

Witness

A proof technique

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What is witness?



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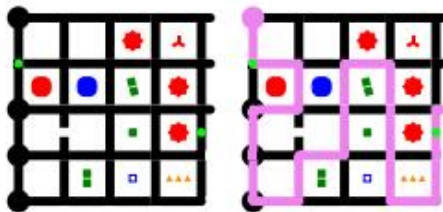


Figure 1 A small Witness puzzle featuring all clue types (left) and its solution (right). (Not from the actual video game.)

[ABC⁺19]

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- Its main idea can be concluded as: if something (contrary to what you want to prove) happens, then there exists a **certain kind of combinatorial structure** (the "**witness**") whose existence has very low probability.

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- Its main idea can be concluded as: if something (contrary to what you want to prove) happens, then there exists a **certain kind of combinatorial structure** (the "**witness**") whose existence has very low probability.
- Then usually we can take a union bound over all possible such combinatorial structures to finish the proof.

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There are n vertices $1, 2, \dots, n$, arranged in a cycle.

1. Every vertex has exactly one of the two states in $\{0, 1\}$. Initially, all vertices are in state 0.
2. Visit vertices in the cyclical order $1, 2, \dots, n, 1, \dots$, each time when we visit a vertex v , we do the following:
 - 2.1 If v is not adjacent to any other vertex in state 0, then the state of v becomes 1.
 - 2.2 Otherwise, the state of v becomes 1 with probability $\frac{2}{3}$, and becomes 0 with probability $\frac{1}{3}$.

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The problem is: what's the (asymptotic) expected number of visits before all vertices are in state 1? How to formally prove it?

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- Algorithmic Lovász local lemma
 - Approach predating Moser and Tardos' work [[Bec91](#), [Alo91](#), [MR99](#), [Sri08](#), [Mos09](#)]
 - Moser and Tardos's approach [[MT10](#)]
- Information Percolation for proving rapid mixing of Glauber dynamics [[HSZ19](#), [JPV21](#), [HSW21](#)]

Constraint Satisfaction Problems(CSP)

- **Variables:** $V = \{x_1, x_2, \dots, x_n\}$ where $x_i \in [q]$ for each $i \in [n]$
- **(local)Constraints:** $C = \{C_1, C_2, \dots, C_m\}$
 - Each C_i is defined on a subset $\text{vbl}(C_i)$ of variables

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- **Examples:**
 - k -CNF, (hyper)graph coloring, set cover, unique games, ...
 - vertex cover, independent set, matching, perfect matching, ...

Lovász local lemma

- Given a CSP formula $\Phi = (V, C)$, let \mathcal{P} be the product distribution where each $x \in V$ takes a uniform random value from $[q]$.
- For each $c \in C$, define its neighbourhood $\Gamma(c)$ as

$$\Gamma(c) = \{c' \in C \mid \text{vbl}(c) \cap \text{vbl}(c') \neq \emptyset\}$$

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Lovász Local lemma [\[EL75\]](#)

Let $p \triangleq \max_i \Pr_{\mathcal{P}}[\neg C_i]$ and $\Delta \triangleq \max_i |\Gamma(C_i)|$, then

$$4p\Delta \leq 1 \implies \Pr_{\mathcal{P}}\left[\bigwedge_{i=1}^m \neg C_i\right] > 0$$

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- However, it (and its proof) doesn't directly imply how to find one such solution.
- And this is what algorithmic (constructive) Lovász local lemma focuses on.

Work on algorithmic Lovász local lemma:

- [Sri08]: One can find a solution in $n^{O(\Delta, k)}$ time if $p\Delta^4 \leq c$ for some constant c .
- [MT10]: One can find a solution in $O(ndk)$ time if $p\Delta \leq c$ for some constant c .

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Algorithm in [Sri08]

Phase One: Randomly assign a uniform random values in $[q]$ to any unassigned variable. When the violation probability of some constraint exceeds p' , "freeze" all its unassigned variables, keep assigning until all variables are assigned or frozen.

Phase Two: For each remaining connected component in H_Φ after simplifying, using an exhaustive enumeration to find one solution.

Proof sketch

- One can always find a solution for each connected component after **Phase One** of the algorithm(guaranteed by $4p'q\Delta \leq 1$ and local lemma).

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- Let's call a constraint "bad" if its violation probability exceeds p' in **Phase One**. Denote the set of such constraints as B .
- Let $Lin(H_\Phi)$ be the line graph of H_Φ , and let $L^2(B)$ be the graph whose vertices are B and $B_i \neq B_j \in B$ are adjacent if and only if $dist_{Lin(H_\Phi)}(B_i, B_j) \leq 2$.

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Observation

After **Phase One**, each not satisfied constraint is either bad or share at least one frozen variable with some bad constraint.

Corollary

Distinct connected component in $L^2(B)$ are disconnected in $Lin(H_\Phi)$.

Proof sketch(Cont'd)

- A major observation is that each connected component in $L^2(B)$ after **Phase One** is small.

Lemma

If $16p\Delta^3 \leq p'$, after **Phase One**, the probability that $L^2(B)$ has a connected component of size at least L is at most $n\Delta \cdot 2^{-L/\Delta}$.

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Lemma

If $16p\Delta^3 \leq p'$, after **Phase One**, the probability that $L^2(B)$ has a connected component of size at least L is at most $n\Delta \cdot 2^{-L/\Delta}$.

- Proof idea: Find some **witness** that happens with very low probability if L is large.

Proof sketch(Cont'd)

Definition($\{2, 3\}$ -tree)[Alo91]

Let $G = (V, E)$ be a graph. A set of vertices $T \subseteq V$ is a $\{2, 3\}$ -tree if

- (1) for any $u, v \in T$, $\text{dist}_G(u, v) \geq 2$;
- (2) if one adds an edge between every $u, v \in T$ such that $\text{dist}_G(u, v) = 2$ or 3 , then T is connected.

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[Alo91], Lemma 2.1

Let $G = (V, E)$ be a graph with maximum degree Δ . Then, for any $v \in V$, the number of $\{2, 3\}$ -trees in G of size t containing v is at most $\frac{(e\Delta^3)^{t-1}}{2}$.

Proof sketch(Cont'd)

(corollary for [GLLZ18], Lemma 14)

Let $H = (V, E)$ be a hypergraph such that each hyperedge in E intersects at most Δ other hyperedges (equivalently, the degree of $\text{Lin}(H)$ is at most Δ). Let $B \subseteq E(H)$ be a set of hyperedges which induces a connected subgraph in $L^2(H)$, and $e^* \in B$ be an arbitrary hyperedge. There exists a $\{2, 3\}$ -tree $T \subseteq B$ such that $e^* \in T$ in $\text{Lin}(H)$ and $|T| \geq \frac{|B|}{\Delta}$.

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- So for each connected component of size $\geq L$, we can find a $\{2, 3\}$ -tree in $\text{Lin}(H_\Phi)$ with size $\geq \frac{L}{\Delta}$, by Markov's inequality, such $\{2, 3\}$ -tree occurs with probability at most $\left(\frac{p}{p'}\right)^{\frac{L}{\Delta}}$.

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- As there are at most $|B|(e\Delta^3)^{\frac{L}{\Delta}}$ such trees, taking a union bound leads to the desired answer.

Short summary

- The trick here is to use $\{2, 3\}$ -tree as a **witness** for a large connected component. As all constraints in a $\{2, 3\}$ -tree are independent, we can easily bound its probability of occurrence.

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- The trick here is to use $\{2, 3\}$ -tree as a **witness** for a large connected component. As all constraints in a $\{2, 3\}$ -tree are independent, we can easily bound its probability of occurrence.
- Although this algorithm was outperformed by Moser-Tardos algorithm that we are going to introduce next, the idea of this random assignment approach still find its use in a harder problem **sampling Lovász local lemma** where one is required to count the number of solutions (sample a solution uniformly at random) and remains the state of art[JPV20].

The Moser-Tardos algorithm

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1. Initialize all variables uniformly at random.
2. While there exists an unsatisfied constraint: pick one (various rules) and resample all its variables.

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Theorem[MT10]

If there exists $\alpha_1, \dots, \alpha_m \in [0, 1]$ s.t.

$$\forall i, \Pr_{\mathcal{P}}[\neg C_i] \leq \alpha_i \prod_{C_j \in \Gamma(C_i)} (1 - \alpha_j),$$

then the Moser-Tardos algorithm terminates within $\sum_{i=1}^m \frac{\alpha_i}{1 - \alpha_i}$ resamples in expectation.

Execution log

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Execution log (Exe-log) Λ of the M-T algorithm:

$$\Lambda_1, \Lambda_2, \dots, \in C :$$

random sequence of resampled constraints

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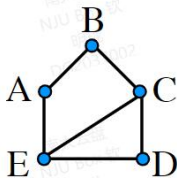
Witness tree $T(\Lambda, t)$: rooted tree, each node u with label $C_{[u]} \in \mathcal{C}$.

- Initially, T contains a single root r with Λ_t
- for $i = t - 1$ to 1:
 - if $\Lambda_i \in \Gamma^+(C_{[u]})$ for some node $u \in T$
add child $v \rightarrow$ deepest such u , labeled with Λ_i
- $T(\Lambda, t)$ is the resulting T .

Inclusive neighbourhood: $\Gamma^+(C_{[u]}) = \Gamma(C_{[u]}) \cup C_{[u]}$

An example

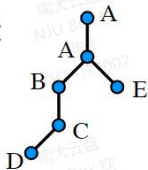
dependency graph:



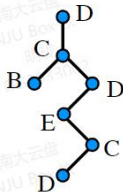
exe-log Λ : D, C, E, D, B, A, C, A, D, ...



$T(\Lambda, 8)$:



$T(\Lambda, 9)$:



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Proposition

$\forall s \neq t, T(\Lambda, s) \neq T(\Lambda, t).$

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Lemma 1

For any particular witness tree τ :

$$\Pr_{\Lambda}[\exists t, T(\Lambda, t) = \tau] \leq \prod_{u \in \tau} \Pr[\neg C_{[u]}]$$

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Proposition

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Lemma 2

For any particular witness tree $\tau \in \mathcal{T}_{C_i}$:

$$\Pr[T_{C_i} = \tau] = \frac{1 - \alpha_i}{\alpha_i} \prod_{u \in \tau} \left[\alpha_{[u]} \prod_{C_j \in \Gamma^+(C_{[u]})} (1 - \alpha_j) \right]$$

Proof sketch(Cont'd)

$$\# \text{ of } \bar{C}_i \text{ in } \Lambda = \sum_{\tau \in \mathcal{T}_{C_i}} \Pr[\exists t, T(\Lambda, t) = \tau]$$

$$(\text{Lemma 1}) \leq \sum_{\tau \in \mathcal{T}_{C_i}} \prod_{u \in \tau} \Pr[\neg C_{[u]}]$$

$$(\text{LLL condition}) \leq \sum_{\tau \in \mathcal{T}_{C_i}} \prod_{u \in \tau} \left[\alpha_{[u]} \prod_{C_j \in \Gamma^+(C_{[u]})} (1 - \alpha_j) \right]$$

$$(\text{Lemma 2}) \leq \frac{\alpha_i}{1 - \alpha_i} \sum_{\tau \in \mathcal{T}_{C_i}} \Pr[T_{C_i} = \tau] \leq \frac{\alpha_i}{1 - \alpha_i}$$

Short summary

- The key idea is the **witness tree** that captures the independent occurrences of various events during the execution of the algorithm.

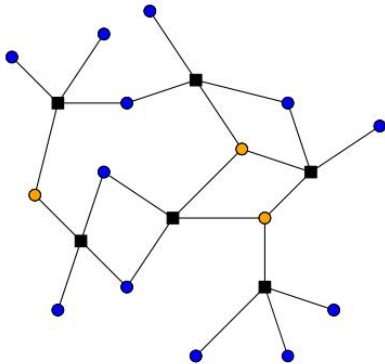
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- The key idea is the **witness tree** that captures the independent occurrences of various events during the execution of the algorithm.
- Furthermore, M-T algorithm is later shown to be working up to [\[KS11\]](#) and go beyond [\[HLS21\]](#) a tighter condition than LLL which is known as Shearer's bound.
- Moser and Tardos won 2021 Gödel Prize for this contribution.

Hypergraph independent sets



$$G = (V, F, E)$$

V : vertices(circles).

F : hyperedges(squares).

Degree Δ , Size k

Hypergraph independent set: Every edge has at least one 0.
—Also known as monotone CNF.

Rapid mixing of Glauber dynamics

Glauber dynamics Pick a vertex, flip a coin, set to new value whenever possible.

mixing time $t_{mix} = \min\{t : d_{TV}(\mathbb{P}^t(\sigma, \cdot)) < \frac{1}{4}\}$

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Theorem[HSZ19]

For any k -hypergraph with maximum degree $\Delta \leq c2^{k/2}$, the Glauber dynamics mixes in $O(n \log n)$ time.

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- Let $t_{coup} \triangleq \min\{t : X_t^\sigma = X_t^\tau, \forall \sigma, \tau \in \Omega_G\}$, it follows that

$$t_{mix} \leq \min\{T : \Pr[t_{coup} > T] \leq 1/4\}$$

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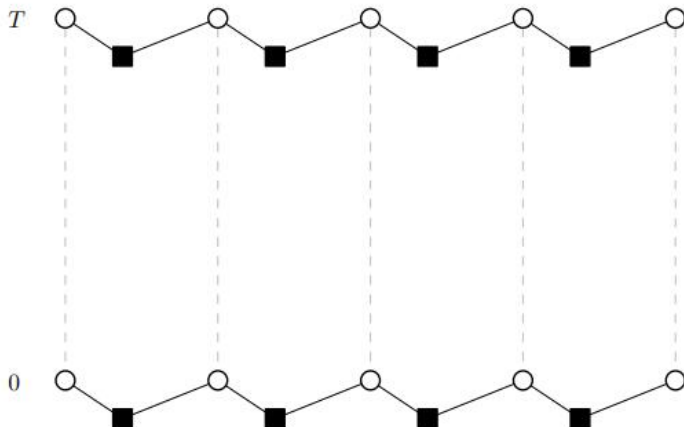
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$$t_{mix} \leq \min\{T : \Pr[t_{coup} > T] \leq 1/4\}$$

- It is enough to bound $\Pr[t_{coup} > T]$ for $T = O(n \log n)$.

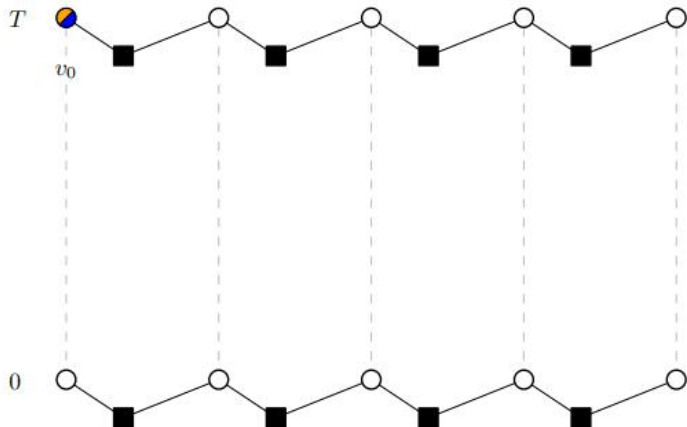
Tracing back the discrepancies

$$t_{\text{coup}} \geq T$$



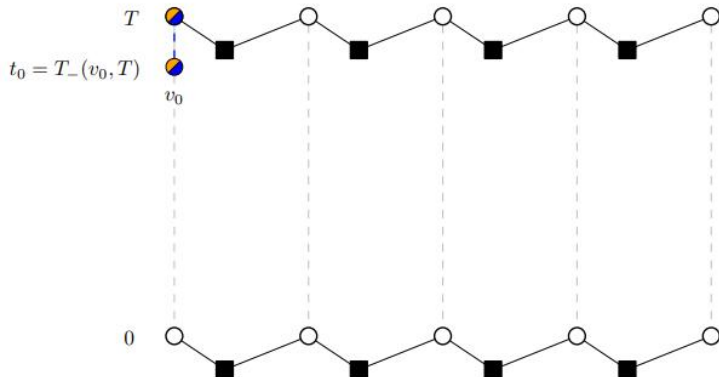
Tracing back the discrepancies(Cont'd)

$t_{coup} \geq T \implies \exists \sigma, \tau \in \Omega_G, v_0 \in V$ such that $X_T^\sigma(v_0) \neq X_T^\tau(v_0)$



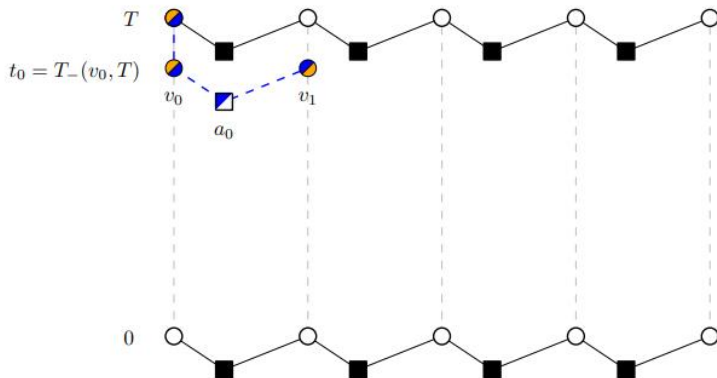
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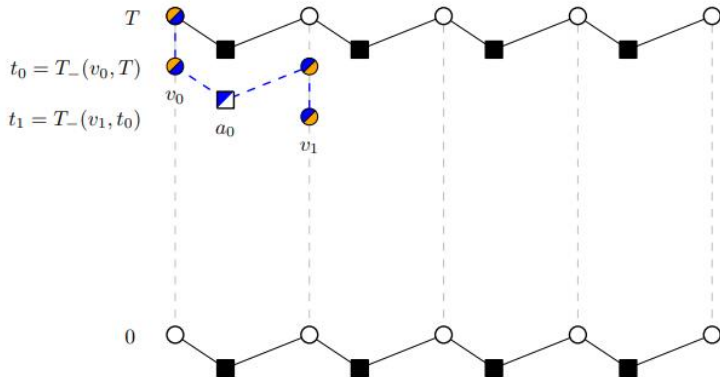
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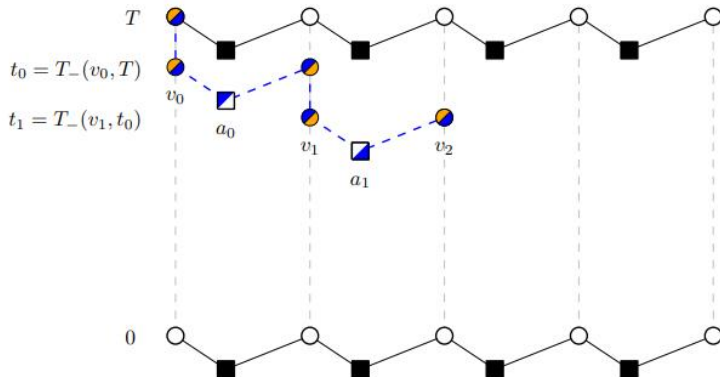
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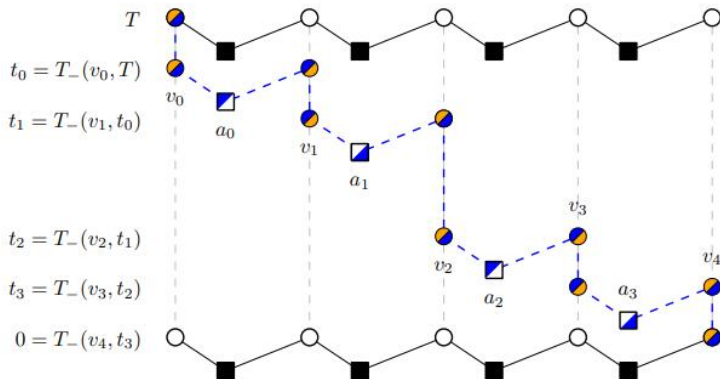
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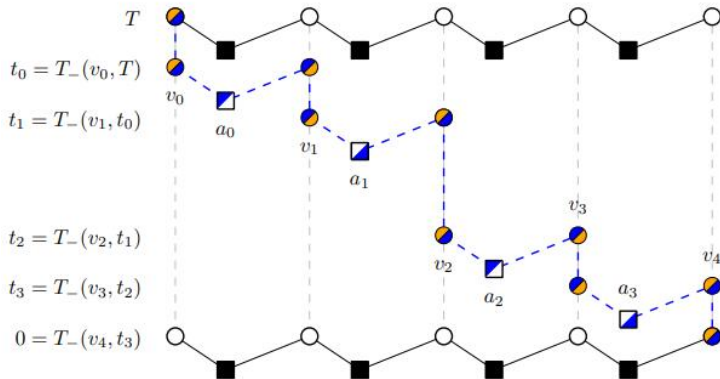


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Tracing back the discrepancies(Cont'd)



$t_{coup} \geq T \implies \exists ((v_l, a_l, t_l))_{0 \leq l \leq L}$ such that for all $0 \leq l \leq L$,

$$(v_l, t_l) \in \text{Updates}, t_l = T_-(v_l, t_{l-1}), \mathbf{X}_{t_l}^\sigma \vee \mathbf{X}_{t_l}^\tau(\text{vbl}(a_l) \setminus \{v_l\}) = \mathbf{1}$$

Proof sketch

- We say that $((v_l, a_l, t_l))_{0 \leq l \leq L}$ is a **discrepancy path** if

$$(v_l, t_l) \in \text{Updates}, t_l = T_-(v_l, t_{l-1}), X_{t_l}^\sigma \vee X_{t_l}^\tau(\text{vbl}(a_l) \setminus \{v_l\}) = \mathbf{1}$$

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- It remains to bound the probability a certain **discrepancy path** occurs and take a union bound over all such paths.
- We'll omit this part as it's a bit involved. One may refer to the paper for more details.

Short summary

- The key idea is observing that a long **discrepancy path** serves as a **witness** that the two chains fail to couple before time T .

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- The key idea is observing that a long **discrepancy path** serves as a **witness** that the two chains fail to couple before time T .
- This approach gets its name as it is similar to the approach of Information Percolation used to prove cutoff for the Ising model[LS16].
- This approach is later extended to work for analysis of (projected)Glauber dynamics for (possibly non-monotone) atomic CSP in the local lemma regime[JPV21, HSW21].

The End

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