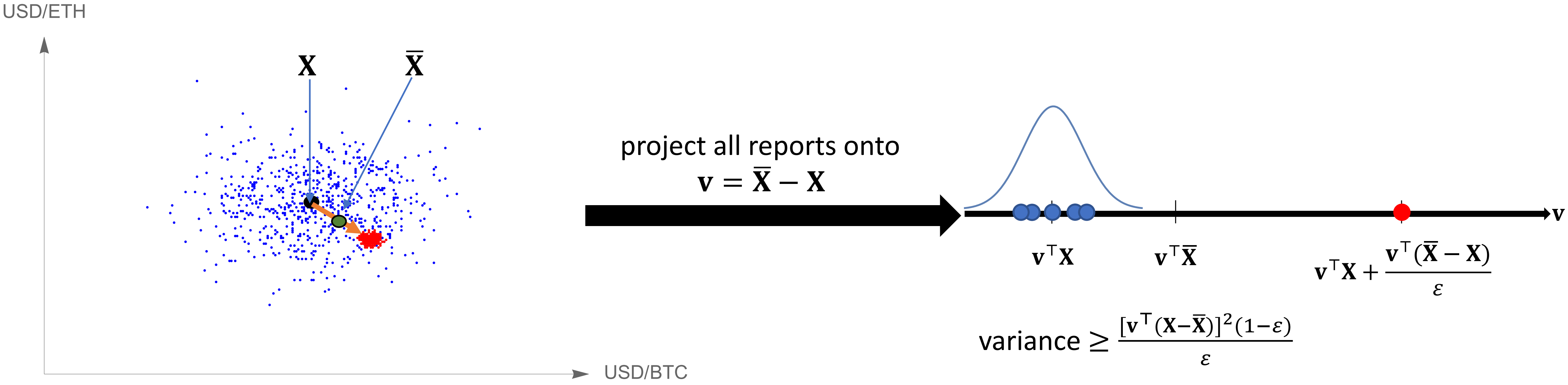
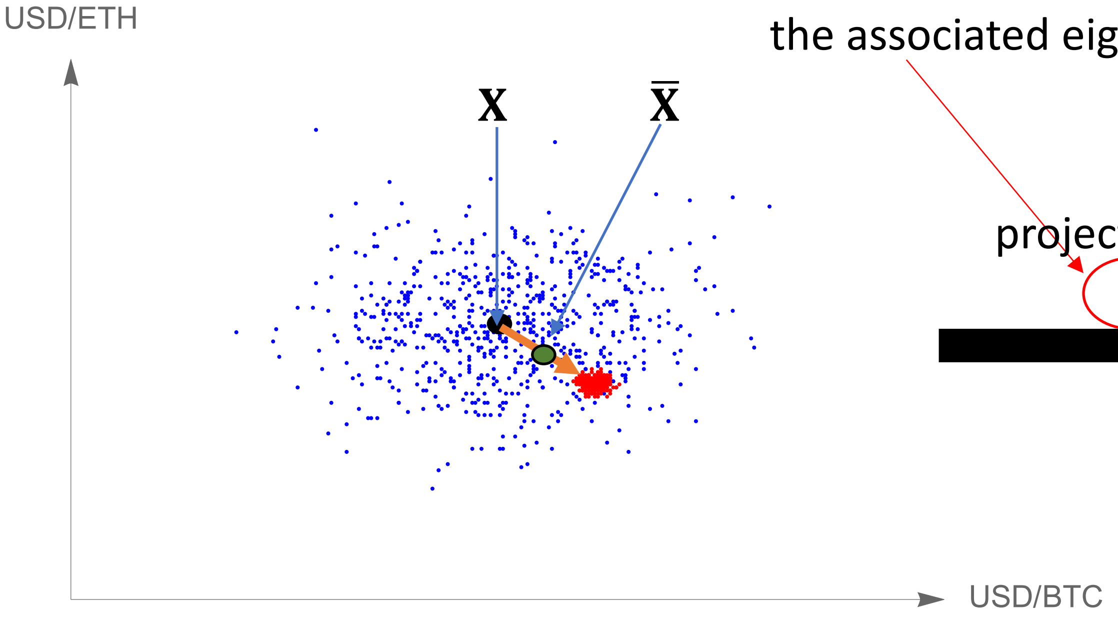

USD/ETH
$\mathbf{X}$
$\bar{\mathbf{X}}$
USD/BTC
$\mathbf{v}^\top \mathbf{X}$
$\mathbf{v}^\top \bar{\mathbf{X}}$
$\mathbf{v}^\top \mathbf{X} + \frac{\mathbf{v}^\top(\bar{\mathbf{X}} - \mathbf{X})}{\varepsilon}$
$\mathbf{v}$

project all reports onto
$\mathbf{v} = \bar{\mathbf{X}} - \mathbf{X}$

variance $\geq \frac{[\mathbf{v}^\top(\mathbf{X} - \bar{\mathbf{X}})]^2 (1-\varepsilon)}{\varepsilon}$

[The high-level idea (Diakonikolas et al., 2016, 2017; Diakonikolas and Kane, 2021): Using the covariance matrix!]

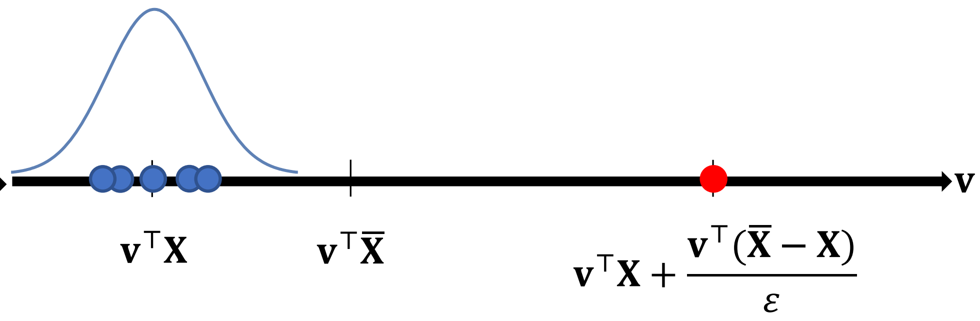
Robust consensus ($\varepsilon < 1/2$)



the associated eigenvector!

project all reports onto

$\mathbf{v} = \overline{\mathbf{X}} - \mathbf{X}$


$\mathbf{v}$
$\mathbf{v}^\top \mathbf{X}$
$\mathbf{v}^\top \overline{\mathbf{X}}$
$\mathbf{v}^\top \mathbf{X} + \frac{\mathbf{v}^\top (\overline{\mathbf{X}} - \mathbf{X})}{\varepsilon}$

variance $\geq \frac{[\mathbf{v}^\top (\mathbf{X} - \overline{\mathbf{X}})]^2 (1-\varepsilon)}{\varepsilon}$

the largest eigenvalue!

[The high-level idea (Diakonikolas et al., 2016, 2017; Diakonikolas and Kane, 2021): Using the covariance matrix!]

Robust consensus ($\varepsilon < 1/2$)

The filtering algorithm (Diakonikolas et al., 2016, 2017; Zhu et al., 2022)

1. Calculate the empirical covariance of the dataset $\mathcal{D}$ and find the largest eigenvalue

2. If the largest eigenvalue is small, then return the empirical mean of $\mathcal{D}$

3. Otherwise,
    - project $\mathcal{D}$ onto the eigenvector that is associated with the largest eigenvalue;
    - Downweight each point according to the distance between its projection and the projection of the empirical mean, and obtain a new dataset $\widetilde{\mathcal{D}}$;
    - replace $\mathcal{D}$ with $\widetilde{\mathcal{D}}$ and return to Step 1

Robust consensus ($\varepsilon < 1/2$)

theoretical lower bound

Theorem (Zhu et al., 2022)
The filtering algorithm will output a consensus $\hat{\mathbf{X}}$ such that

$$\left\|\hat{\mathbf{X}} - \mathbf{X}\right\|_2 \leq \boxed{\sigma\sqrt{\varepsilon}}\left(\frac{1}{\sqrt{1-\varepsilon}} + \frac{\sqrt{2}}{1-2\varepsilon}\right),$$

where σ^2 is an upper bound on the L^2-norm of the noise term’s covariance matrix.

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where σ^2 is an upper bound on the L^2-norm of the noise term's covariance matrix.

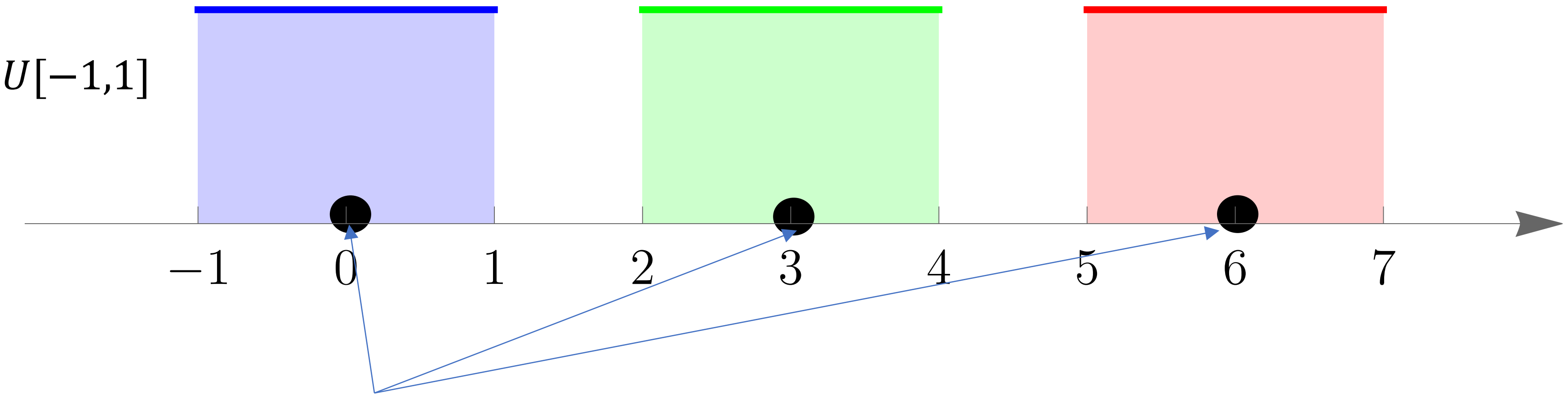
Best 1-d estimator: $\geq \sigma\sqrt{\varepsilon d}$

Robust consensus ($\varepsilon \geq 1/2$)

- Charikar et al. (2017)
  - There is no algorithm can return a unique consensus that is close to the ground truth
  - But we can return a list of candidates, in which at least one of them is “good”
  - A clever clustering algorithm

$\varepsilon = 2/3$

$\mathbf{s}_i = \mathbf{X} + U[-1,1]$



Which point is the ground truth?

Concluding remarks

- In general, no perfect decentralized solution to the oracle problem

- Machine learning can improve the consensus substantially

- All results also shed light on designing replacements for LIBOR

Thank you! ☺