

Domino Tilings and the Arctic Circle Theorem

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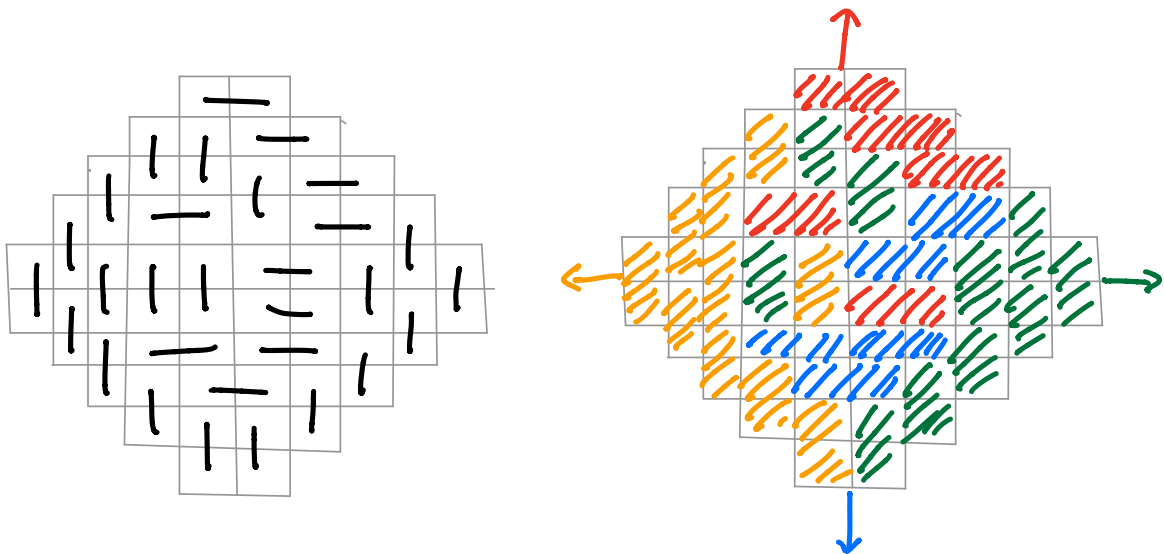
Outline:

Based on Jockusch - Propp - Shor '95, Rost '81

- Review of Aztec diamond and random tilings;
Simplification to partitions and TASEP
- Calculating the density profile:
convergence and inequalities
→ Doing continuous-time for simplicity
- Highlighting differences between
discrete & continuous case.

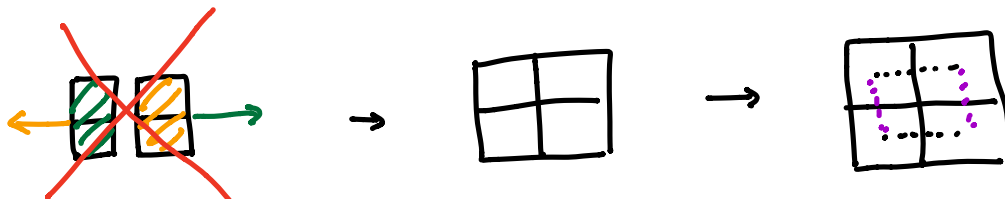
① Review and problem statement

Aztec diamond: tiled with four kinds of dominos.



Thm The size- n Aztec diamond has $2^{n(n+1)/2}$ different tilings.

Proved by shuffling algorithm, which randomly generates uniform tiling recursively.

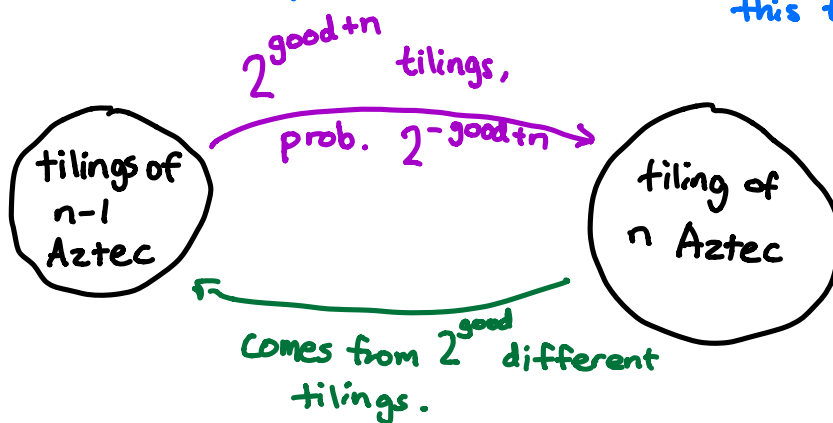


More formally:

- Find all $\begin{array}{|c|c|} \hline \rightarrow & \leftarrow \\ \hline \end{array}$ s and remove them.
- Push all dominos in their corresponding directions.
- For each remaining 2×2 square, fill it $\begin{array}{|c|c|} \hline \uparrow & \\ \hline \downarrow & \\ \hline \end{array}$ or $\begin{array}{|c|c|} \hline \leftarrow & \rightarrow \\ \hline \end{array}$.

Generates uniform tiling because:

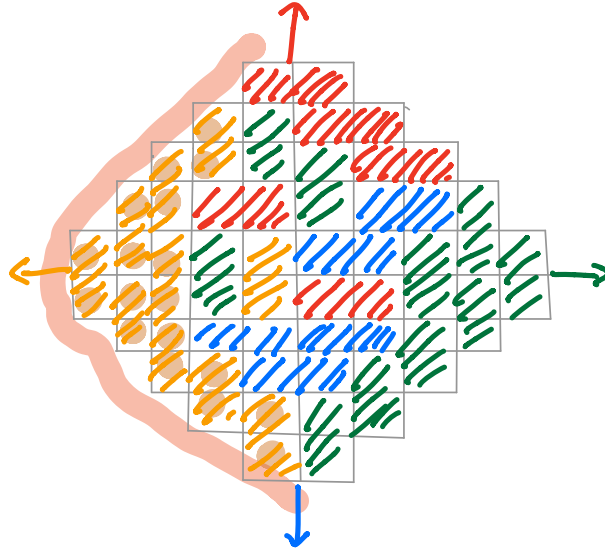
Think about process in reverse. Only blocks of this form. "good"



$$\Rightarrow 2^{-(n-1)n/2} \cdot 2^{-n} = 2^{-n(n+1)/2}.$$

✓

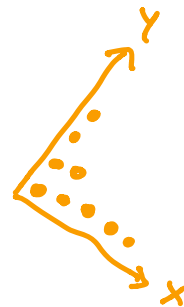
Looking more closely at frozen region:



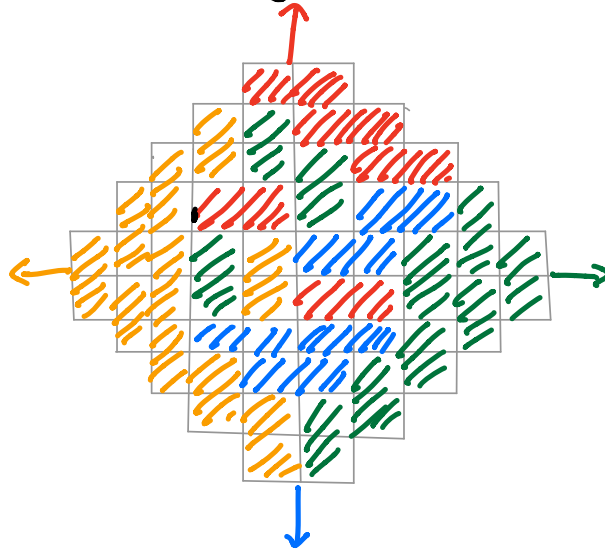
Prop Each frozen region is the set of dominos that "sit" on the marked wall above dominos/wall of that color.

Specifically, no other orange domino touches region above.

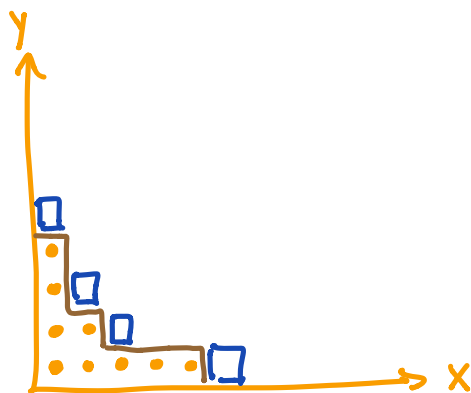
Forms a partition diagram:



Dynamics of shuffling:



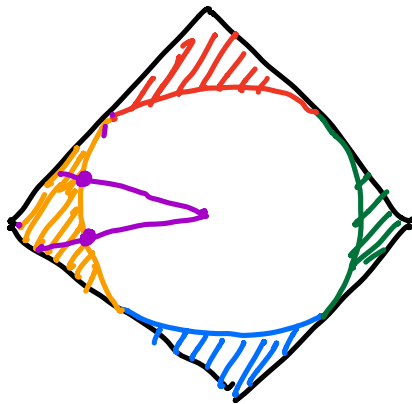
- Where can new orange dominos be added to the frozen region?
- How likely are those to be added?



This is the discrete-time
TASEP

We want to show:

Arctic Circle Thm The frozen regions trace out quarter-circle arcs in the limit $n \rightarrow \infty$ (that is, we're within $o(n)$ distance of this limit shape).



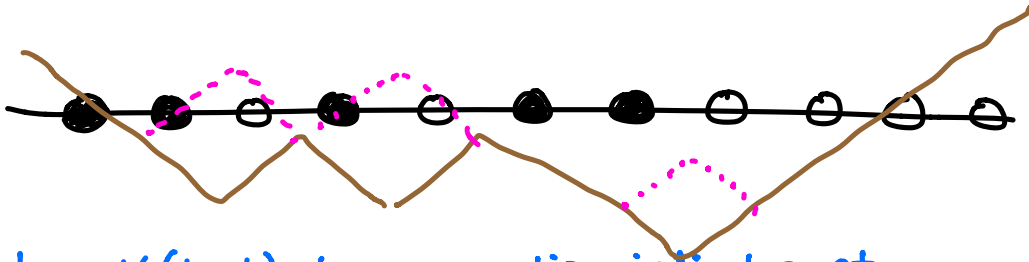
Equivalent to prove:

"Thm" Discrete-time TASEP has a limiting density profile along each line of constant slope (as above).

Idea is that path can only move down and right.

② TASEP and extracting the density profile

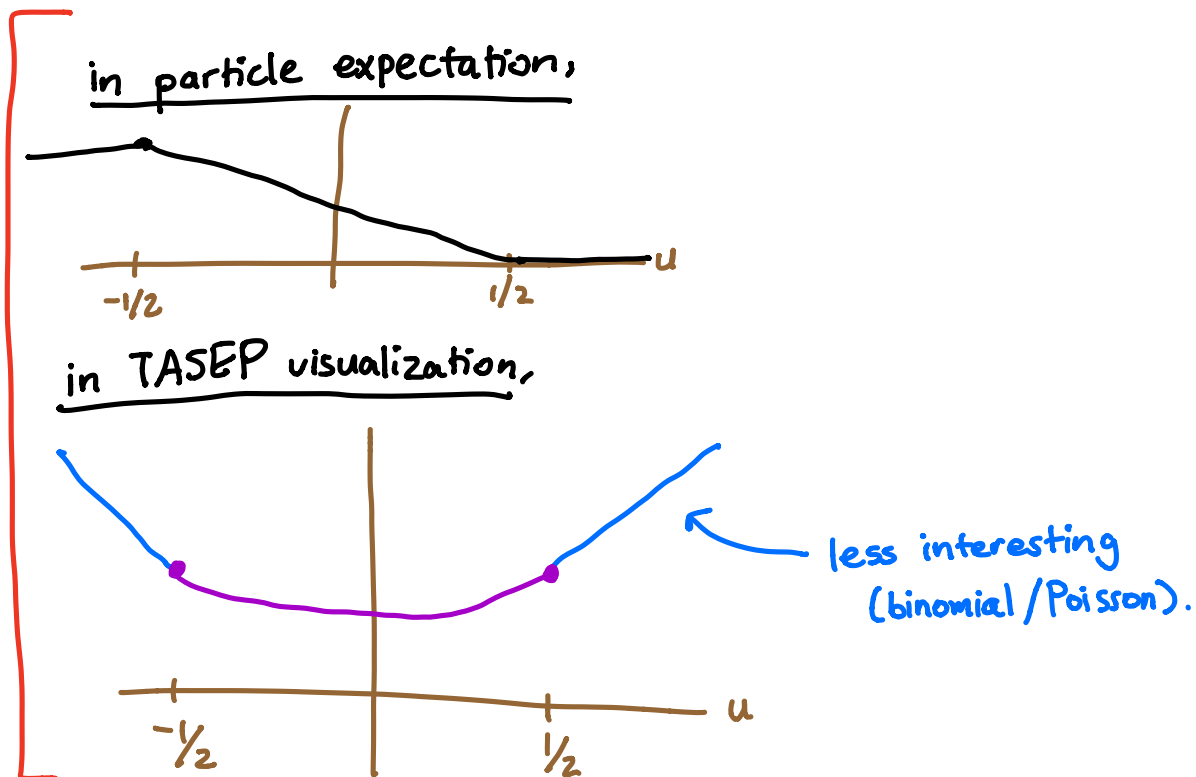
More formally setting up notation:



Let $X(k, t)$ be occupation indicator at position k , time t . Process is $X(t)$.

Interested in $\mathbb{E} X(\lfloor ut \rfloor, t)$.

Should behave like:



Stochastic ordering

Let x_1, x_2 be two points in TASEP state space.

Say $x_1 \leq x_2$ if coordinate-wise \leq .

↳ Induces order on prob. measures:

$\mu \leq \nu$ if there is coupling σ s.t. $\sigma(x_1 \leq x_2) = 1$
and μ, ν are coordinate projections

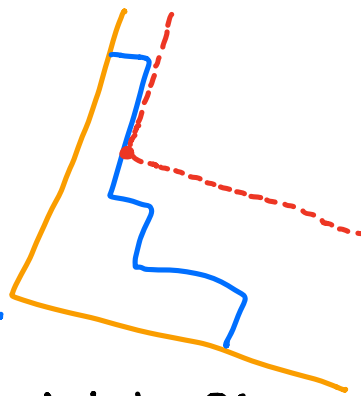
! Lemma Stochastic ordering is preserved under TASEP update.

! Prop Let $S(k, t) = \sum_{i \leq k} X(i, t)$. Then for all k, ℓ, r, t ,
 $\mathcal{L}(S(k, r)) * \mathcal{L}(S(\ell, t)) \geq \mathcal{L}(S(k+\ell, r+t))$.

Use a coupling argument:

let \tilde{S} evolve like S until
time r , then jump to

$$\tilde{S}(j, r) = \begin{cases} S(k, r), & j \geq k \\ S(k, r) + (k-j), & \text{otherwise.} \end{cases}$$



Then $\tilde{S}(k+\ell, r+t) - S(k, r)$ identical to $S(\ell, t)$,
but $\mathcal{L}(\tilde{S}) \geq \mathcal{L}(S)$.

Specializing previous result,

$$\underbrace{\mathbb{P}(S(\lfloor Lr \rfloor, r))}_{\mathcal{L}_r} * \underbrace{\mathbb{P}(S(\lfloor Lt \rfloor, t))}_{\mathcal{L}_t} \geq \mathbb{P}(S(\lfloor Lr \rfloor + \lfloor Lt \rfloor, r+t)) \geq \underbrace{\mathbb{P}(S(\lfloor L(r+t) \rfloor, r+t))}_{\mathcal{L}_{r+t}}.$$

By **Kesten-Hammersley**, this means $\frac{S(\lfloor Lt \rfloor, t)}{t}$ converges to some $h(u)$ almost surely and in L^1 .

Notice that h is convex:

$$\mathbb{E}(S(\lfloor c_1 u \rfloor, c_1 t) + S(\lfloor c_2 v \rfloor, c_2 t)) \geq \mathbb{E}(S(\lfloor (c_1 u + c_2 v) \rfloor, (c_1 + c_2)t))$$

$$\text{so } c_1 h(u) + c_2 h(v) \geq (c_1 + c_2) h(c_1 u + c_2 v).$$

\hookrightarrow **Prop** As long as $\frac{k}{t} \rightarrow u$, we have $\lim_{t \rightarrow \infty} \mathbb{E} X(k, t) = -h'(u)$, as long as h is diff. at u .

$$\text{(Consider } h_n(v) = \int_v^\infty \mathbb{E} X(\lfloor xn \rfloor, n) dx \approx \frac{1}{n} \sum_{k=\lfloor vn \rfloor}^\infty \mathbb{E} X(k, n).$$

We have $h_n(v) \rightarrow h(v)$ as $n \rightarrow \infty$, and each h_n is convex, so we can indeed differentiate.)

(exponential clocks)

From here, we do continuous-time for ease of calculation.

Limiting "independence":

Prop The measures $\mu(\lfloor ut \rfloor, t)$ as $t \rightarrow \infty$ converge to an exchangeable measure

$$\mu^* = \int_0^1 \beta_a \rho(da)$$

↑ Bernoulli of parameter a .

- Similar coupling fact: if $\pi(s, \ell) = \mathbb{P}(\text{Pois}(s) = \ell)$,

$$\begin{aligned} \mu(k, t) &\cong \mu(k+1, t), \\ \mu(k, t+s) &\cong \sum_{\ell} \pi(s, \ell) \mu(k-\ell, t) \end{aligned}$$

- μ^* and its shifted image must be identical, because one-point correlations are the same
- This implies invariance under TASEP semigroup.

↳ these imply exchangeability.

Also use di Finetti's theorem (conditionally independent given the value of a).

Identifying the density

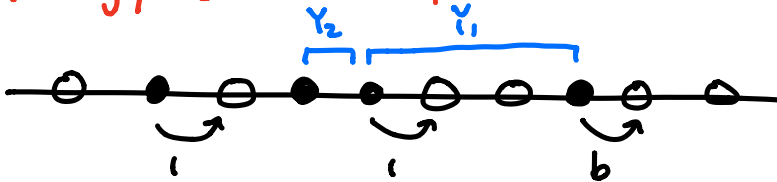
We know

$$h(u) = \lim_{t \rightarrow \infty} \frac{\mathbb{E} S(\lfloor ut \rfloor, t)}{t} = \int_u^{\infty} f(w) dw.$$

$$\left(\text{Want to show that } f(u) = \begin{cases} \frac{1}{2}(1-u) & u < -1 \\ 0 & -1 \leq u \leq 1 \\ 0 & u > 1 \end{cases} \right)$$

Prop $h(u) \geq \frac{1}{4}(1-u)^2$ for all u in $[-1, 1]$.

Strategy: slow down particle in the front.



Study gaps γ_i . Invariant measure (γ^b) : all γ_i iid with $\mathbb{P}(\gamma_i > m) = b^m$.

* Our initial measure \leq invariant measure, so

$$\begin{aligned} \mathbb{E}_{\text{slow}} \left(\sum_{i=1}^k \gamma_i(t) \right) &\leq \int \left(\sum_{i=1}^k \overset{\text{(invariant)}}{\gamma_i} \right) \gamma^b(dy). \\ &= k \sum_{m \geq 0} \overset{\text{slow}}{\mathbb{P}}(\gamma_i > m) = \frac{k}{1-b}. \end{aligned}$$

Take $k = \lfloor ut \rfloor$, $t \rightarrow \infty$. Dividing through by t ,

$$\limsup_{t \rightarrow \infty} \frac{1}{t} \mathbb{E}_{\text{slow}} \sum_{i=1}^{\lfloor \lambda t \rfloor} Y_i(t) \leq \frac{a}{1-b},$$

• Use Law of Large Numbers on

$$\text{LHS} = \frac{1}{t} \left(\underbrace{\text{Poisson}(bt)}_{\text{position of front particle}} - (\text{position of } \lfloor \lambda t \rfloor \text{th particle}) \right),$$

to get (letting Z be pos. of particle)

$$\lim_{t \rightarrow \infty} \mathbb{P}^{\text{slow}} \left(\frac{Z(\lfloor \lambda t \rfloor, t)}{t} < b - \frac{a}{1-b} - \epsilon \right) = 0$$

for any $\epsilon > 0$.

Also true for $\mathbb{P}^{\text{regular}}$ instead of \mathbb{P}^{slow} , also maximize RHS at $b = 1 - \sqrt{a}$ to find

$$\lim_{t \rightarrow \infty} \mathbb{P} \left(\frac{Z(\lfloor \lambda t \rfloor, t)}{t} < 1 - 2\sqrt{a} - \epsilon \right) = 0,$$

$$\text{so } \mathbb{P} \left(\frac{S((1-2\sqrt{a}-\epsilon)t, t)}{t} > a \right) = 1.$$

$$\Rightarrow h(1-2\sqrt{a}) \geq a$$

$$\Rightarrow h(u) \geq \frac{1}{4}(1-u)^2. \quad \square$$

Prop $h(u) \leq \frac{1}{4}(1-u)^2$ for all $|u| \leq 1$.

Strategy: .. clever resummation?

Idea: $S(Lu+1, t)$ is # particles faster than a person traveling at speed u .

$$\mathbb{E} S(k, \frac{k}{u}) = \sum_{i=1}^k \mathbb{E} (S(i, \frac{i}{u}) - S(i-1, \frac{i}{u})) + \mathbb{E} (S(i-1, \frac{i}{u}) - S(i-1, \frac{i-1}{u}))$$

$$= - \sum_{i=1}^k \mathbb{E} (X(i, \frac{i}{u})) + \sum_{i=1}^k \mathbb{E} (\text{jumps from } i-1 \text{ to } i \text{ in time } \frac{1}{u}.)$$

↓ scale by $\frac{u}{k}$, $k \rightarrow \infty$

$$\star h(u) = -u h'(u) + \lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T \mu(Lu+1, t) \cdot \mathbb{1}_{\{(X_0, X_1) = (1, 0)\}}$$

Now Jensen's inequality: integrand is limiting to $\int a(1-a) p(da)$, so

because $f(u) = \int a p(da)$, we have

$$\star f(u)(1-f(u)) \geq \dots$$

$$\star : h(u) \leq -u f(u) + f(u)(1-f(u)) \leq \frac{1}{4}(1-u)^2$$

minimized at $f(u) = \frac{1-u}{2}$

□

③ Differences in the discrete-time case

- Markov measures μ_d are more complicated.

→ Shift-invariant Markov measure depends on

$$p_1 = \mathbb{P}(X_0 = 1), \text{ also } q_{ij} = \mathbb{P}(i \rightarrow j).$$

if d , turns out $\mathbb{P}(X_1 = 0 | X_0 = 0)$ is $\frac{-d + \sqrt{d^2 + (1-d)^2}}{1-d}$.

Requirement: $q_{01} q_{10} = 2q_{00} q_{11}$

(think about stationary measure on a cycle).

→ Verify invariant under TASEP evolution.

- "All stationary, translation-invariant measures are convex combinations of the μ_d s."

↳ Clever coupling makes this easier to prove than "exchangeable measures" argument above.

- Lower bound (LLN, etc):

γ^b invariant measure is now

$$\mathbb{P}(y_i \geq m) = \begin{cases} 1 & m=0 \\ b\left(\frac{b}{2-b}\right)^{m-1} & \text{otherwise.} \end{cases}$$

- Upper bound (Jensen):

Instead of $\mathbb{P}((X_0, X_1) = (1, 0)) = a(1-a)$,

we have $1 - \sqrt{a^2 + (1-a)^2}$.

But the general analytic techniques remain the same.

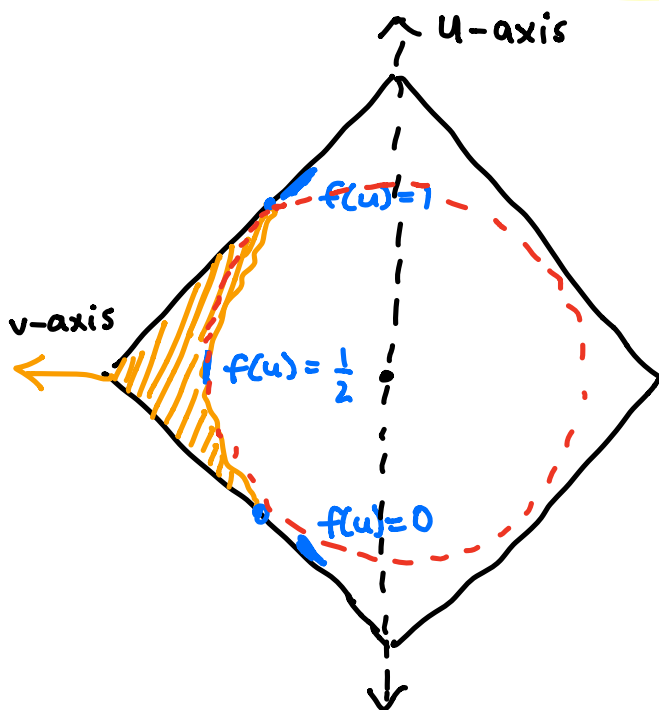
Verifying the final calculation:

(for discrete-time TASEP,)

$$h(u) = \begin{cases} -u & u < -1/2 \\ \frac{1-u}{2} - \frac{1}{2} \sqrt{\frac{1}{2} - u^2} & -\frac{1}{2} \leq u \leq \frac{1}{2} \\ 0 & u > 1/2 \end{cases}$$

so

$$f(u) = \begin{cases} 1 & u < -1/2 \\ \frac{1}{2} - \frac{u}{\sqrt{2-4u^2}} & |u| \leq \frac{1}{2} \\ 0 & u > 1/2. \end{cases}$$



Indeed, for

$$u^2 + v^2 = \frac{1}{2}$$

slope at u is

$$m = \frac{dv}{du} = \frac{+u}{v} = \frac{+u}{\sqrt{\frac{1}{2} - u^2}}$$

Corresponds to

$$f(u) = \frac{1-m}{2} = \frac{1}{2} - \frac{u}{\sqrt{2-4u^2}}$$

as predicted.

□

References:

- [1] Rost, H. Non-equilibrium behavior of a many-particle process: Density profile and local equilibria. <https://doi.org/10.1007/BF00536194>
- [2] Jockusch, W., Propp, J., and Shor, P. Random domino tilings and the arctic circle theorem. arxiv.org/abs/math.CO/9801068

Any questions?