

Graphical Inequalities for the Linear Ordering Polytope

Jean-Paul Doignon

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Joint work with

Samuel Fiorini and *Gwenaël Joret*

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Binary Choice Probabilities

Take

Z some finite set of cardinality n ,

Π the collection of the $n!$ rankings or linear orderings of Z .

To each probability distribution P on Π ,

we associate the

binary choice probabilities p_{ij} , for $i, j \in Z$ and $i \neq j$,

defined by

$$\begin{aligned} p_{ij} &= P \{ i \text{ is ranked before } j \} \\ &= \sum \{ P(L) : L \in \Pi \text{ and } i L j \}. \end{aligned}$$

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Binary Choice Probabilities on $\{a, b, c\}$

Example

For

$$Z = \{a, b, c\},$$

$$\Pi = \{abc, acb, bac, bca, cab, cba\},$$

we have by definition

$$p_{ab} = P(abc) + P(acb) + P(cab),$$

$$p_{ba} = P(bac) + P(bca) + P(cba),$$

$$p_{ac} = P(abc) + P(acb) + P(bac),$$

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A Question

Can the following data be produced in this way?

$$\begin{array}{ll} \rho_{ab} = 0.12, & \rho_{ba} = 0.82, \\ \rho_{ac} = 0.56, & \rho_{ca} = 0.44, \\ \rho_{bc} = 0.75, & \rho_{cb} = 0.25. \end{array}$$

More precisely: is there some probability distribution P on Π that would give the following?

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Main Problem: Characterizing Binary Choice Prob.

Given real numbers p_{ij} for all $i, j \in Z$ with $i \neq j$,

can we find some probability distribution P on Π such that the p_{ij} 's are the binary choice probabilities defined by P ?

More precisely:

find a necessary and sufficient condition on the p_{ij} 's
for the existence of P .

The usual comment:

characterizing binary choice probabilities is ...

... a hopeless problem!

An algorithmically tractable answer would lead to P = NP?

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Some Obvious Necessary Conditions

Binary choice probabilities always satisfy

$$p_{ij} \geq 0,$$

$$p_{ij} + p_{ji} = 1,$$

$$p_{ij} + p_{jk} + p_{ki} \leq 2.$$

These necessary conditions are also sufficient

exactly when $n \leq 5$:

Motzkin (≤ 1960); ... (19..); Dridi (1980); ... (19..)

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A Geometric Point of View

Vectors of binary choice probabilities p belong to $\mathbb{R}^{Z \times Z}$

(a space with one real coordinate for each pair (i, j) of distinct objects).

Example

For $Z = \{a, b, c\}$, we have 6-dimensional vectors

$$(p_{ab}, p_{ba}, p_{bc}, p_{cb}, p_{ac}, p_{ca}).$$

As we know $p_{ab} + p_{ba} = 1$, $p_{ac} + p_{ca} = 1$, $p_{bc} + p_{cb} = 1$, we may work with only

$$(p_{ab}, p_{bc}, p_{ca}).$$

The collection of all (projected) vectors form a polyhedron in \mathbb{R}^3 :

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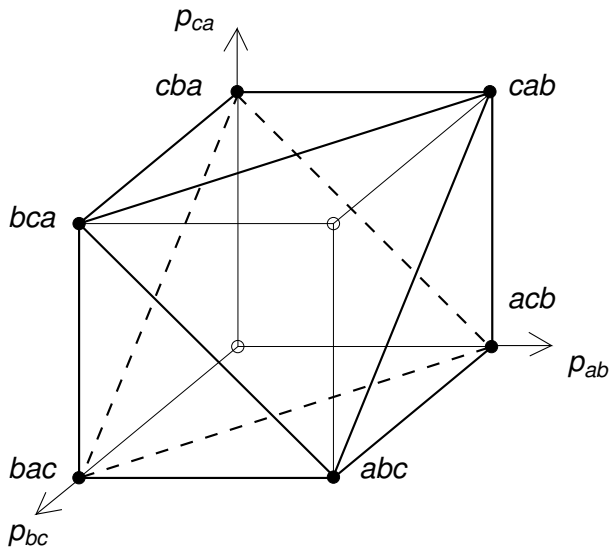
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The Projected Polyhedron for $Z = \{a, b, c\}$



The Linear Ordering Polytope

Let $n = |Z|$.

The binary choice probabilities form a convex polytope in $\mathbb{R}^{Z \times Z}$

of dimension $\frac{n \cdot (n - 1)}{2}$,

with one vertex x^L per ranking L of Z :

$$x_{ij}^L = \begin{cases} 1 & \text{if } i L j, \\ 0 & \text{if } j L i. \end{cases}$$

This polytope is the **binary choice polytope**

or **linear ordering polytope** P_{LO}^Z .

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Rephrasing the Main Problem

The linear ordering polytope P_{LO}^Z has the vertices x^L , for $L \in \Pi$;

find the facets of the linear ordering polytope P_{LO}^Z .

And the usual comment: the problem is hopeless!

A manageable solution would give $P = NP$.

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Origins of the Problem

In mathematical psychology/economics:

Guilbaud (1953), Block and Marschak (1960).

In discrete mathematics:

Megiddo (1977).

In operations research:

Grötschel, Jünger and Reinelt (1985).

In voting theory:

Saari (1999).

Examples of Facet-defining Inequalities for P_{LO}^n

Remember our obvious necessary conditions.

Theorem

The following affine (linear) inequalities on $\mathbb{R}^{Z \times Z}$ define facets:

$$\begin{aligned} p_{ij} &\geq 0 && \text{(trivial inequalities),} \\ p_{ij} + p_{jk} + p_{ki} &\leq 2 && \text{(triangular inequalities).} \end{aligned}$$

A first scheme of nonobvious facets is due independently to Cohen and Falmagne (1978, published in 1990), Grötschel, Jünger and Reinelt (1985).

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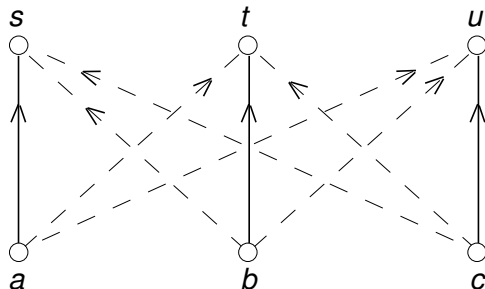
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First Example of Fence Inequality

The following inequality is facet-defining:

$$x_{as} + x_{bt} + x_{cu} - (x_{at} + x_{bs}) - (x_{au} + x_{cs}) - (x_{bu} + x_{ct}) \leq 1.$$



The Fence Inequality

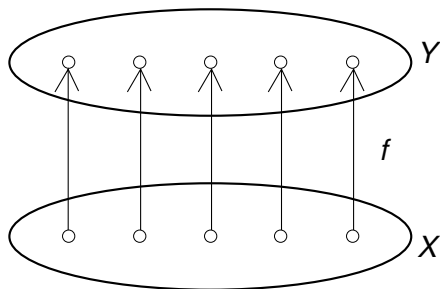
In general, let $X, Y \subset Z$ with

$$X \cap Y = \emptyset,$$

$$|X| = |Y|,$$

$f : X \rightarrow Y$ a bijective mapping

(we keep the notation throughout).



The Fence Inequality

Definition

The **fence inequality** is

$$\sum_{i \in X} x_{if(i)} - \sum_{i, j \in X, i \neq j} (x_{if(j)} + x_{jf(i)}) \leq 1.$$

Theorem (Cohen and Falmagne, 1978; Grötschel, Jünger and Reinelt, 1985)

For $|X| \geq 3$, the fence inequality defines a facet of the linear ordering polytope P_{LO}^n .

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A Structural Generalization of the Fence Inequality

Several steps:

McLennan (1990), Fishburn (1990), Koppen (1991), etc.

leading to a marvelous result by Koppen (1995).

Let $G = (V, E)$ be a (simple) graph.

The **stability number** $\alpha(G)$ of G is the largest number of vertices no two of which are adjacent.

Assume $f : X \rightarrow Y$ as before, and moreover $V = X$.

Definition

The **graphical inequality** of G reads

$$\sum_{i \in V} x_{i,f(i)} - \sum_{\{i,j\} \in E} (x_{i,f(j)} + x_{j,f(i)}) \leq \alpha(G).$$

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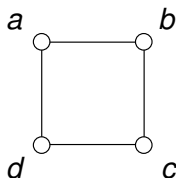
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An Example of Graphical Inequality

Example

For the graph



with the bijection

$$f: \quad a \mapsto s, \quad b \mapsto t, \quad c \mapsto u, \quad d \mapsto v,$$

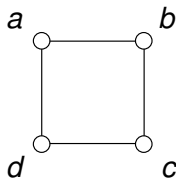
we get the inequality

$$\begin{aligned} & x_{as} + x_{bt} + x_{cu} + x_{dv} \\ & - (x_{at} + x_{bs}) - (x_{bu} + x_{ct}) - (x_{cv} + x_{du}) - (x_{ds} + x_{av}) \end{aligned}$$

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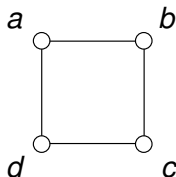
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$\leq 2.$

Main Result in Koppen (1995)

Theorem (Koppen, 1995)

The graphical inequality of G is valid for the linear ordering polytope.

*It defines a facet if and only if G is
different from K_2 ,
connected,
and stability critical.*

Definition

A graph is **stability critical** when its stability number increases whenever any of its edges is deleted.

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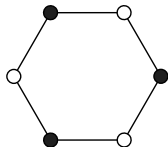
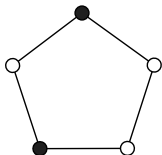
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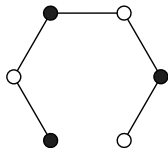
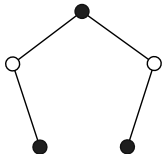
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An Example of Stability-Critical Graph

Examples



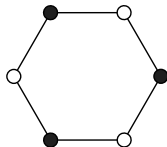
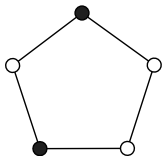
Delete any edge:



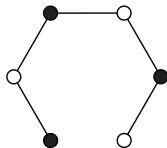
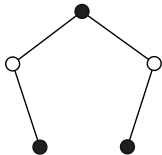
Thus: the 5-cycle is stability critical but the 6-cycle is not.

An Example of Stability-Critical Graph

Examples



Delete any edge:



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A Weighted Generalization of the Fence Inequality

Independently: Leung and Lee (1994), Suck (1992).

Theorem

For $|X| \geq 3$, the *reinforced fence inequality*

$$\sum_{i \in X} t x_{i,f(i)} - \sum_{i,j \in X, i \neq j} (x_{i,f(j)} + x_{j,f(i)}) \leq \frac{t(t+1)}{2}$$

defines a facet of P_{LO}^n if and only if the constant value t satisfies

$$1 \leq t \leq |X| - 2.$$

Our Contribution (D., F. and J.)

Schematically:

fence inequality

graphical inequality of
a stability critical graph

reinforced fence inequality
(of a complete graph)

A common generalization?

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A common generalization?

Preparing a General Graphical Inequality

Let (G, μ) be a **weighted graph**, with $G = (V, E)$ and $\mu : V \rightarrow \mathbb{Z}$.

Definition

For $S \subseteq V$, the **worth** (or net weight) $w(S)$ equals the total weight $\mu(S)$ minus the number of edges in S .

A subset of S is **tight** if it maximizes the worth.

Notation

$$\alpha(G, \mu) = \max_{S \subseteq V} w(S).$$

Remark

If $\mu = \mathbf{1}$ (constant weight 1), then $\alpha(G, \mathbf{1}) = \alpha(G)$.

Thus $\alpha(G, \mu)$ is a true generalization of $\alpha(G)$.

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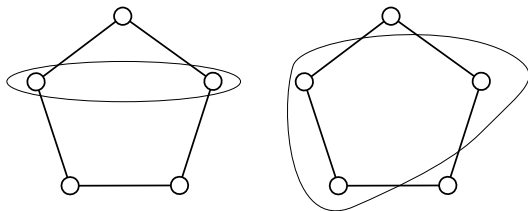
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Examples of Tight Sets

Example

For the pentagon with $\mu = 1$, here are tight sets:



Remember that tight sets S maximize

$$w(S) = \mu(S) - \|S\|.$$

Graphical Inequalities

Let (G, μ) be a weighted graph, with $G = (V, E)$ and $\mu : V \rightarrow \mathbb{Z}$.

Definition

Let $f : X \rightarrow Y$ be bijective with $X, Y \subset Z$, $X \cap Y = \emptyset$, and assume $V = X$.

The **graphical inequality** of (G, μ) reads

$$\sum_{i \in V} \mu(i) x_{i,f(i)} - \sum_{\{i,j\} \in E} (x_{i,f(j)} + x_{j,f(i)}) \leq \alpha(G, \mu).$$

Proposition

The graphical inequality is always valid for the linear ordering polytope P_{LO}^Z .

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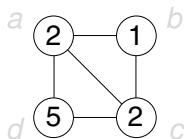
An Example of Graphical Inequality

Example

Consider $X = \{a, b, c, d\}$, $Y = \{s, t, u, v\}$, and the bijection

$$f: \quad a \mapsto s, \quad b \mapsto t, \quad c \mapsto u, \quad d \mapsto v.$$

Take the graph



Its graphical inequality is

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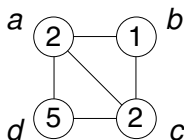
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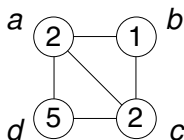
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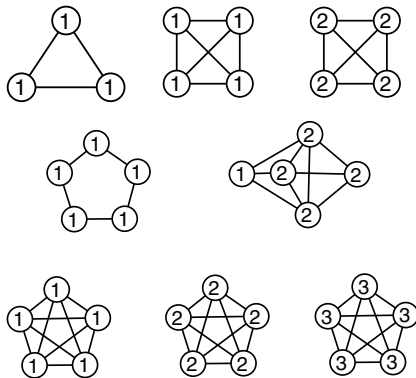
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Facet-defining Graphs

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A weighted graph is **facet defining** or a **FDG** if its graphical inequality defines a facet of P_{LO}^n .

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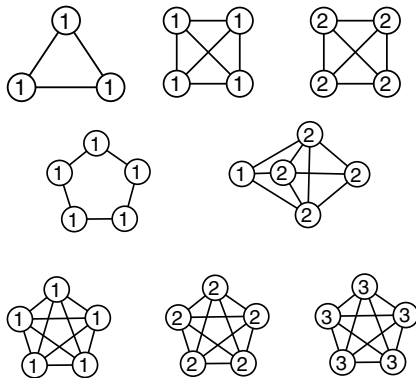


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A Subsidiary Problem

Problem

To understand FDGs, e.g. to classify them.

Remark

FDGs include connected, stability critical graphs with more than 2 vertices.

Hard (although only partial) results were obtained in classifying the latter graphs, see e.g. Lovász (1993).

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Let (G, μ) be a weighted graph with more than two vertices.

Then (G, μ) is a FDG

if and only if

for each nonzero valuation $\lambda : V(G) \cup E(G) \rightarrow \mathbb{Z}$ there is a tight set T of (G, μ) with

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Sketch of the proof

Take $f : X \rightarrow Y$ as in the definition of the graphical inequality.

Take the restrictions to $X \times Y$ of all linear orderings L of Z .

The resulting relations from X to Y coincide with the “biorders” from X to Y (Doignon, Ducamp and Falmagne, 1984).

The **biorder polytope** $P_{\text{Bio}}^{X \times Y}$ is defined in $\mathbb{R}^{X \times Y}$ (Christophe, Doignon and Fiorini, 2004).

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First Results on Facet Defining Graphs

Theorem

For any FDG (G, μ) , the graph G is 2-connected.

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If (G, μ) is a FDG, so is $(G, \deg - \mu)$.

[Here $(\deg - \mu)(v) = \deg(v) - \mu(v)$.]

Thus most stability critical graphs produce two FDGs:

one with $\mu = \mathbf{1}$, another one with $\mu = \deg - \mathbf{1}$.

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For any graph $G = (V, E)$ (no weight here), define its **defect**

$$\delta(G) = |V| - 2\alpha(G).$$

Consider here a connected, stability critical graph G .

Theorem (Erdős and Gallai, 1961)

$$\delta(G) \geq 0.$$

Theorem (Hajnal, 1965)

Any vertex v of G satisfies $\deg(v) \leq \delta(G) + 1$.

Corollary (Hajnal, 1965)

$$\delta(G) = 0 \iff G = K_2;$$

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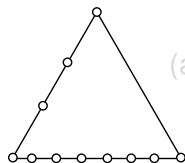
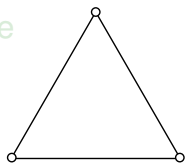
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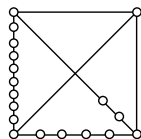
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(an 11-cycle)

Theorem (Andrásfai, 1967)

The connected stability critical graphs with defect 2 are the odd-subdivision of K_4 .

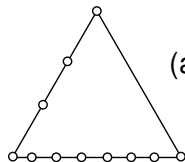
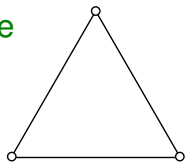


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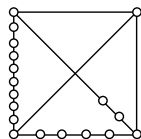
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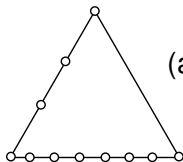
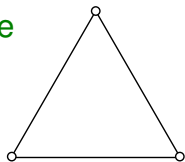


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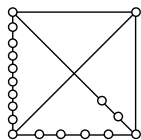
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The Basis Theorem for Stability Critical Graphs

Theorem (Lovász, 1978)

For any natural number $\delta > 0$, there is a finite collection \mathcal{S}_δ of graphs such that

G is a connected stability critical graph with $\delta(G) = \delta$



G is an odd-subdivision of some graph in \mathcal{S}_δ .

Examples

\mathcal{S}_1 :

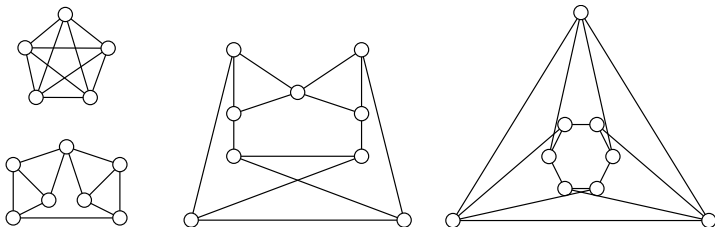


\mathcal{S}_2 :



The Basis of Stability Critical Graphs with defect 3

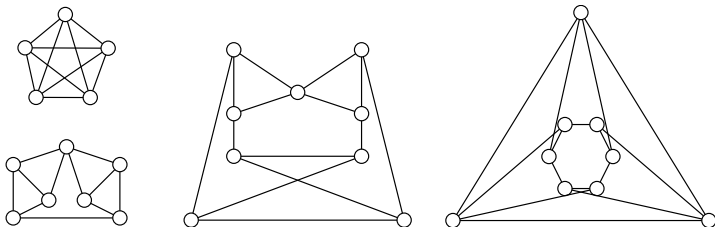
Among the graphs in \mathcal{S}_3 , we show only those with minimum degree 3:



There are 7 other graphs in \mathcal{S}_δ (according to Gwen).

The Basis of Stability Critical Graphs with defect 3

Among the graphs in \mathcal{S}_3 , we show only those with minimum degree 3:



There are 7 other graphs in \mathcal{S}_δ (according to Gwen).

The Defect of Facet-Defining Graphs (FDGs)

How to define the defect of a weighted graph (G, μ) ?

In our case, with $G = (V, E)$, we use

$$\delta(G, \mu) = \mu(V) - 2\alpha(G, \mu).$$

Notice $\delta(G, \mathbf{1}) = \delta(G)$ and $\delta(G, \mu) = \delta(G, \deg - \mu)$.

Let (G, μ) be any FDG.

Theorem

For each vertex v of G

$$1 \leq \deg(v) - \mu(v) \leq \delta(G, \mu).$$

The proof is much more involved than in the case $\mu = \mathbf{1}$.

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More Results on FDGs

Corollary

$$\mu(v) \leq \delta(G, \mu).$$

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If $\delta(G, \mu) = 1$, then $\mu = 1$ and G is an odd cycle.

Theorem (Joret, next talk)

For any vertex v of an FDG (G, μ) :

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