

Requirements on the rule base [Driankov et al. 1993]

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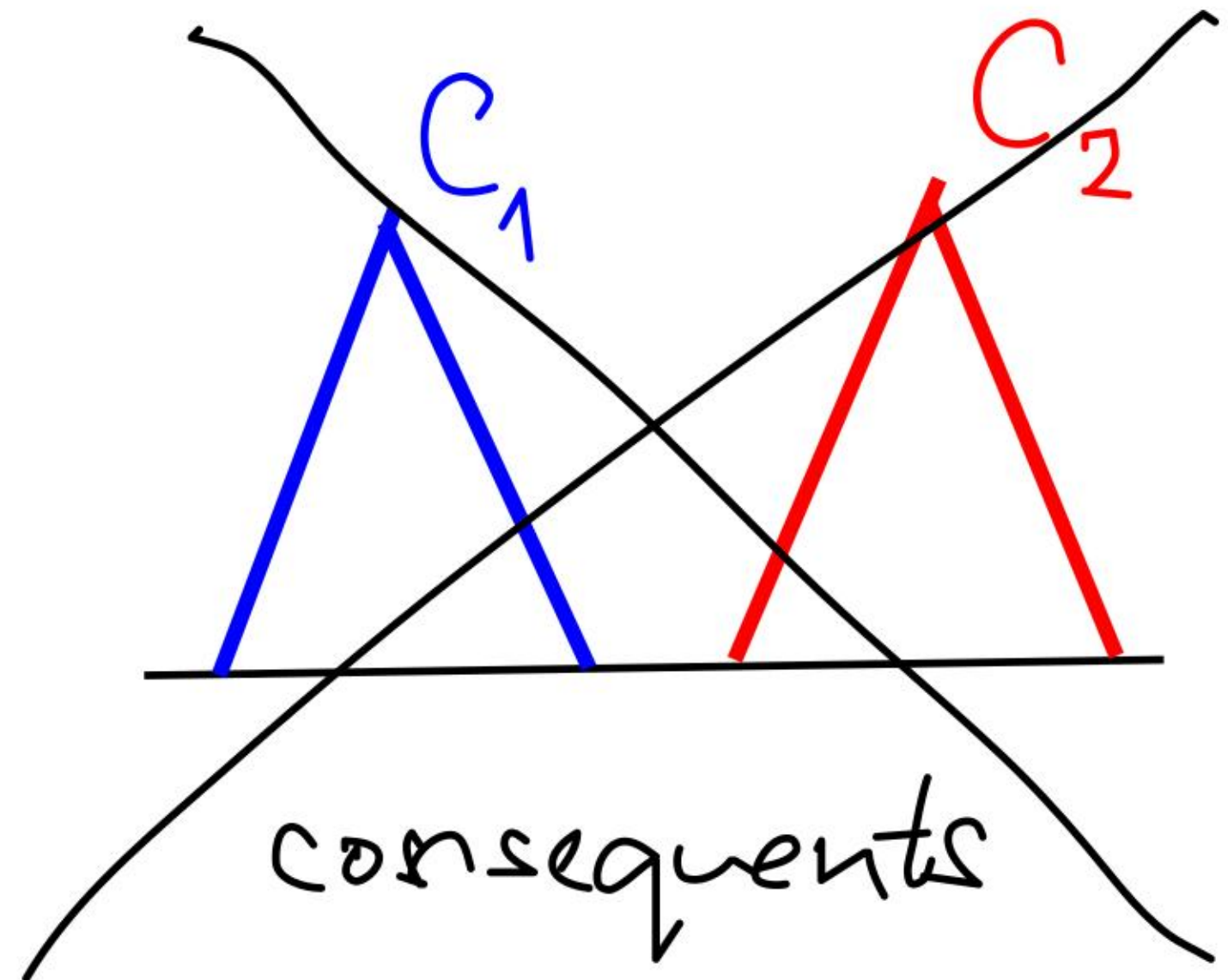
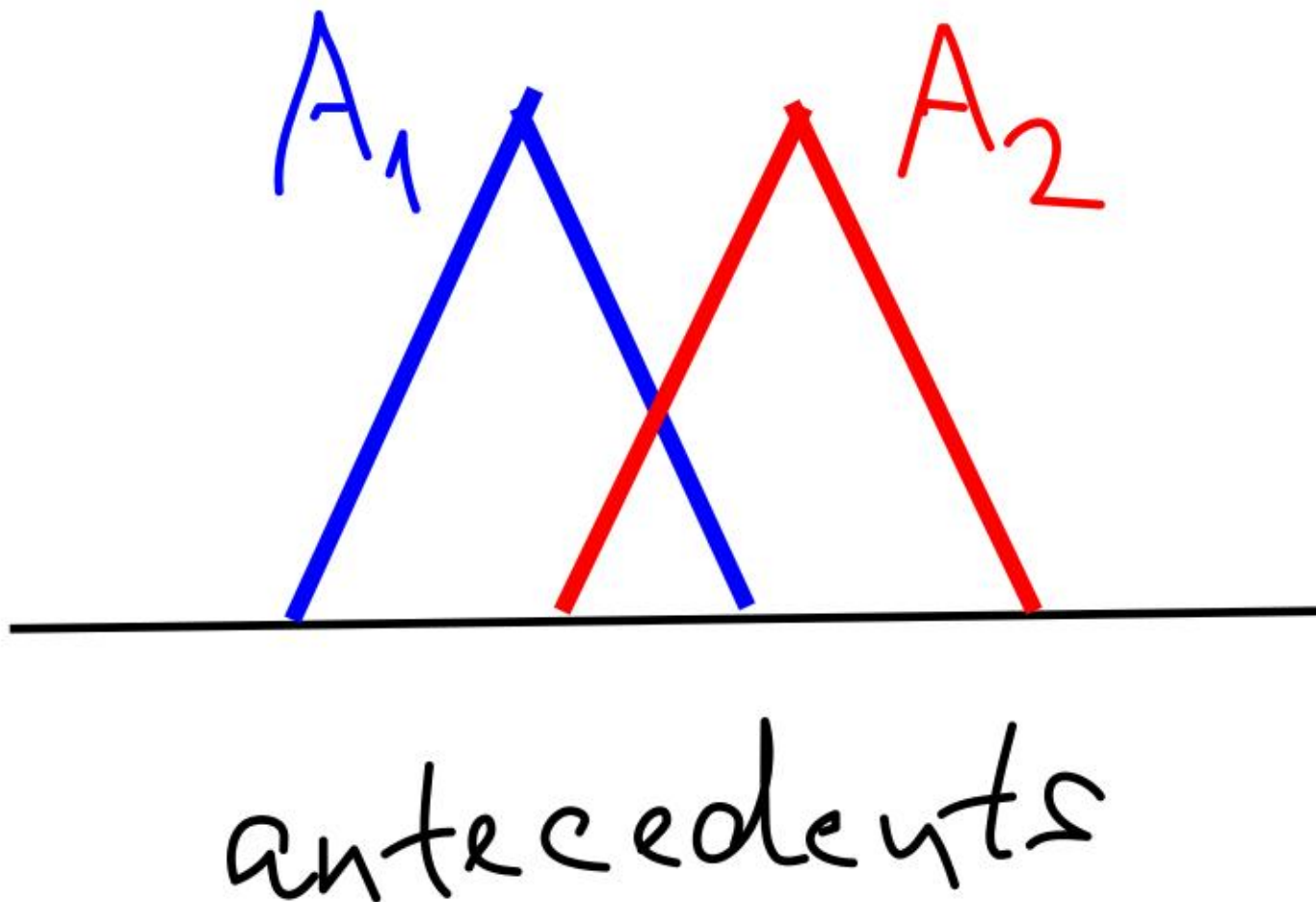
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4. **Interaction** or **(local) correctness** ([Thiele 1995]): $\forall j : \Phi(A_j) = C_j$.

The output of the controller should be the fuzzy union of the outputs of separate rules (i.e., FATI=FITA);
this weaker form always holds for a Mamdani–Assilian controller;
see also [Lehmke, Reusch, Temme, Thiele 1998] for more general sufficient conditions for this equality).

Recommendations on the rule base [Driankov et al. 1993]

Antecedents (one-dimensional) should be

- ◆ **normal**, $\forall i \exists x \in \mathcal{X} : A_i(x) = 1$,
- ◆ continuous,
- ◆ symmetric (when possible, usually not at the borders of the input space!).

The recommended degree of overlapping of neighbouring antecedents (computed using the standard t-norm, $\min$) is 0.5.

The recommended endpoints of the support of an antecedent are the peaks of the neighbouring antecedents.

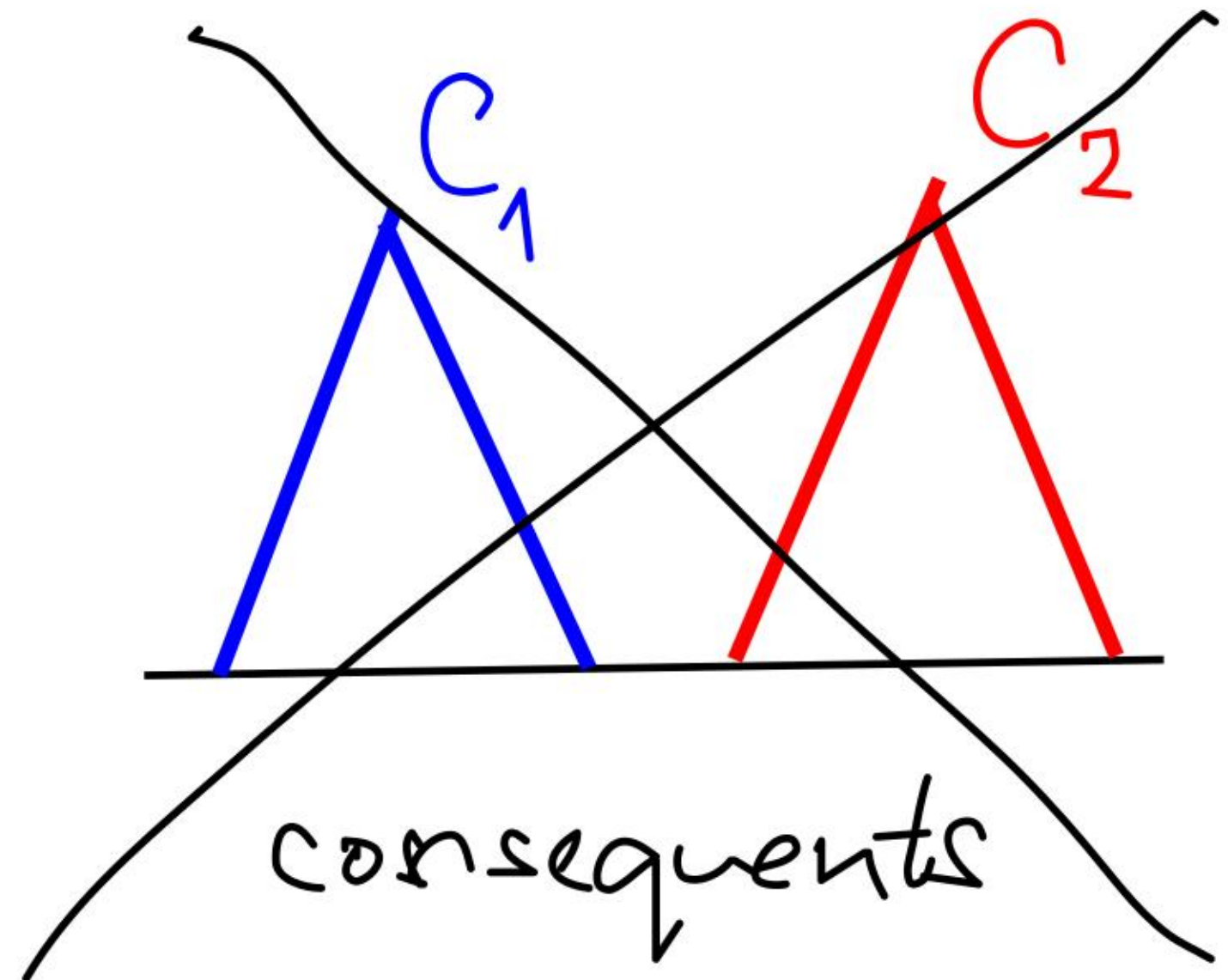
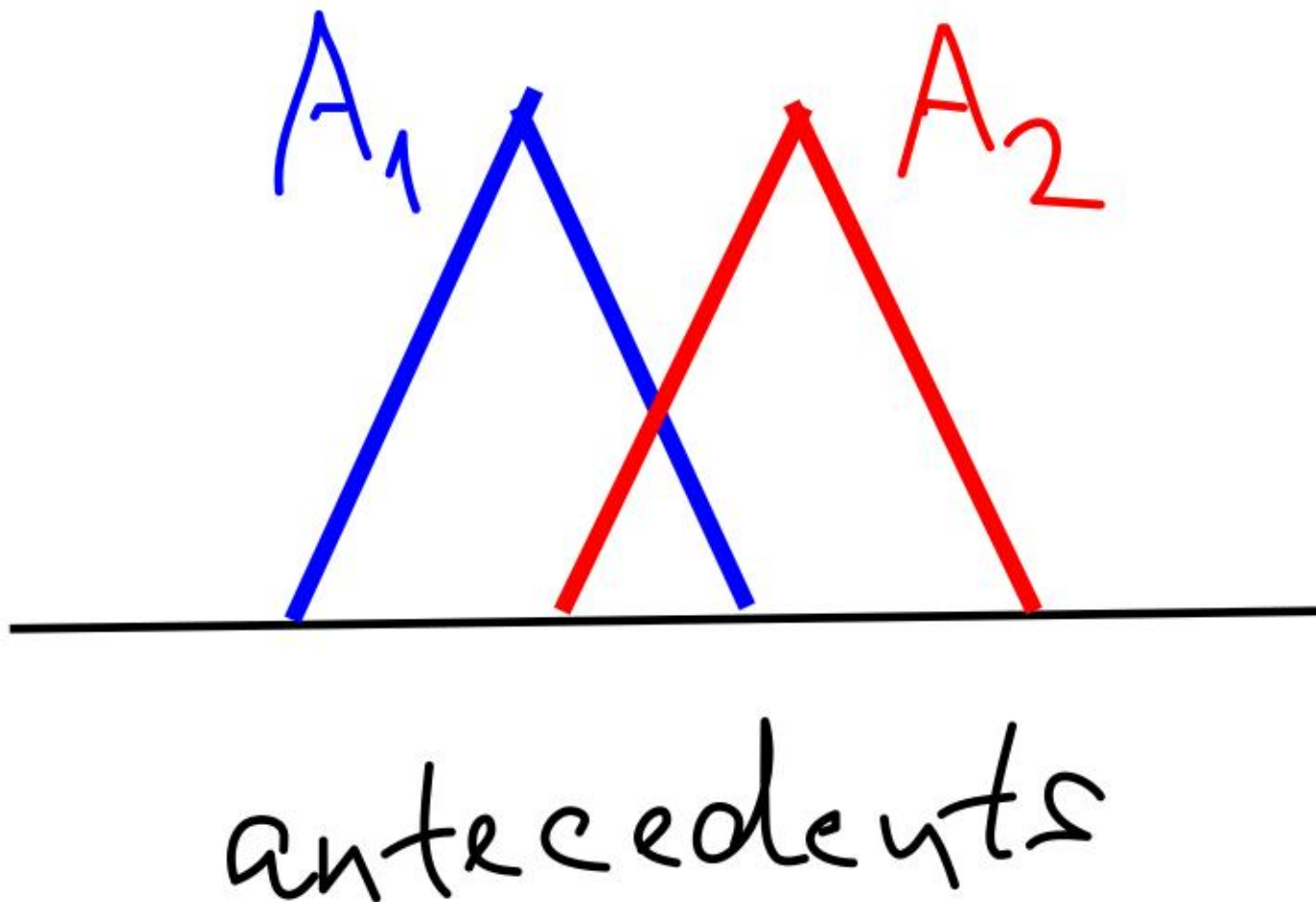
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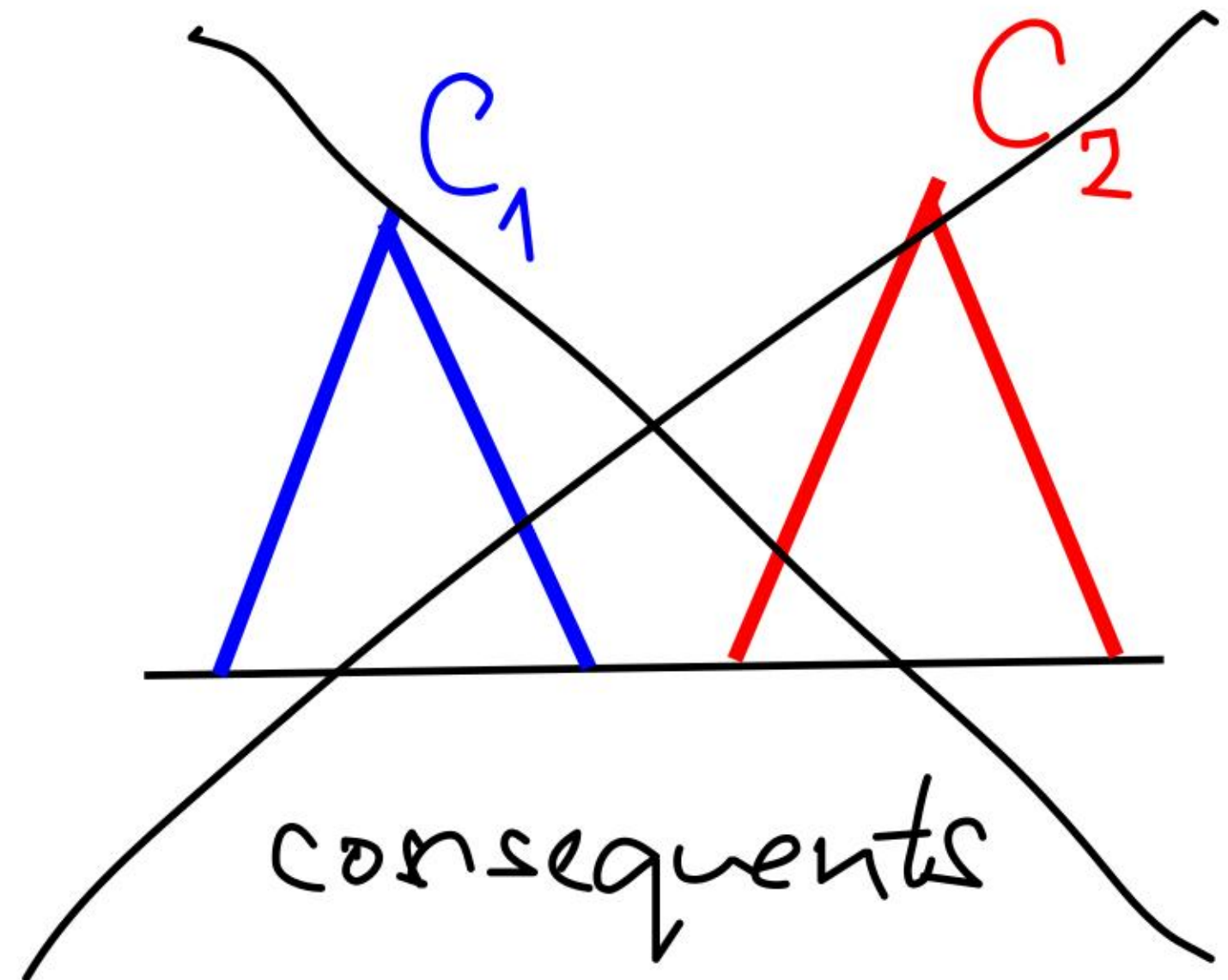
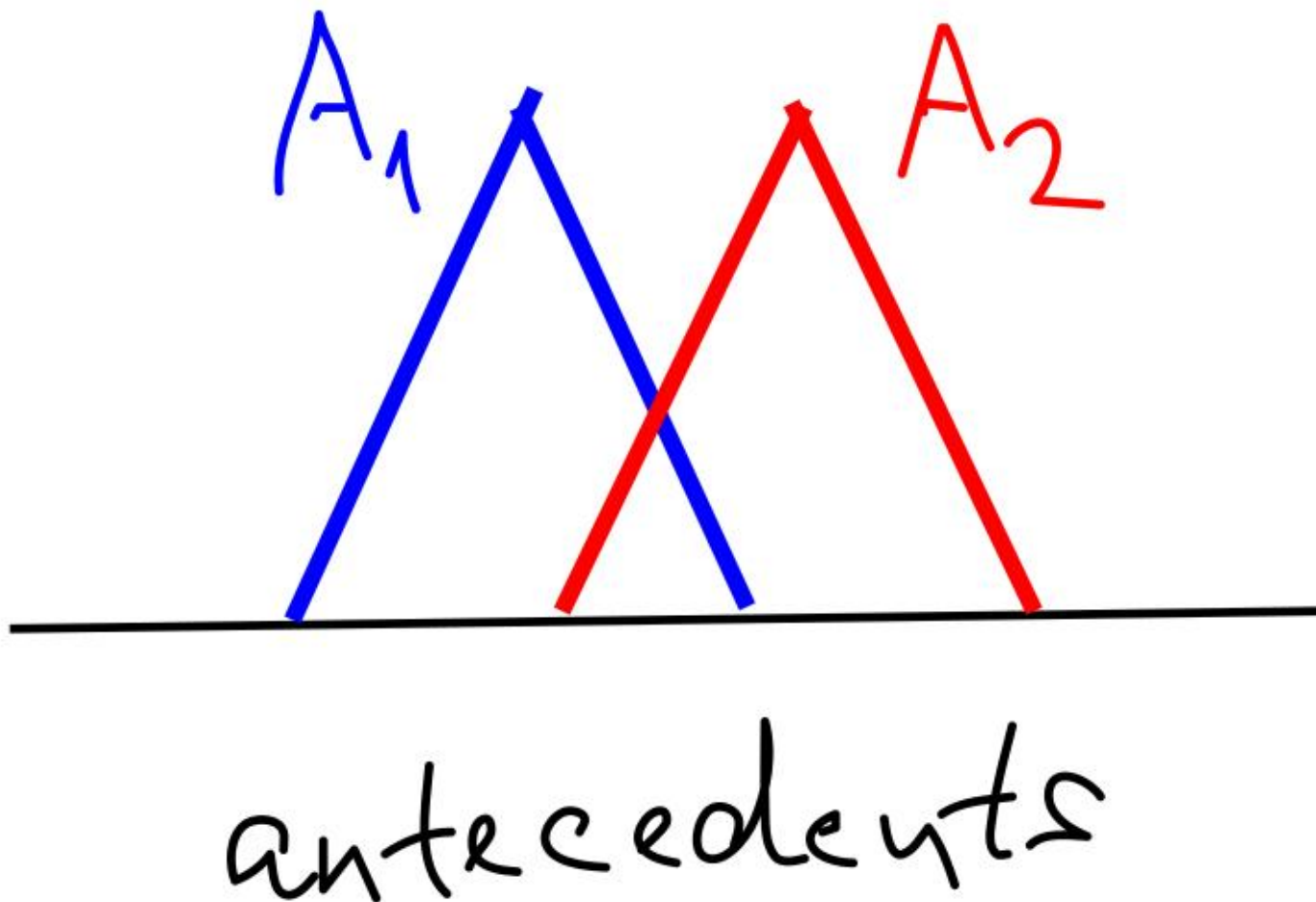
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Generalized Compositional Rule of Inference 2

[Thiele 1995], [Lehmke, Reusch, Temme, Thiele 1998]

FITA principle (First Inference, Then Aggregation)

$$R_{\text{FITA}_i}(x, y) = \pi_i(A_i(x), C_i(y)) ,$$

where $\pi_i: [0, 1]^2 \rightarrow [0, 1]$.

$$\Phi_{\text{FITA}_i}(X)(y) = Q_i\{\kappa_i(X(x), R_{\text{FITA}_i}(x, y)) \mid x \in \mathcal{X}\} ,$$

where $\kappa_i: [0, 1]^2 \rightarrow [0, 1]$, $Q_i: \mathcal{P}([0, 1]) \rightarrow [0, 1]$.

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Particular cases:

FITA Mamdani–Assilian controller: $\pi_i = \wedge, \quad \kappa_i = \wedge, \quad Q_i = \sup, \quad \alpha = \max.$

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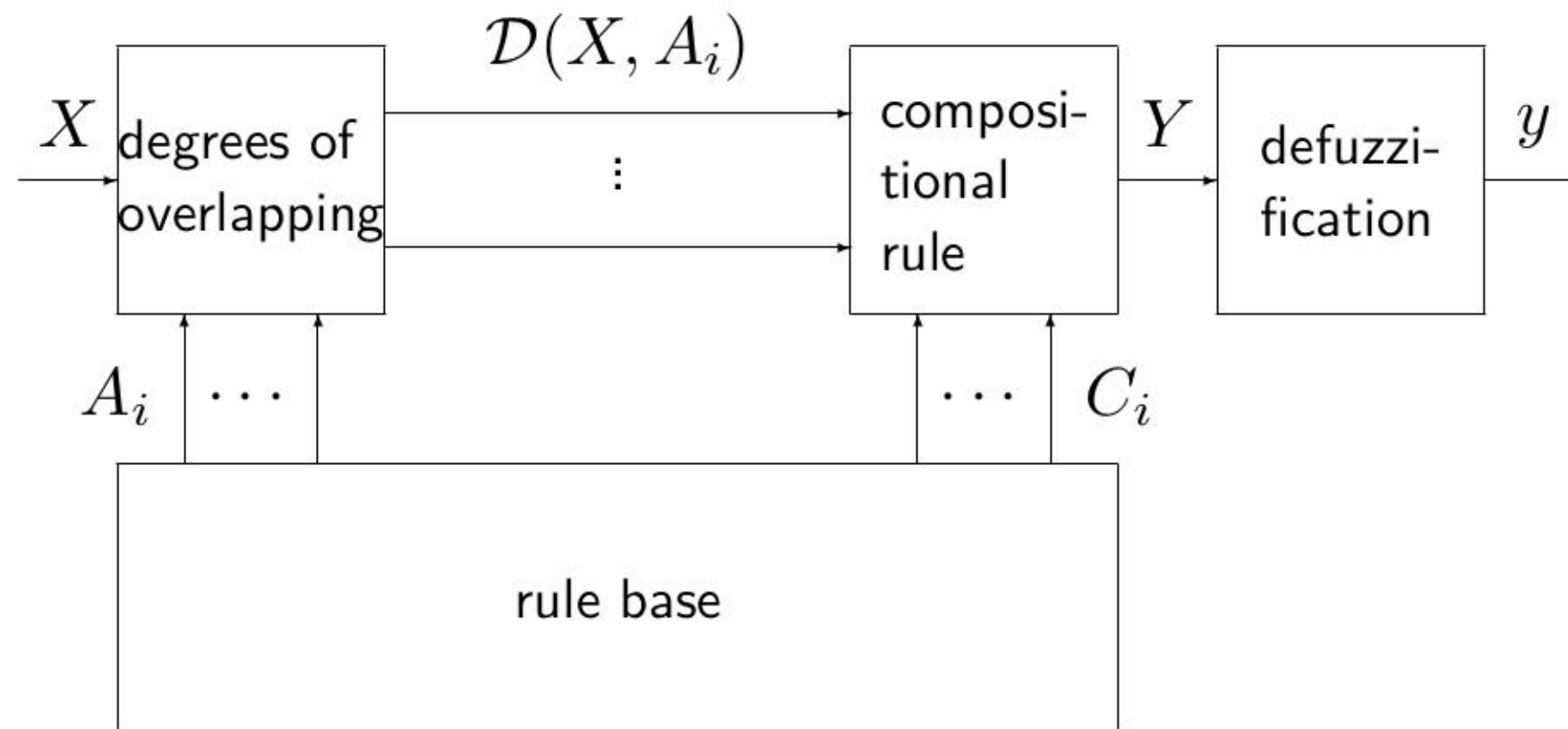
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Principle of Mamdani–Assilian controller — block diagram



Comparison of residuum-based and Mamdani–Assilian controllers

Continuity:

R_{RES} only for $\wedge$ nilpotent,
 R_{MA} always.

Computational efficiency:

$$\Phi_{\text{RES}}(X)(y) = \sup_x \left(X(x) \wedge \min_i (A_i(x) \rightarrow C_i(y)) \right)$$

requires **three** nested cycles (over $\mathcal{X}$ and $\mathcal{Y}$ and over the number of rules).

$$\begin{aligned} \Phi_{\text{MA}}(X)(y) &= \sup_x \left(X(x) \wedge \max_i (A_i(x) \wedge C_i(y)) \right) \\ &= \max_i \sup_x \left(X(x) \wedge A_i(x) \wedge C_i(y) \right) \\ &= \max_i (\mathcal{D}(X, A_i) \wedge C_i(y)) . \end{aligned}$$

$\mathcal{D}(X, A_i) = \sup_x (X(x) \wedge A_i(x))$... the **degree of overlapping (non-disjointness)**,
here equal to the **degree of firing (applicability)**.

Requires **two** nested cycles (over $\mathcal{X}$ and the number of rules) resulting in real numbers $\mathcal{D}(X, A_i)$, $i = 1, \dots, n$; **then two** nested cycles (over $\mathcal{Y}$ and the number of rules).

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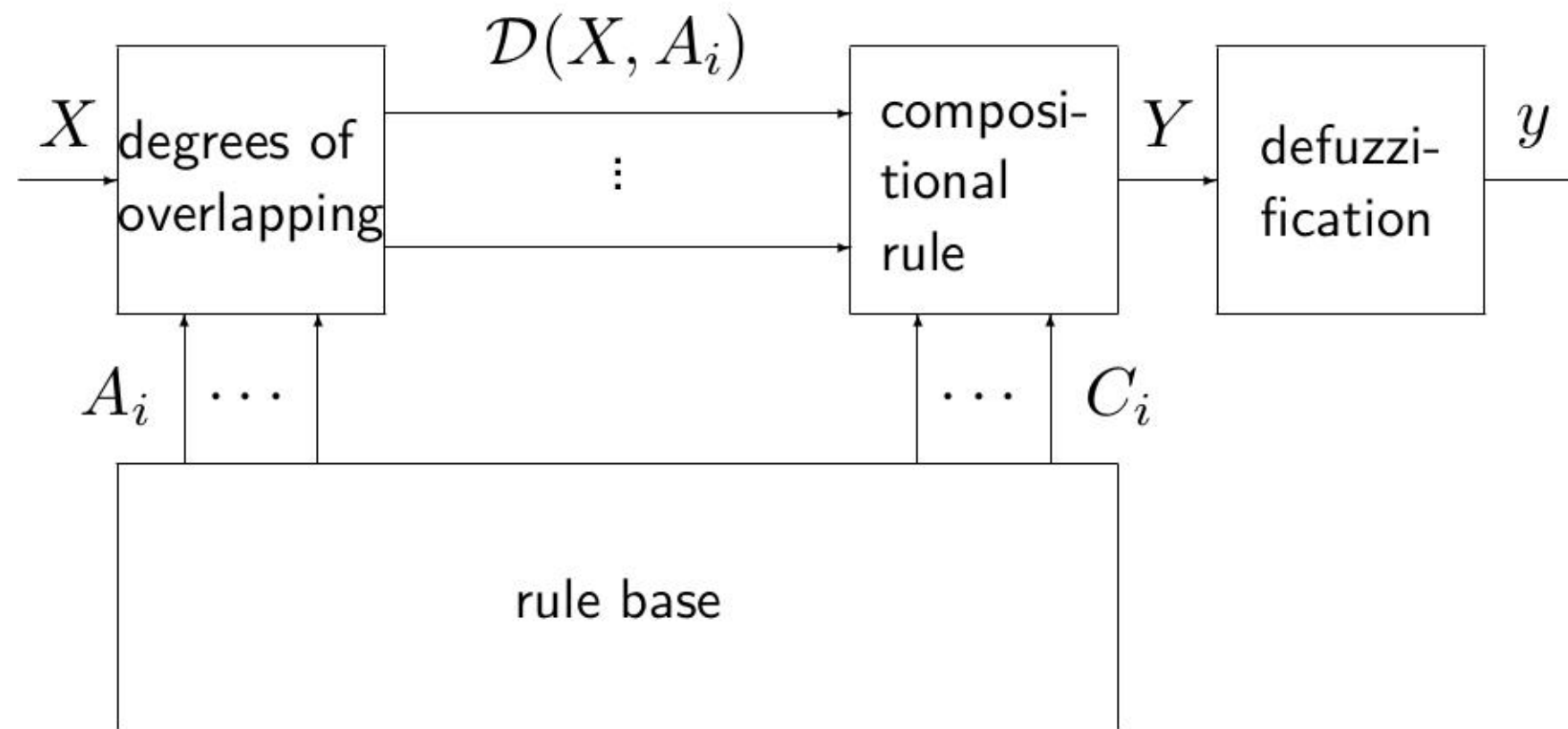
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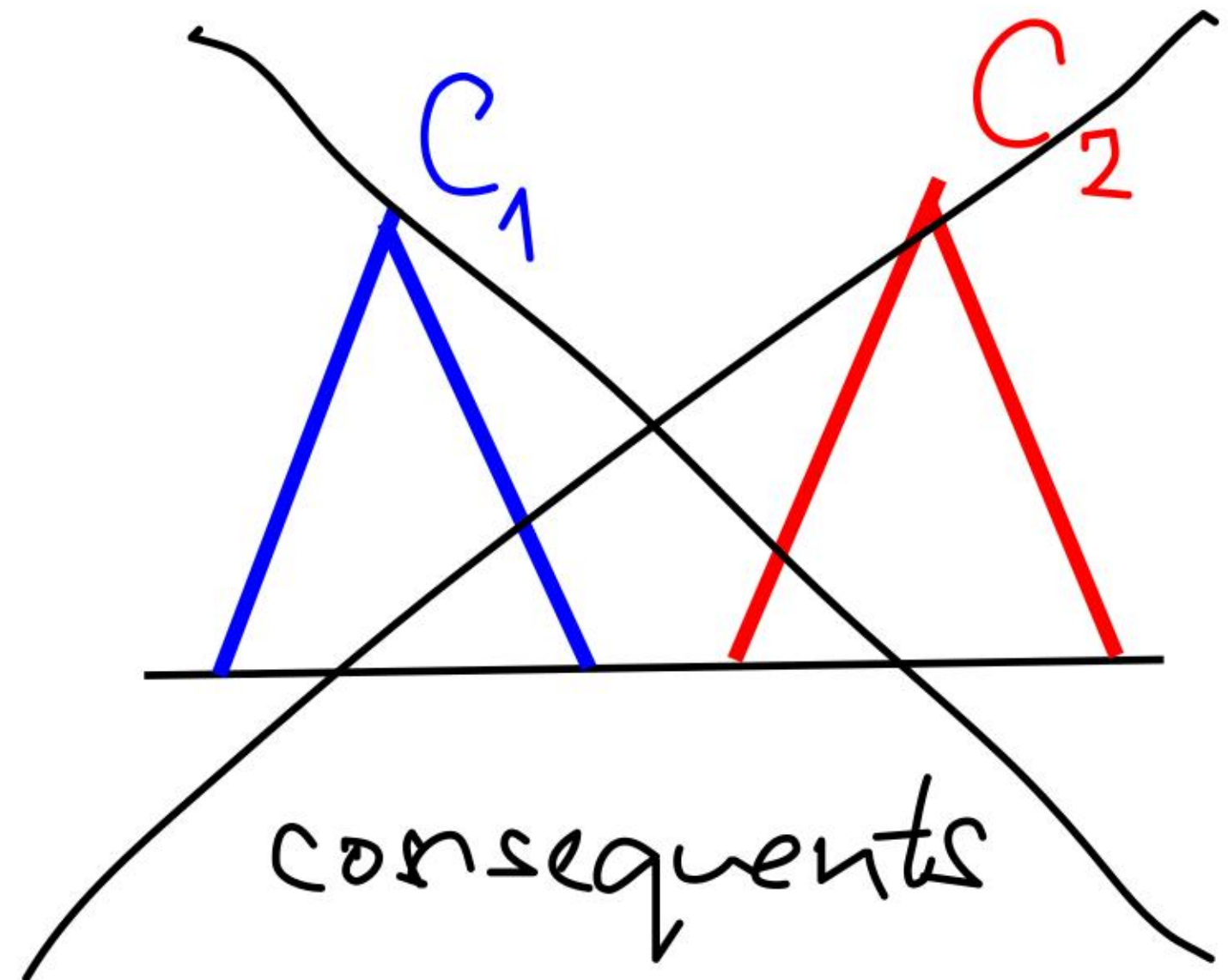
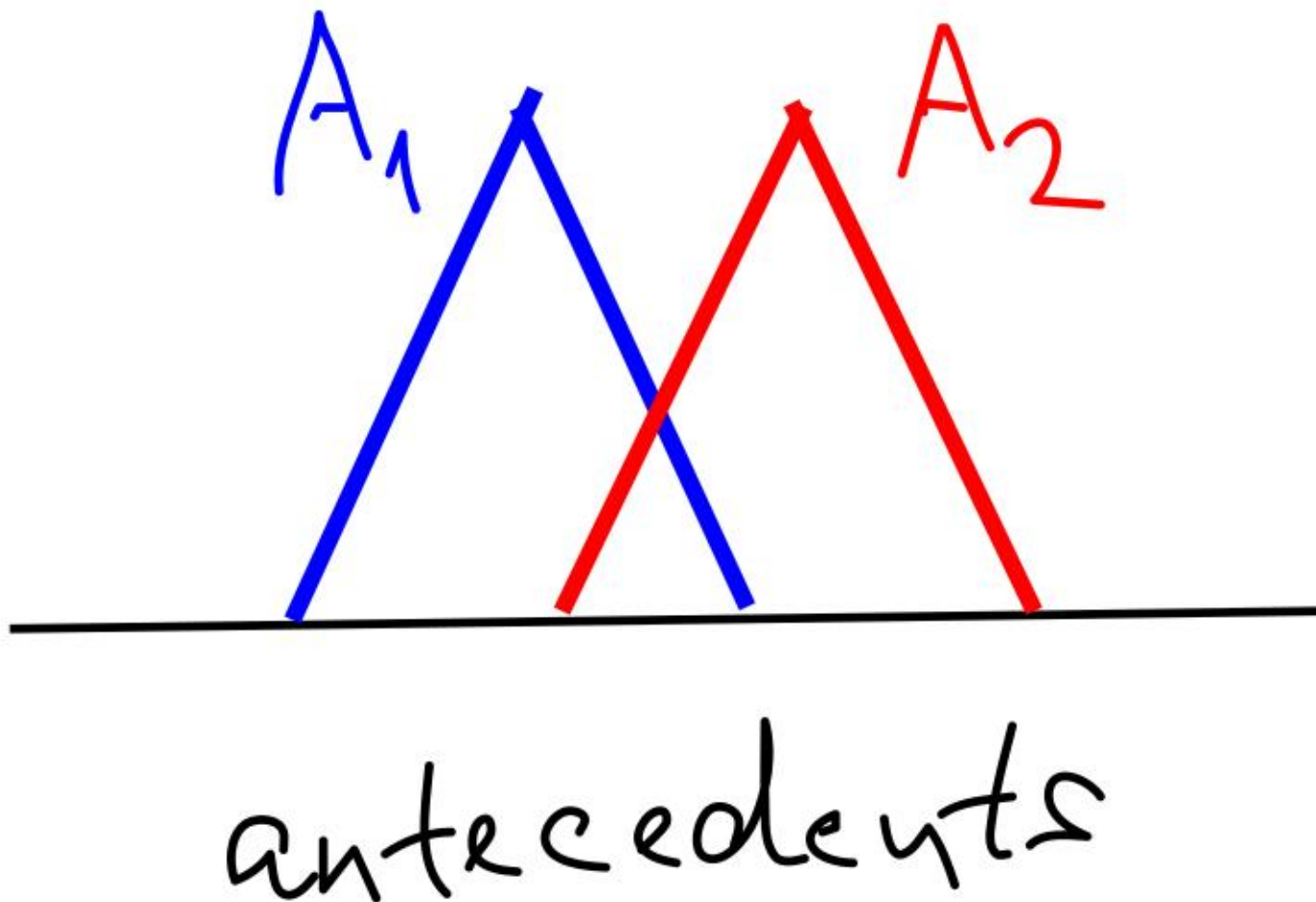
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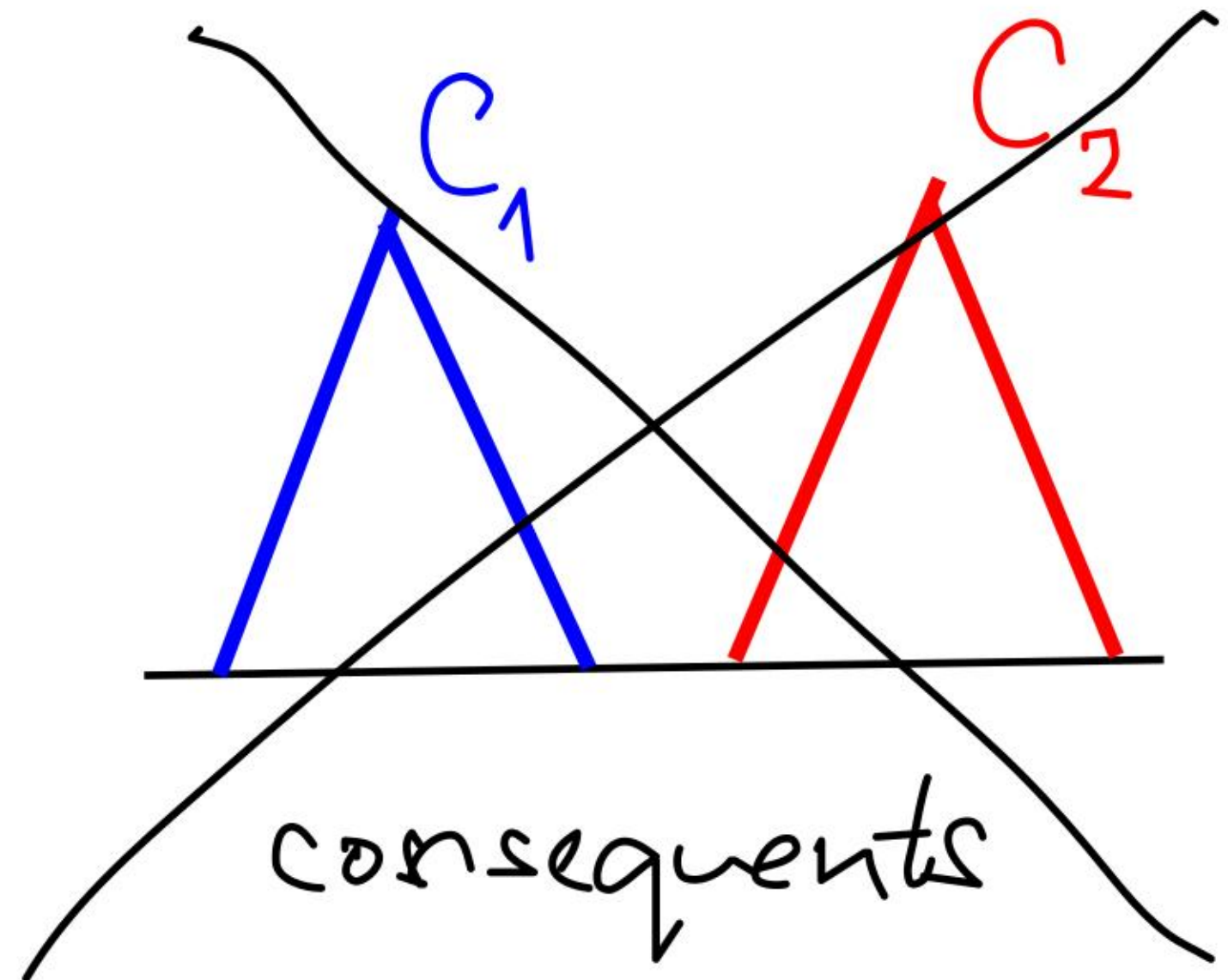
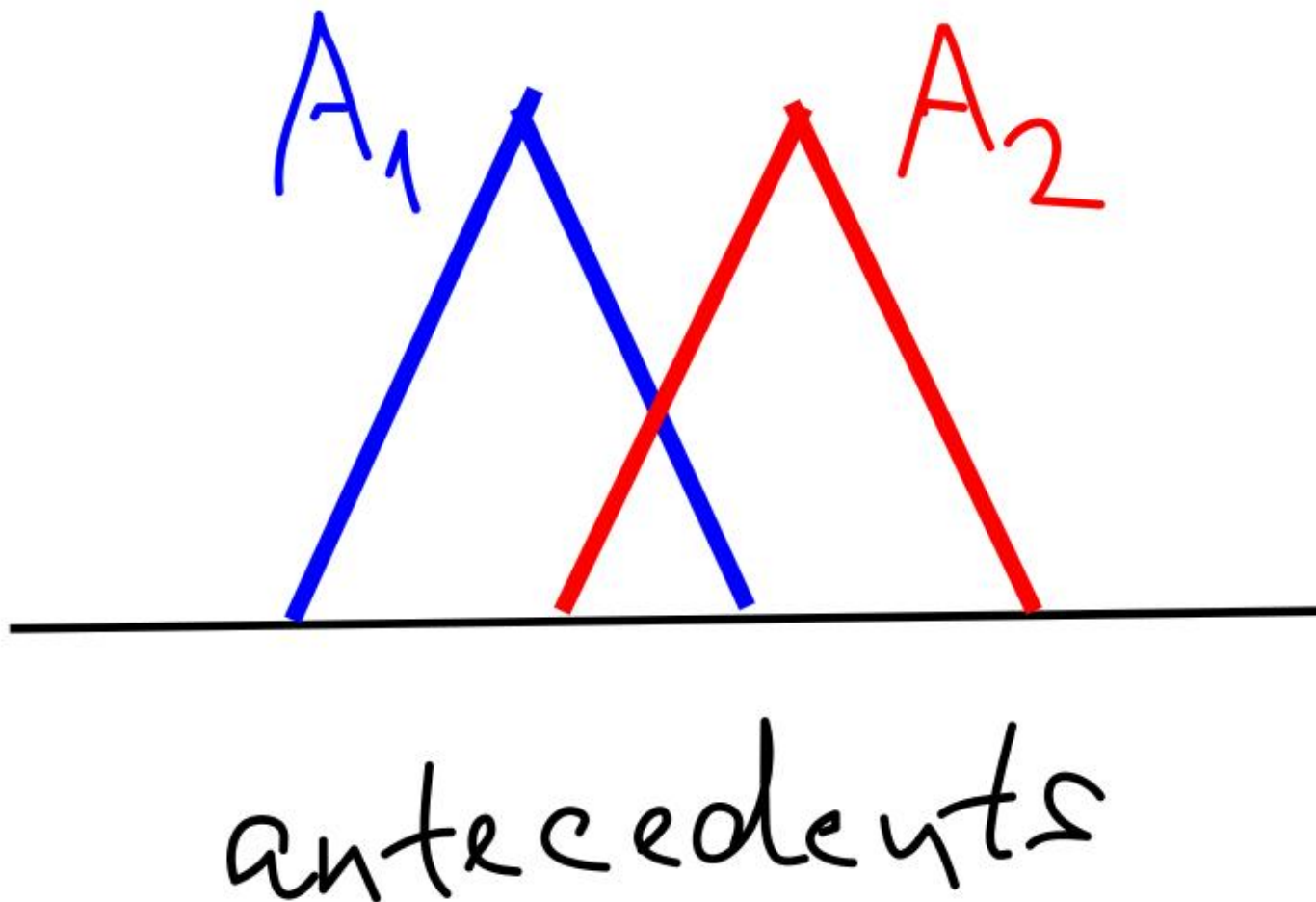
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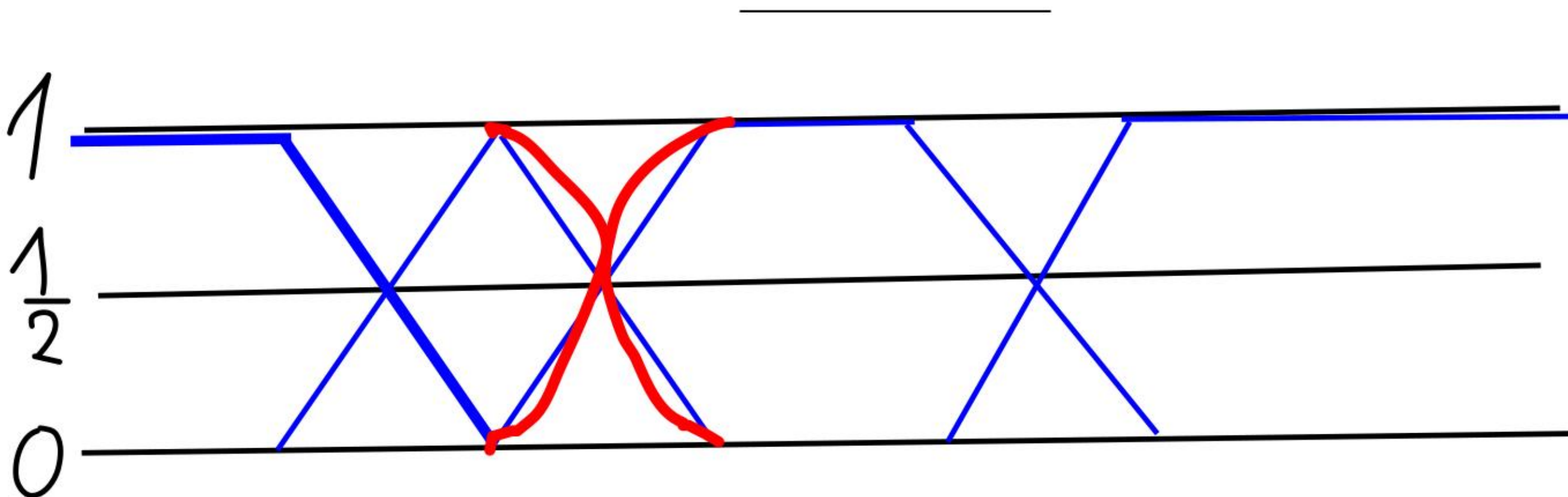
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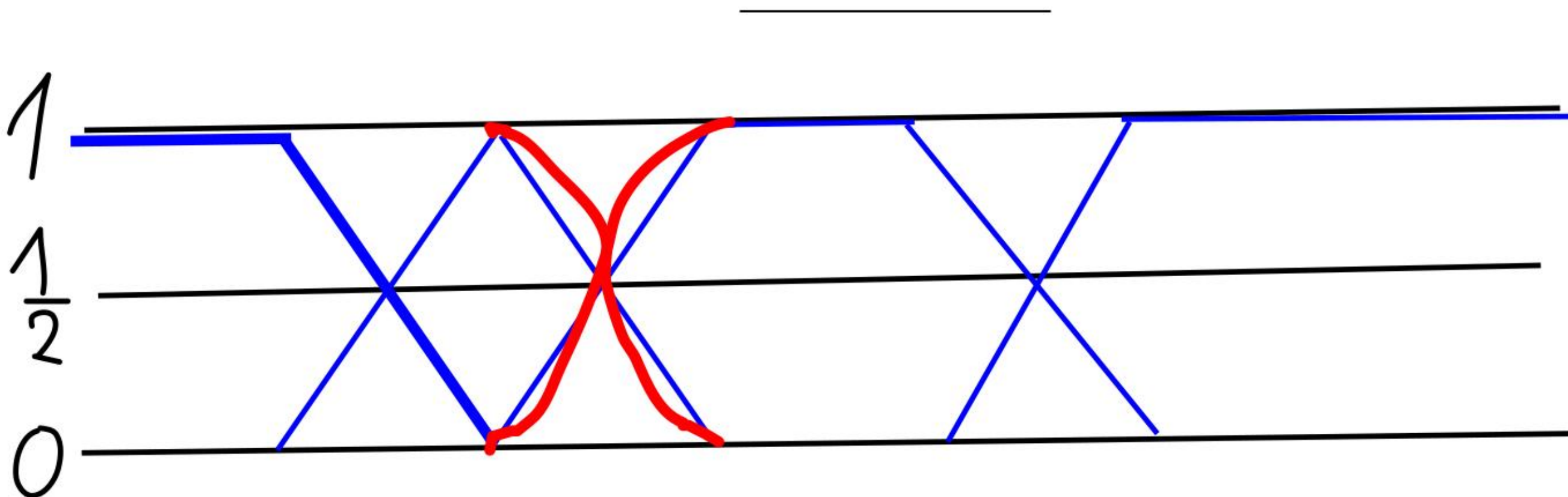
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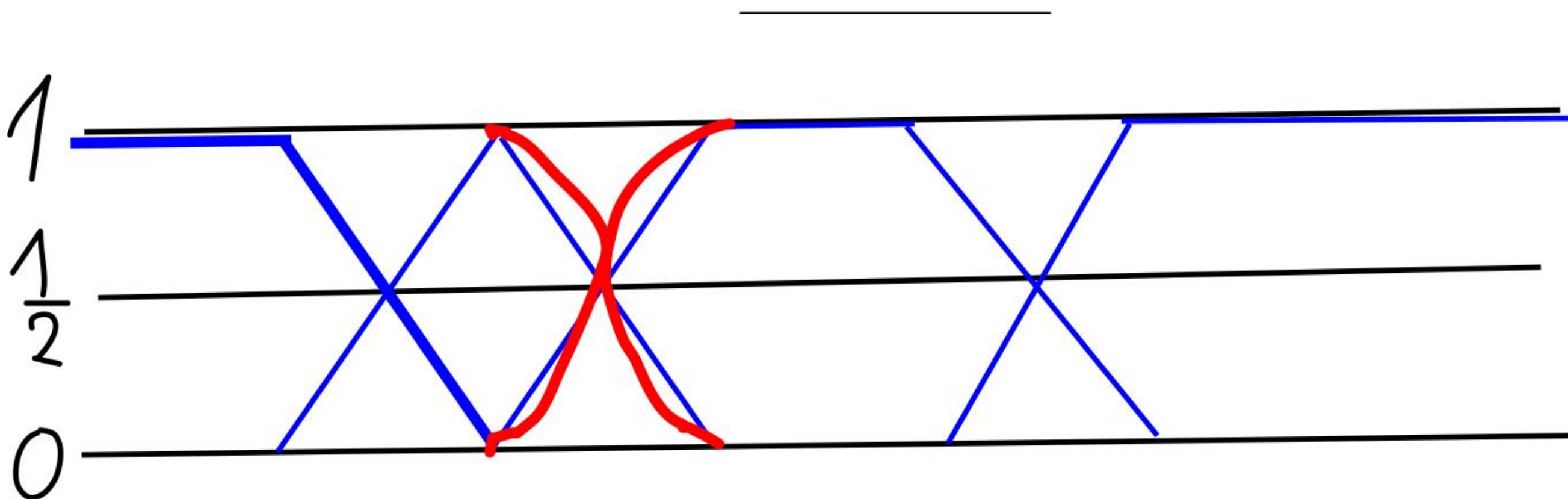
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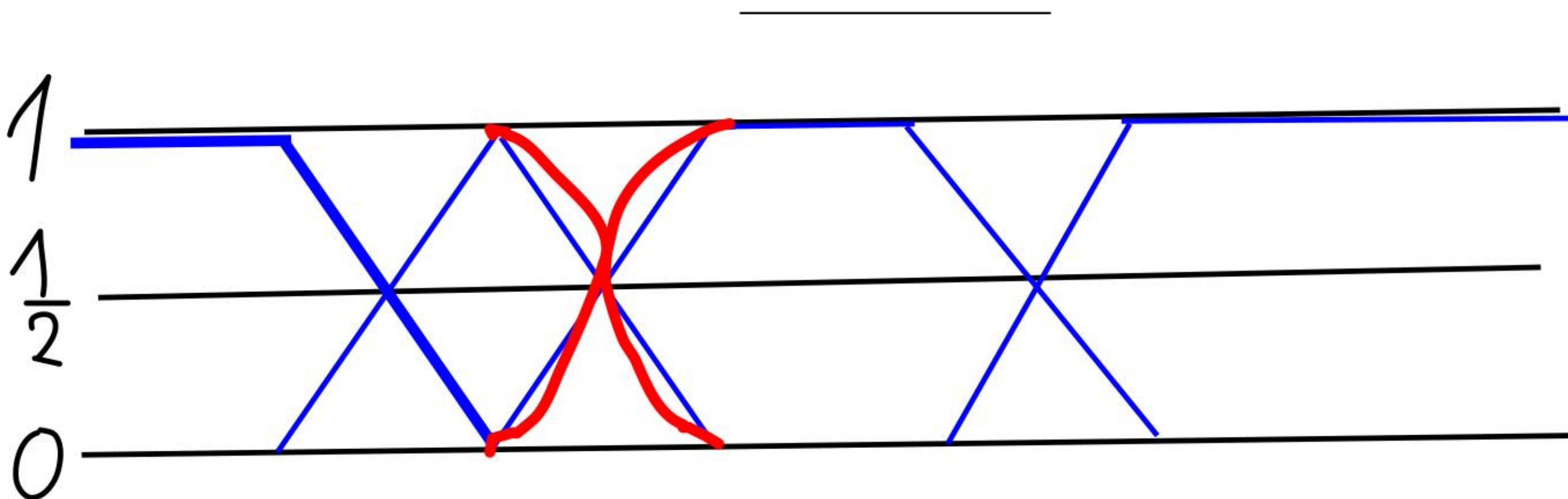
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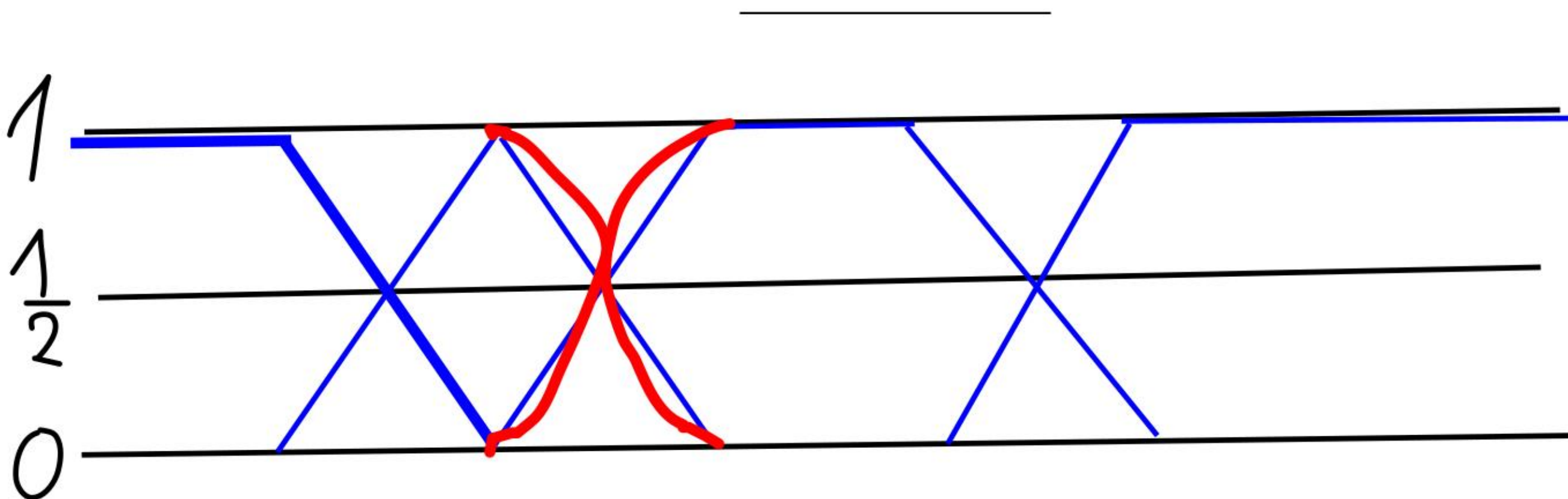
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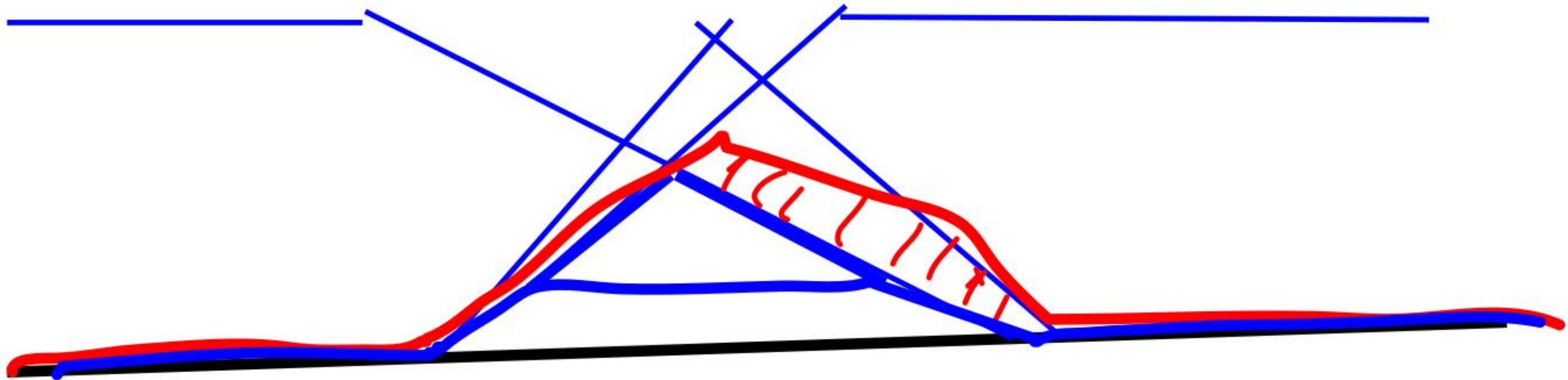
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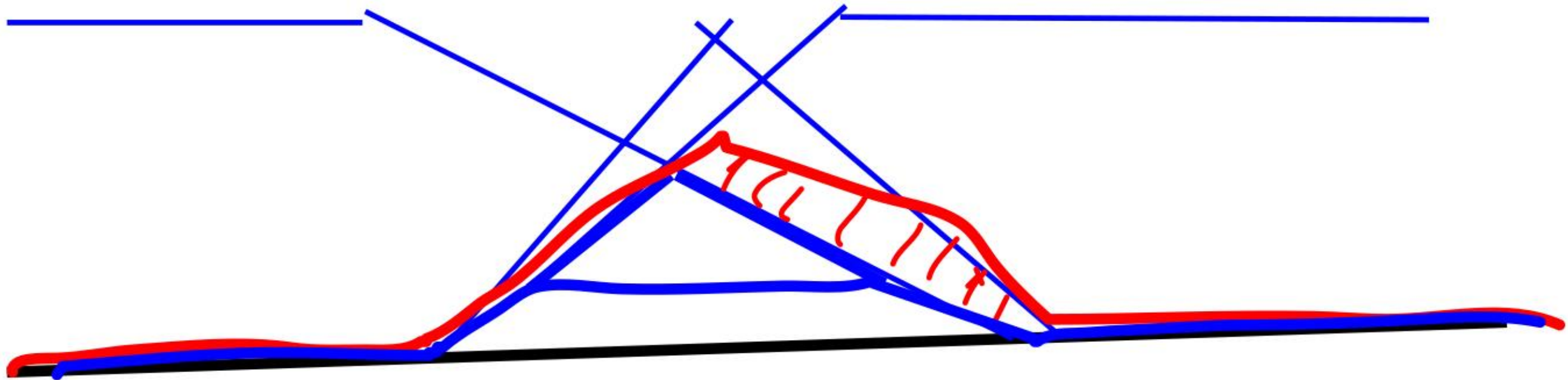


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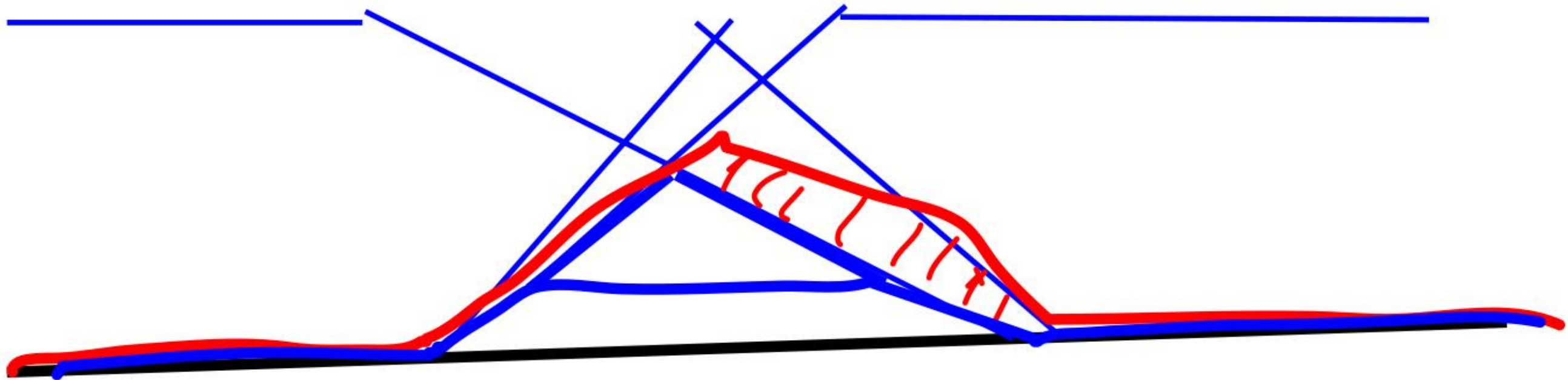
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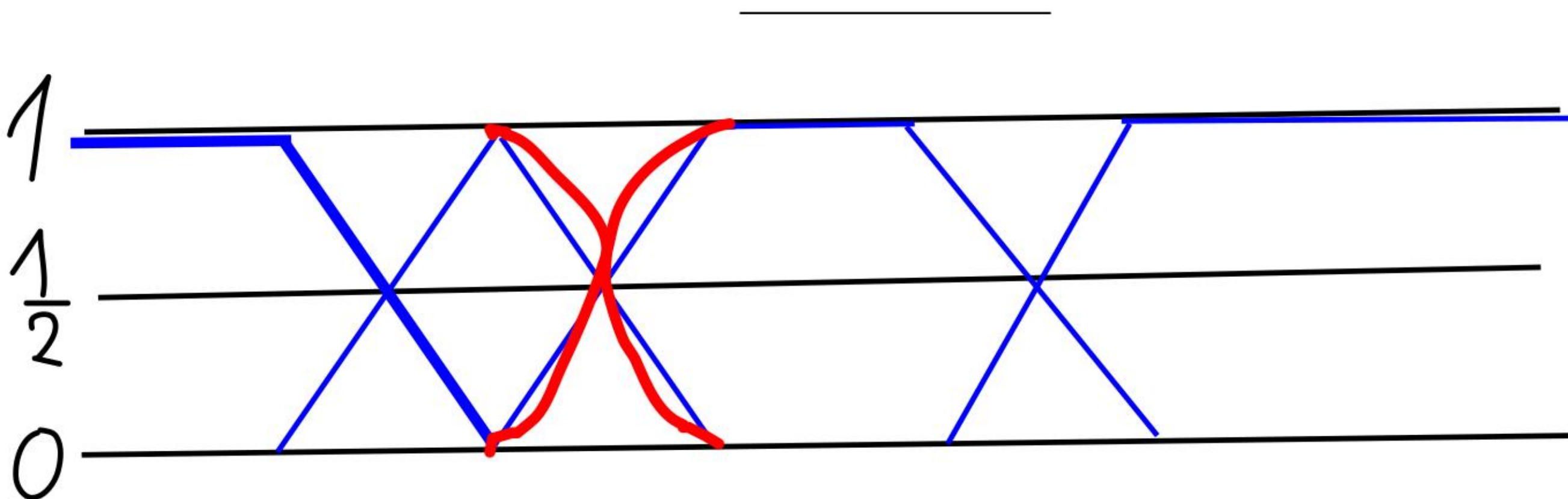
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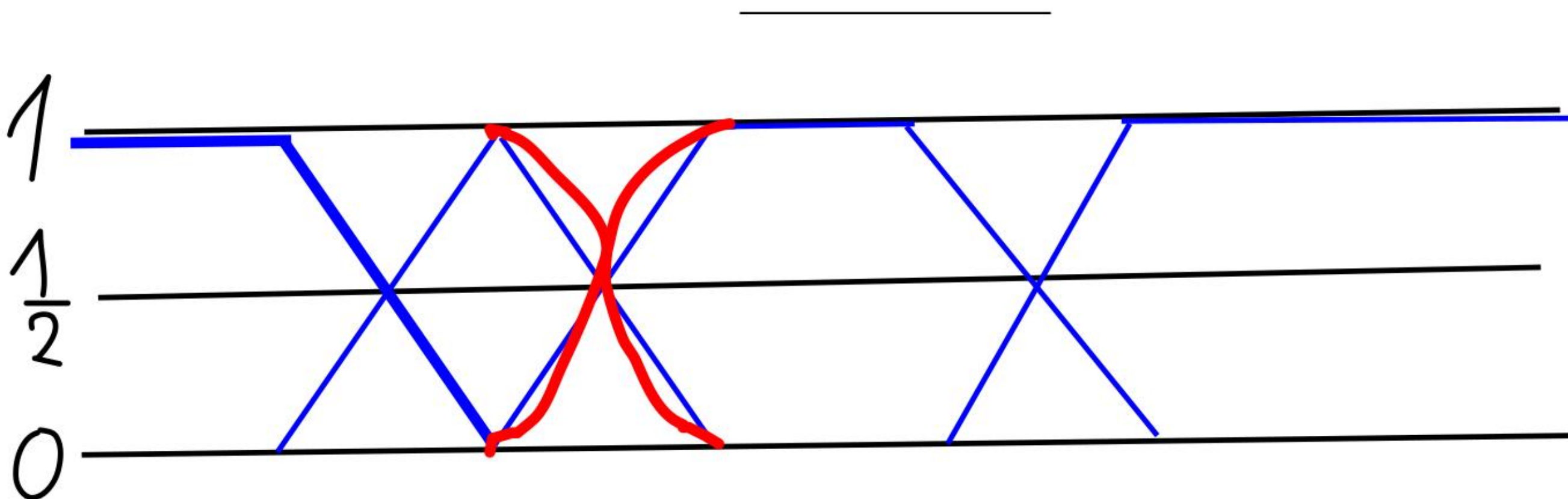
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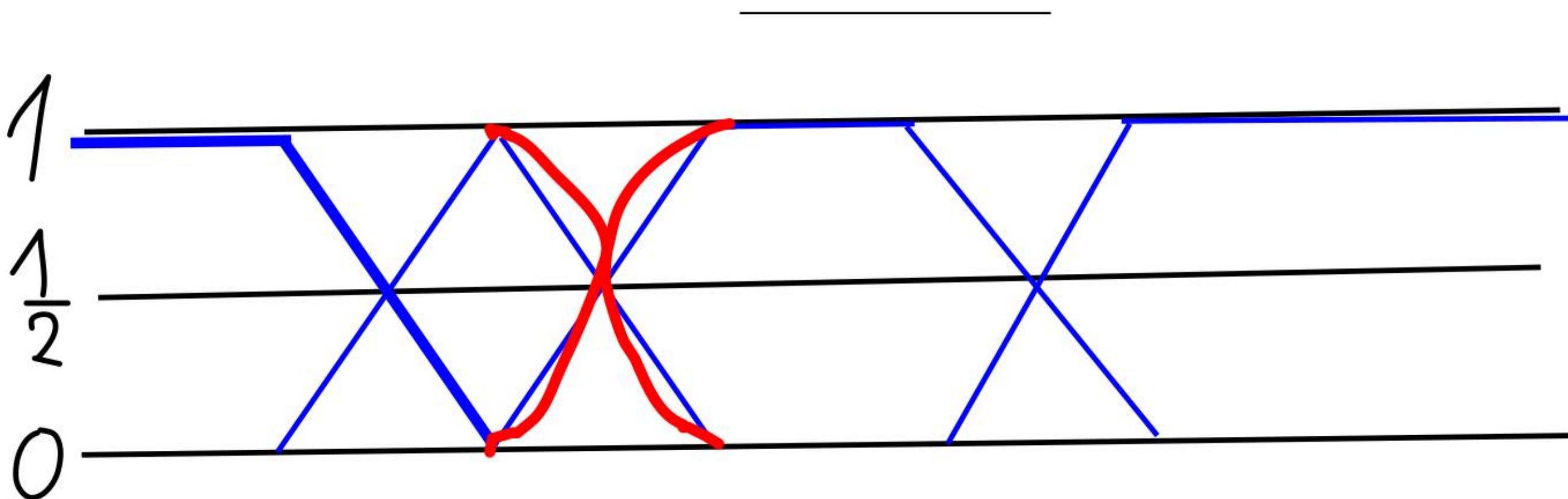
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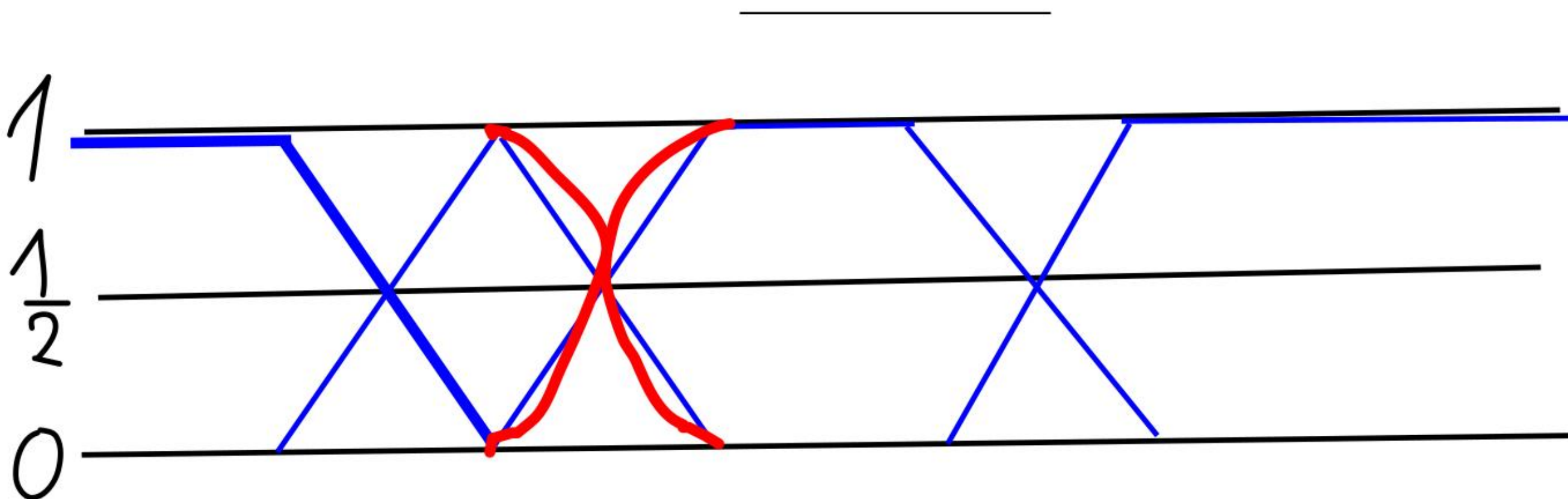
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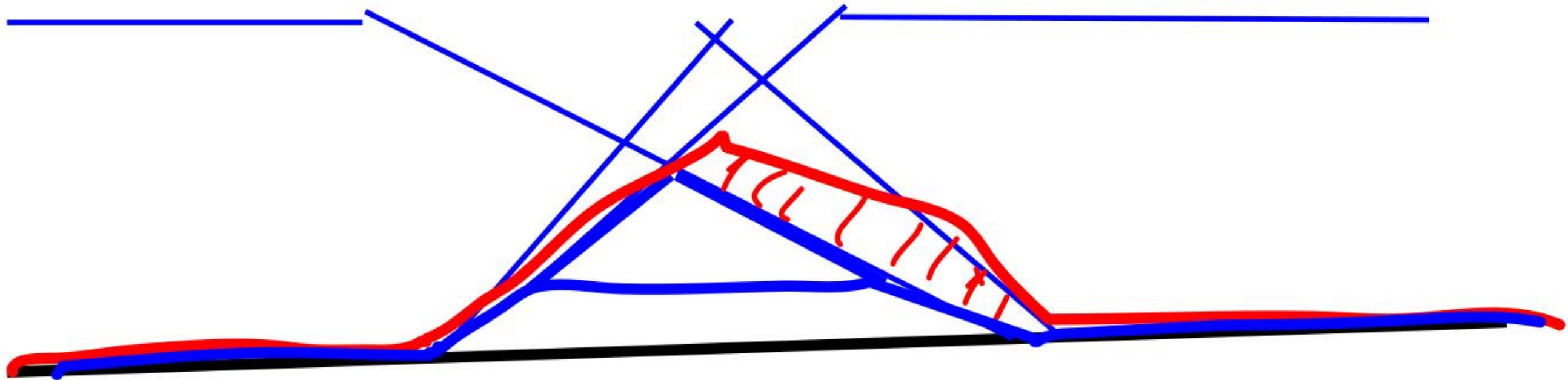


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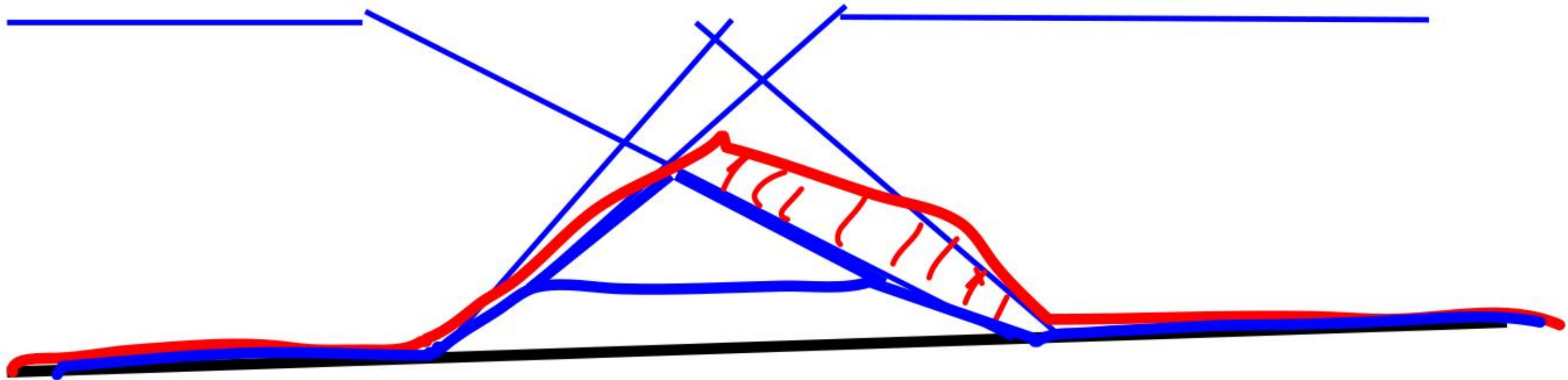
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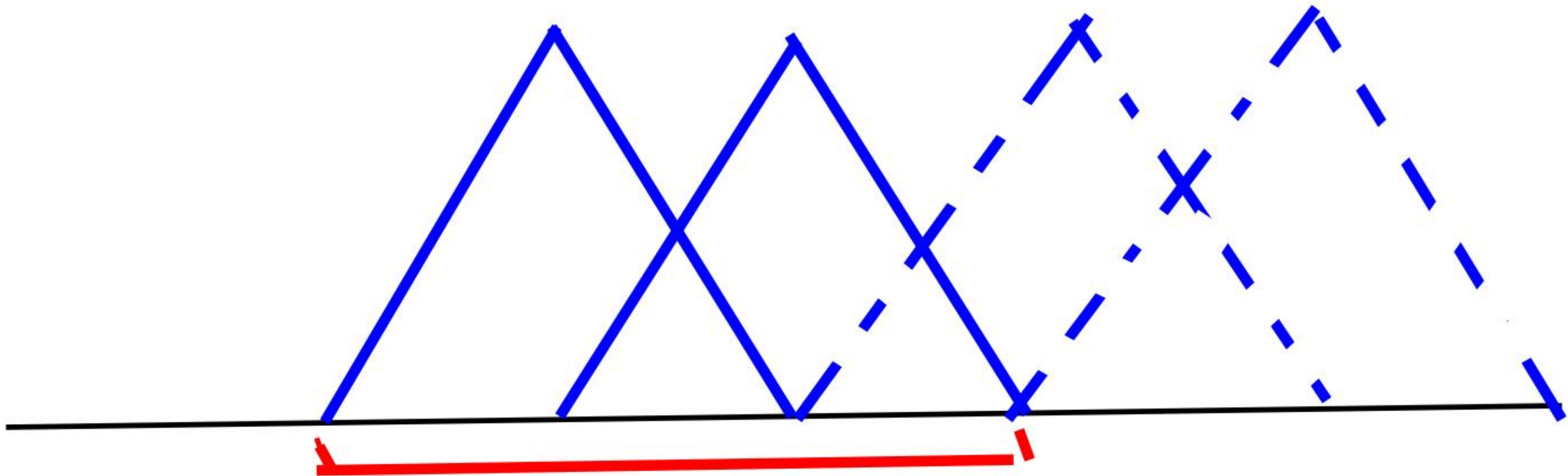


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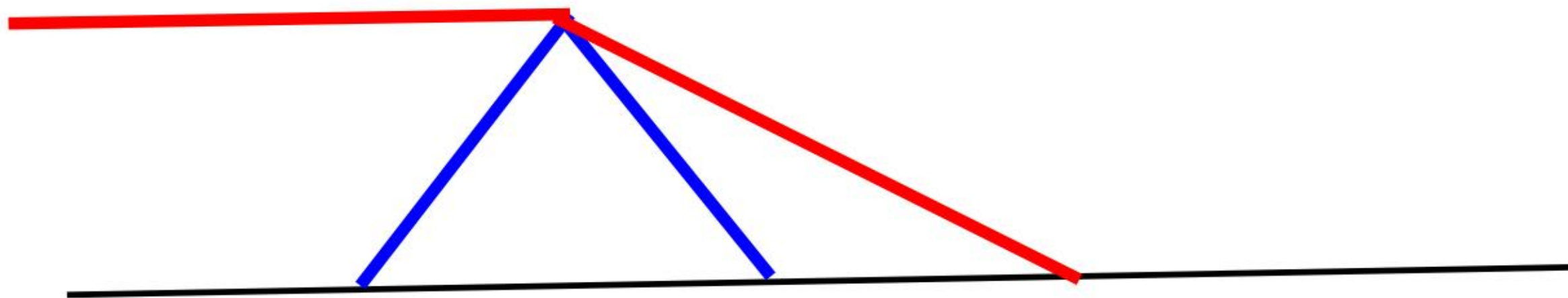


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Nevertheless, non-completeness is sometimes tolerated for the following reasons:

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- ◆ The input is impossible (then do not include it in the input space!).
- ◆ The input values are fuzzified so that they always overlap with some antecedent.
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The latter case can be formally described by an additional “**else rule**” [Amato, Di Nola, Navara 2003].

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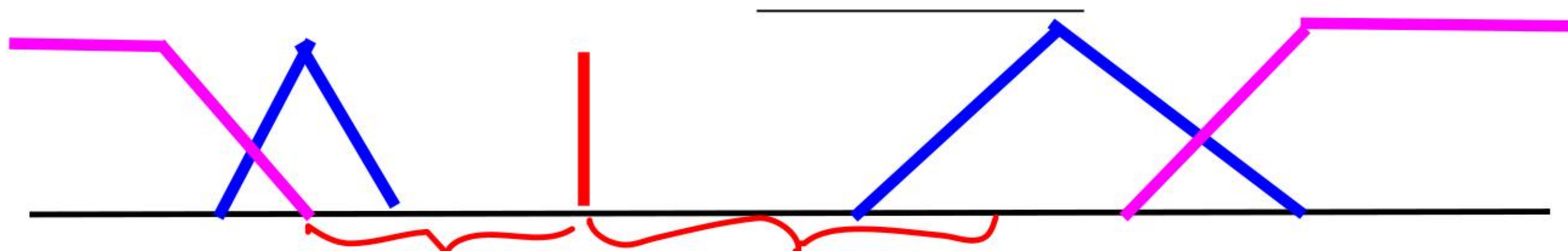
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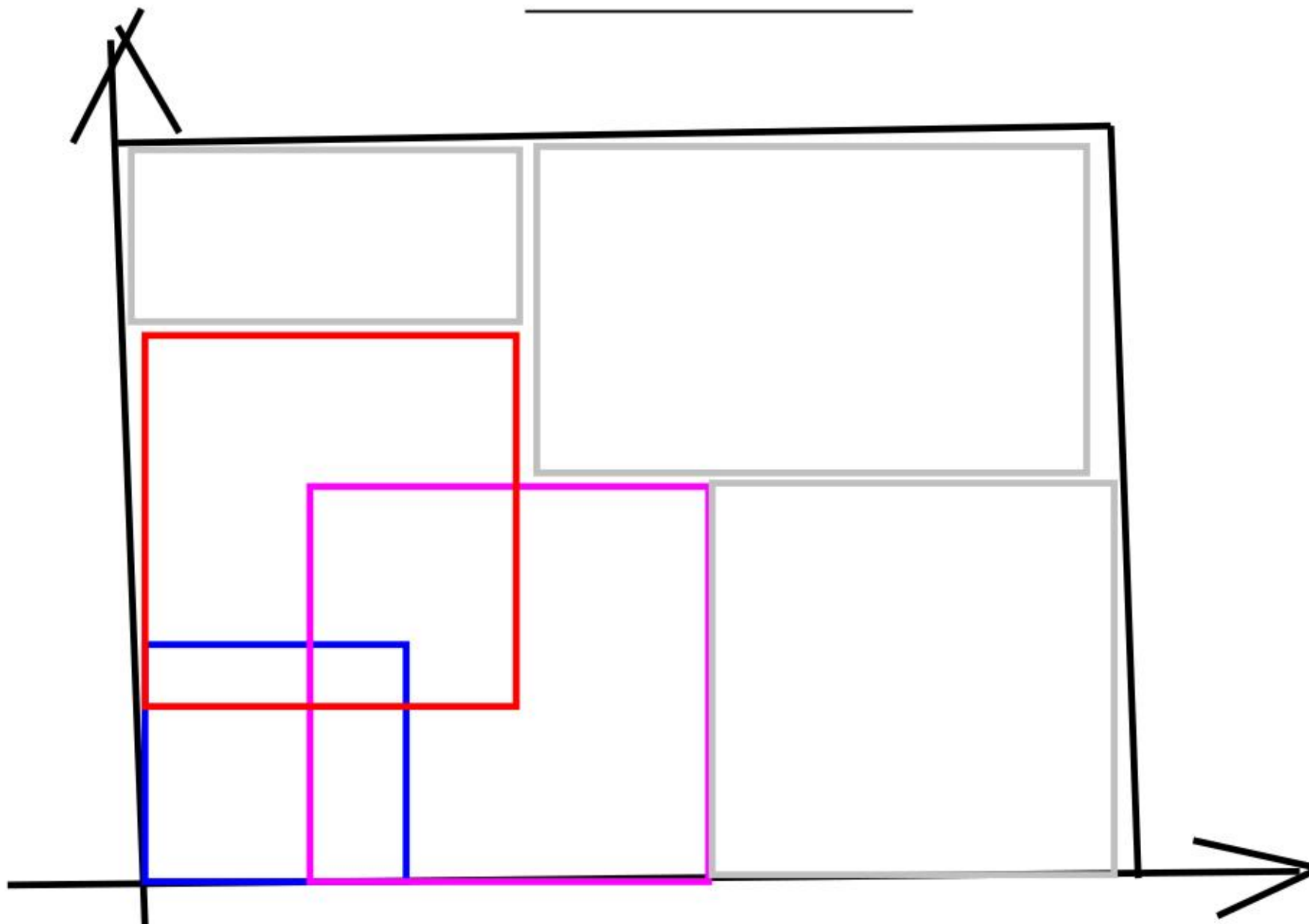
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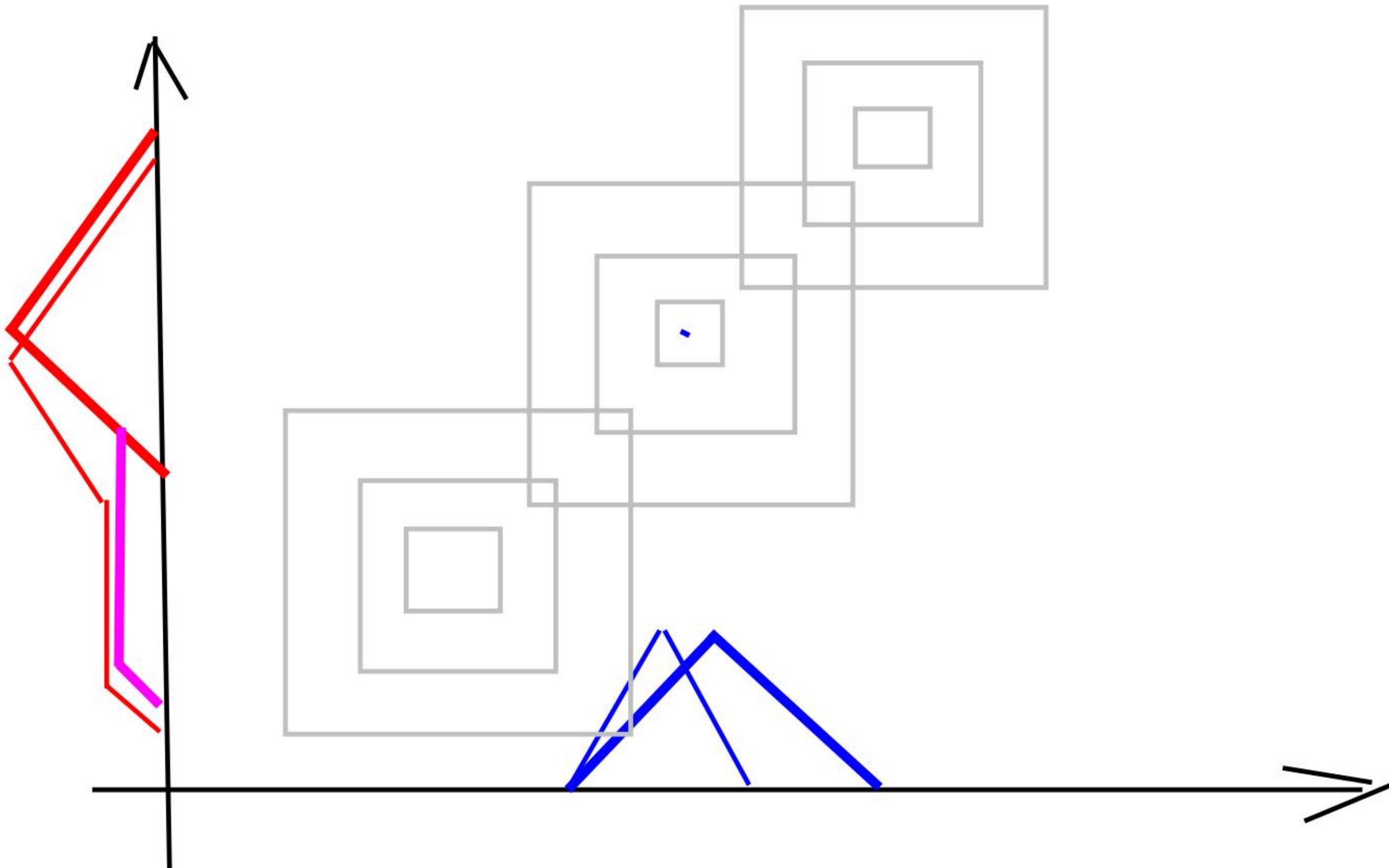


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For Mamdani–Assilian controller:

Theorem: $\forall j : \Phi_{\text{MA}}(A_j) \geq C_j$.

Proof: $X := A_j$,

$\mathcal{D}(X, A_j) = \mathcal{D}(A_j, A_j) = 1$ (due to normality),

$$\Phi_{\text{MA}}(A_j)(y) = \max_i (\mathcal{D}(A_j, A_i) \wedge C_i(y)) \geq \underbrace{\mathcal{D}(A_j, A_j)}_1 \wedge C_j(y) = C_j(y).$$

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Theorem [de Baets 1996, Perfilieva, Tonis 1997]: $(\forall j : \Phi_{\mathbf{MA}}(A_j) = C_j)$ iff $(\forall i \forall j : \mathcal{D}(A_i, A_j) \leq \mathcal{I}(C_i, C_j))$,
 where $\mathcal{I}(C_i, C_j) = \inf_y (C_i(y) \rightarrow C_j(y))$
 (the implication $\rightarrow$ has to be the residuum of $\wedge$).

Instead of $\mathcal{I}(C_i, C_j)$ we may use $\mathcal{E}(C_i, C_j) = \inf_y (C_i(y) \leftrightarrow C_j(y))$
 (**degree of indistinguishability (equality)**),
 where $\alpha \leftrightarrow \beta = \min(\alpha \rightarrow \beta, \beta \rightarrow \alpha) = (\alpha \rightarrow \beta) \wedge (\beta \rightarrow \alpha)$.

Proof: The negation of the left-hand side is

$$\begin{aligned}
 & \exists j \exists y : \Phi_{\mathbf{MA}}(A_j)(y) > C_j(y), \\
 & \exists j \exists y \exists x : A_j(x) \wedge R_{\mathbf{MA}}(x, y) > C_j(y), \\
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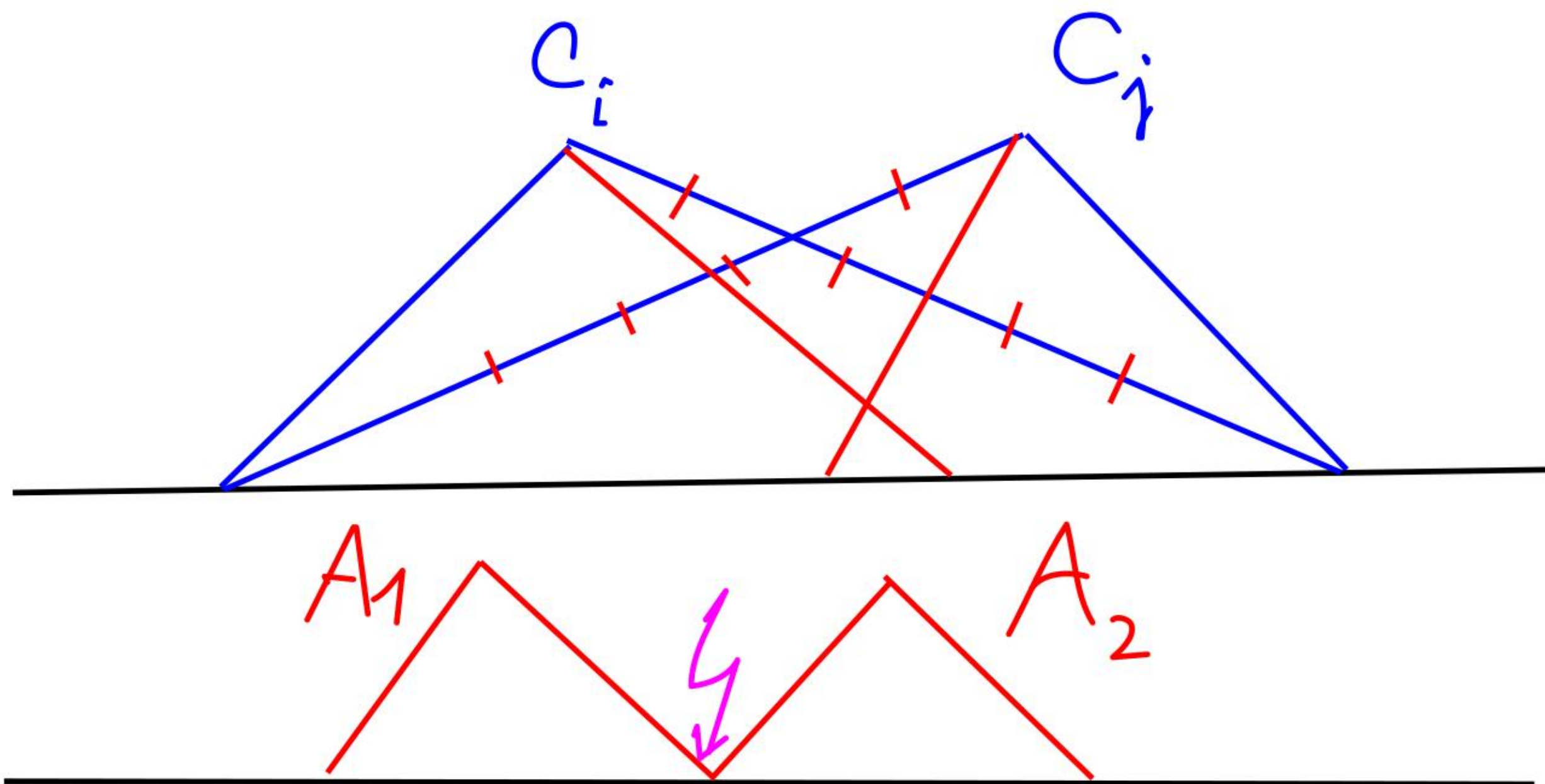
- ◆ $\mathcal{E}(C_i, C_j) > 0$; then $\text{Supp } C_i = \text{Supp } C_j$, which is rather unusual,
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Correctness of residuum-based controller

Theorem: $\forall j : \Phi_{\text{RES}}(A_j) \leq C_j$.

Proof: $X := A_j$,

$$\begin{aligned} \Phi_{\text{RES}}(A_j)(y) &= \sup_x (A_j(x) \wedge \min_i (A_i(x) \rightarrow C_i(y))) \\ &\leq \sup_x (A_j(x) \wedge (A_j(x) \rightarrow C_j(y))) \leq C_j(y). \end{aligned}$$

Theorem: If there is a fuzzy relation R such that $\forall j : A_j \circ R = C_j$, then also R_{RES} satisfies these equalities (and it is the largest solution).

Proof: $\forall j \forall x \forall y :$

$$\begin{aligned} A_j(x) \wedge R(x, y) &\leq C_j(y) \\ R(x, y) &\leq A_j(x) \rightarrow C_j(y) \\ R(x, y) &\leq \min_i (A_i(x) \rightarrow C_i(y)) = R_{\text{RES}}(x, y), \end{aligned}$$

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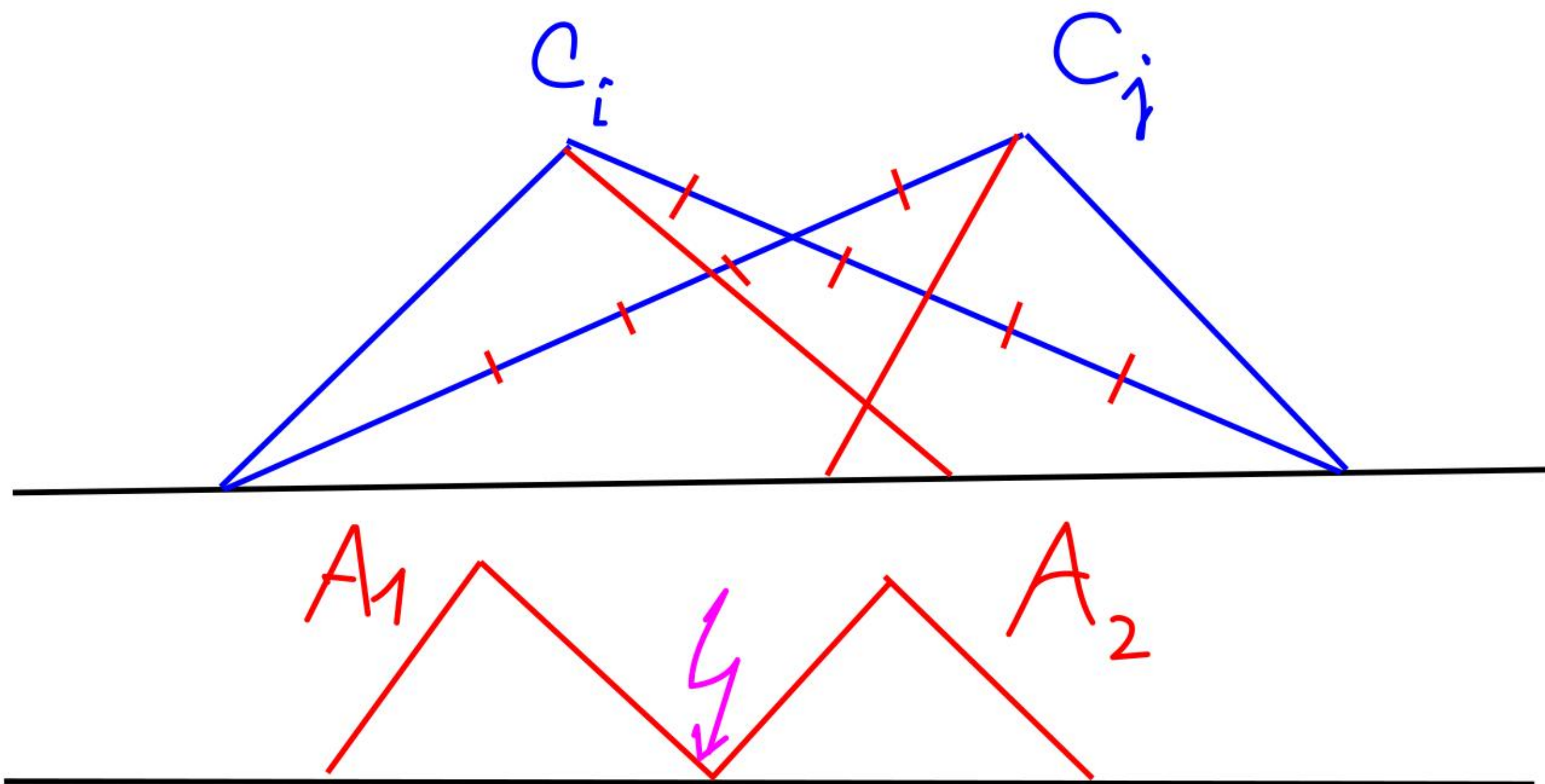
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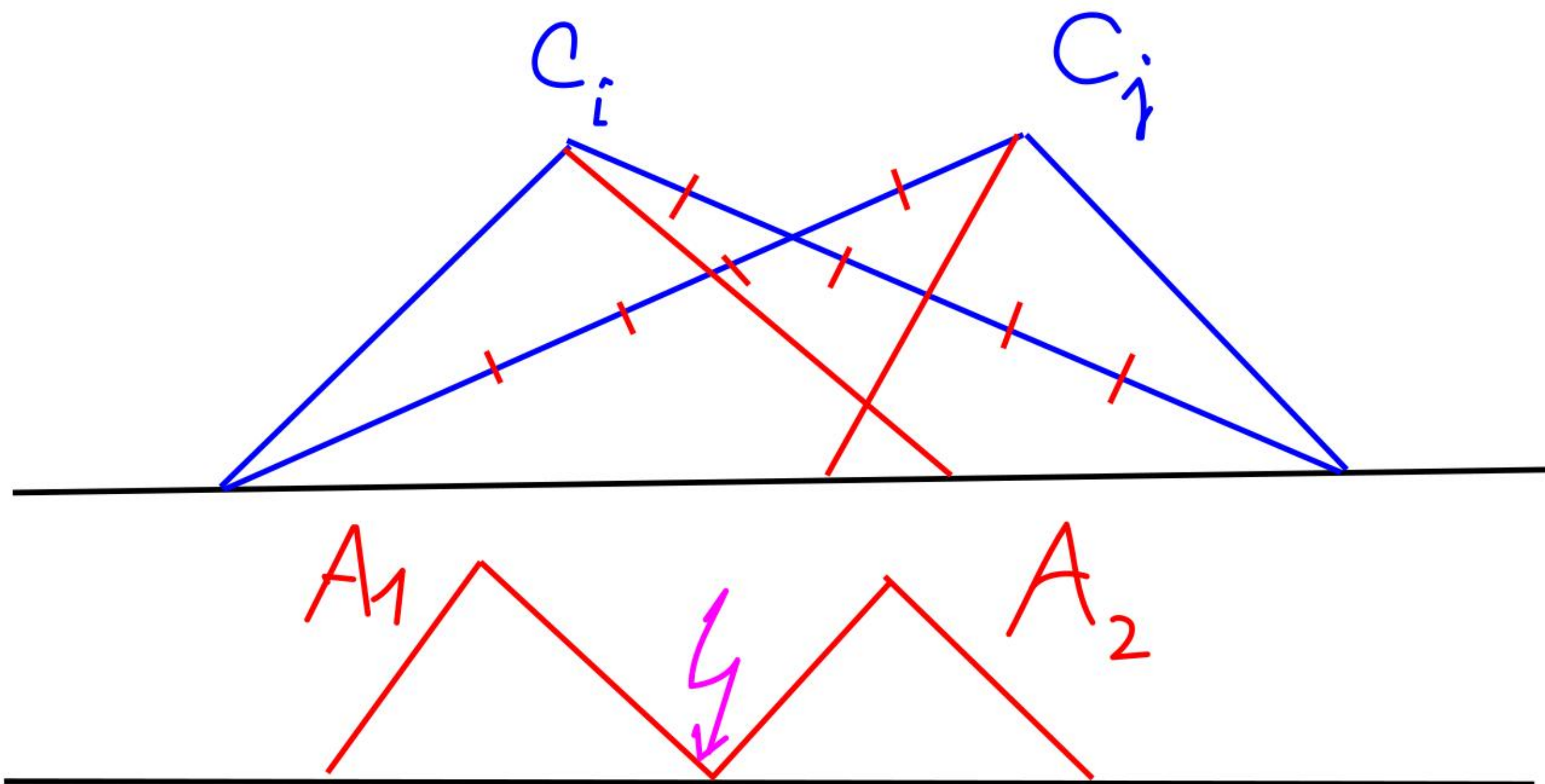


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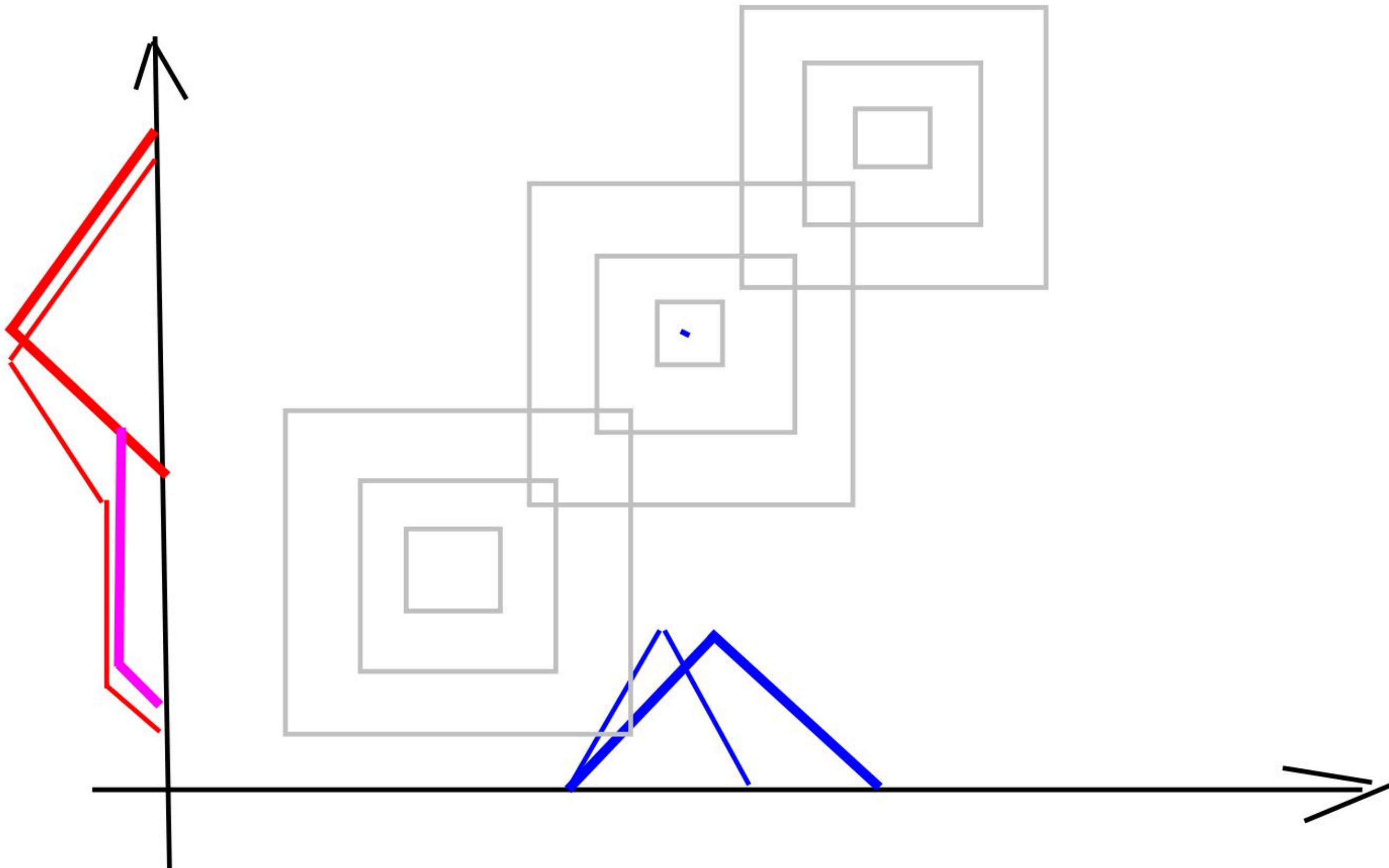
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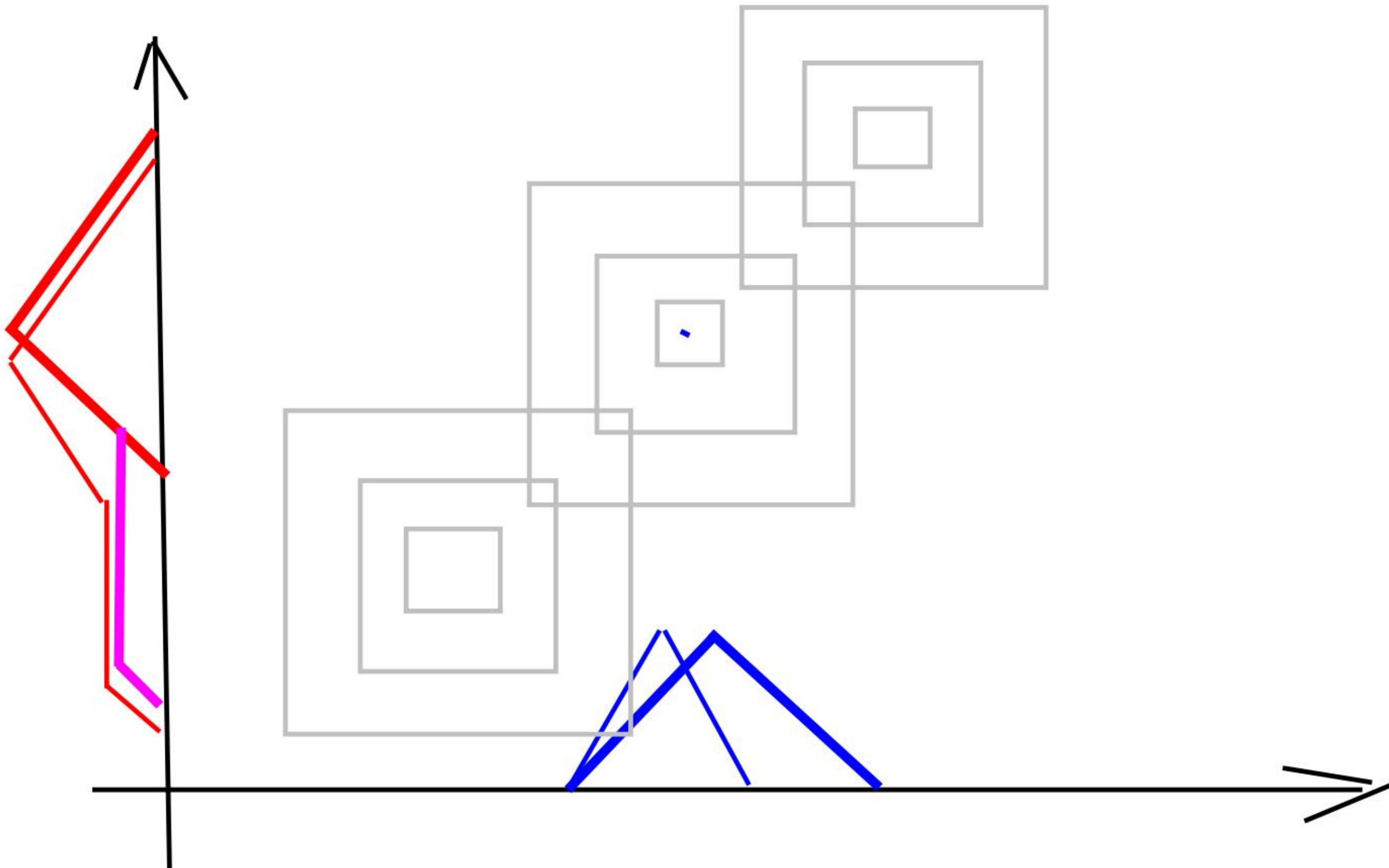
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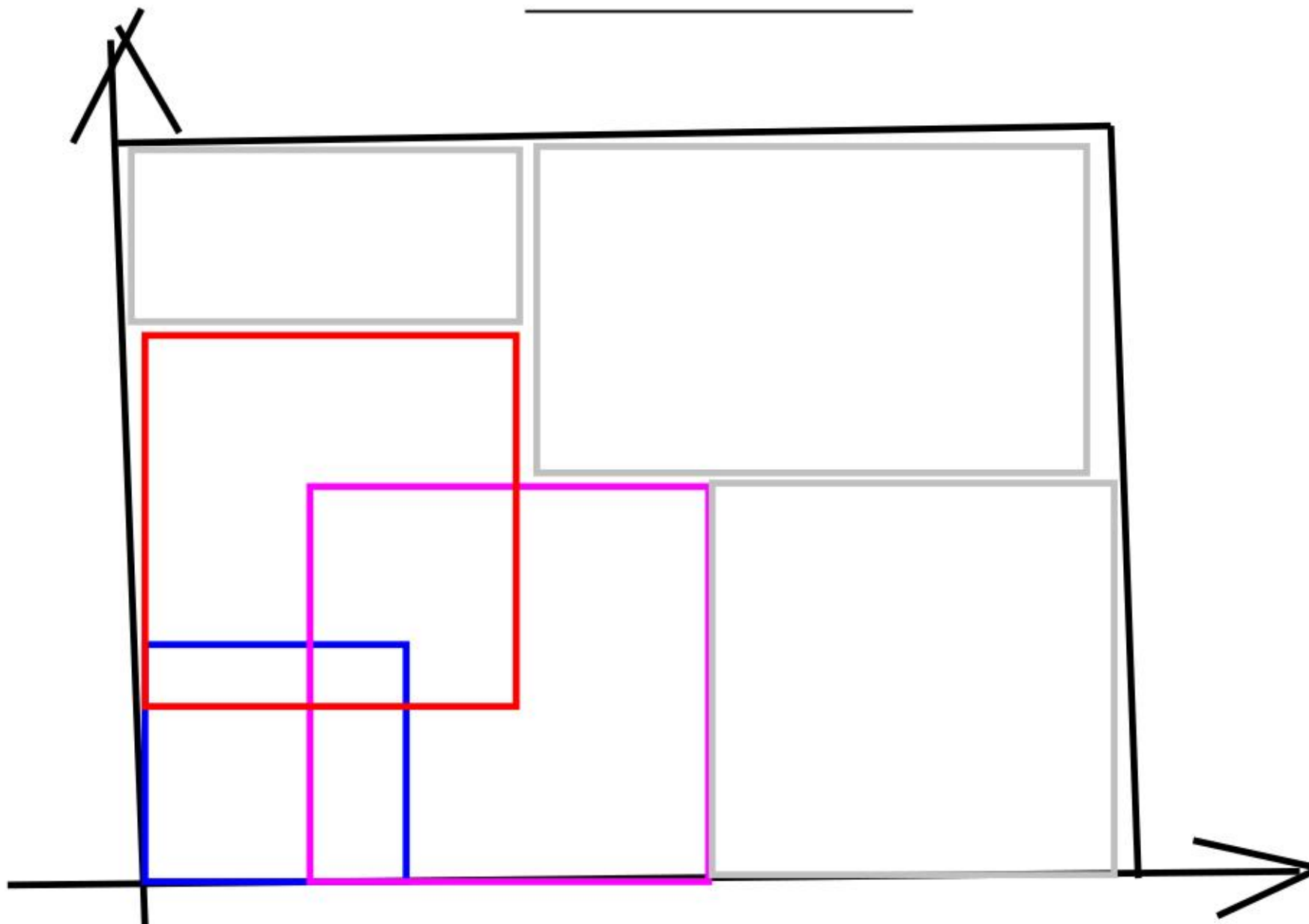


Completeness of the rule base

Omitting rules for some situations is motivated by the attempt to reduce the number of rules (**curse of dimensionality**).

Sometimes the table of linguistic rules does not cover some combinations of linguistic variables.

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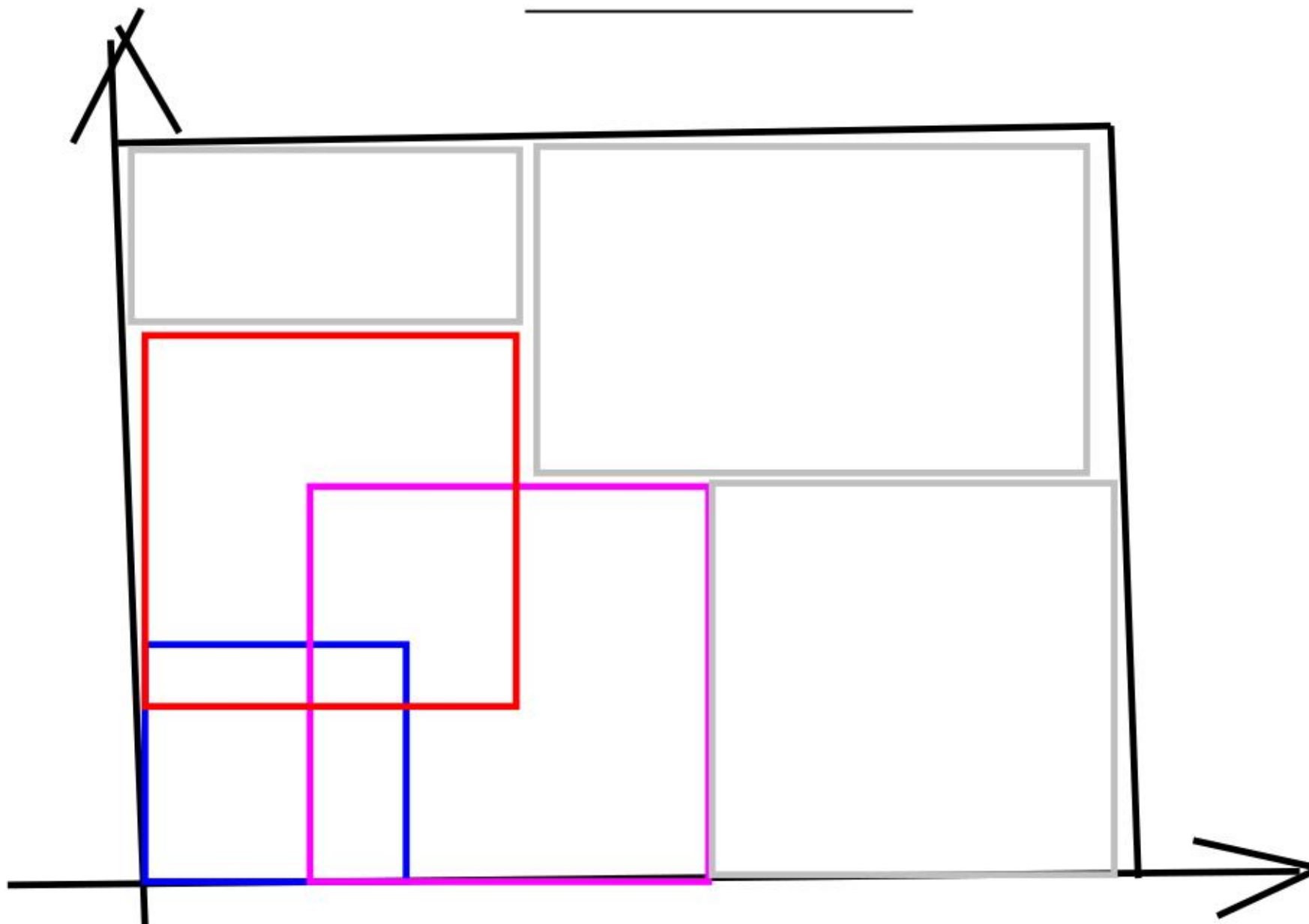


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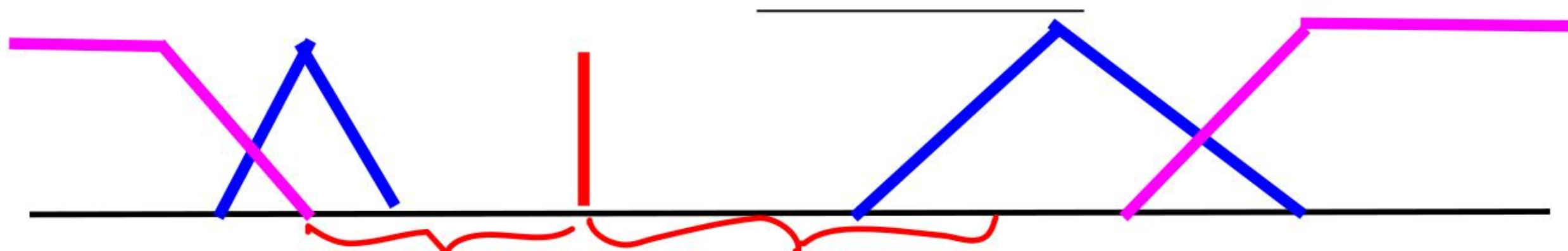
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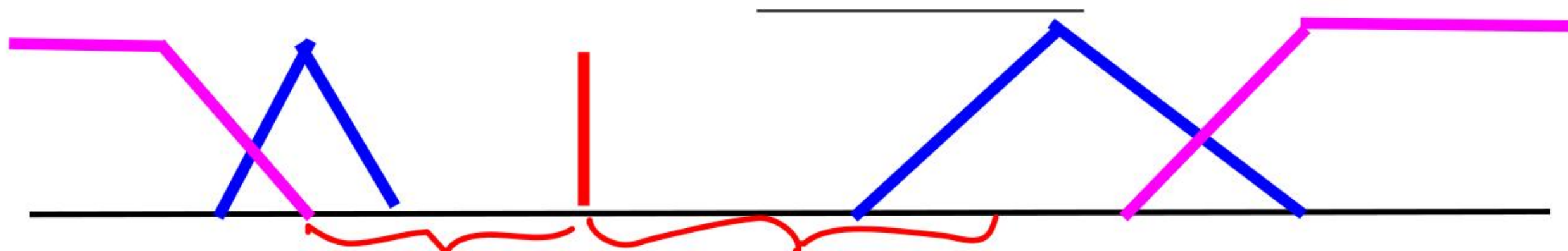
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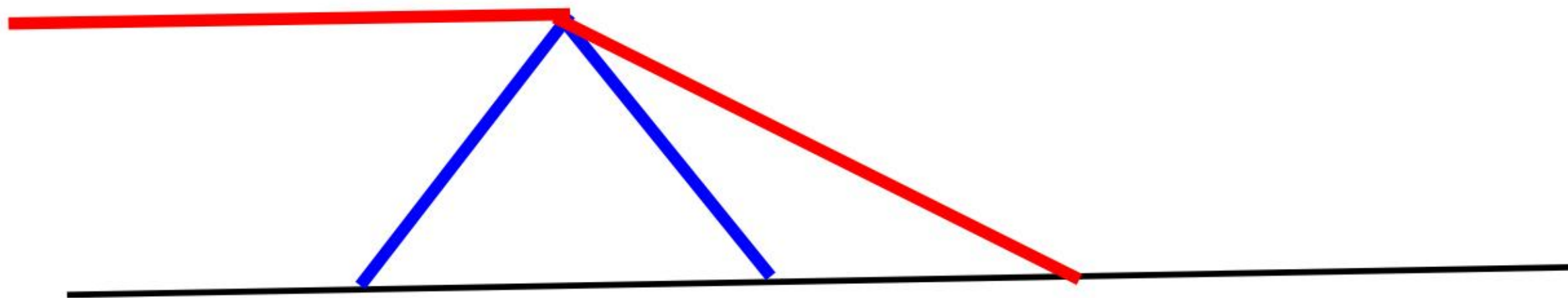
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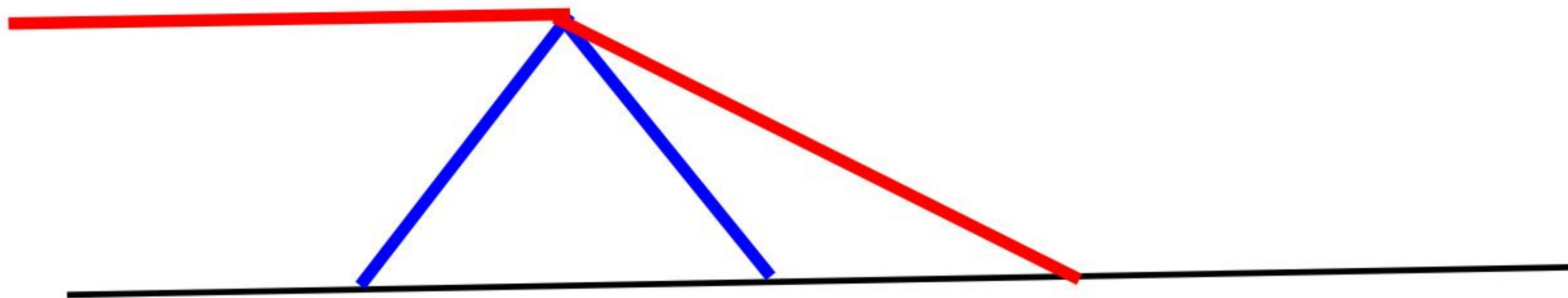
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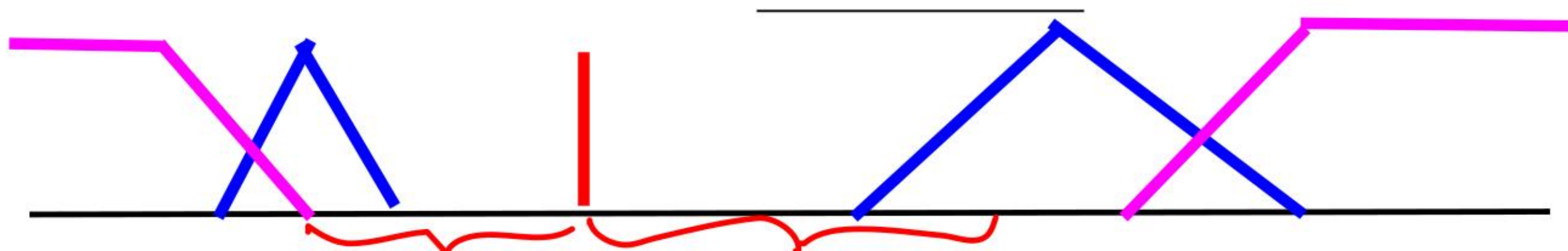
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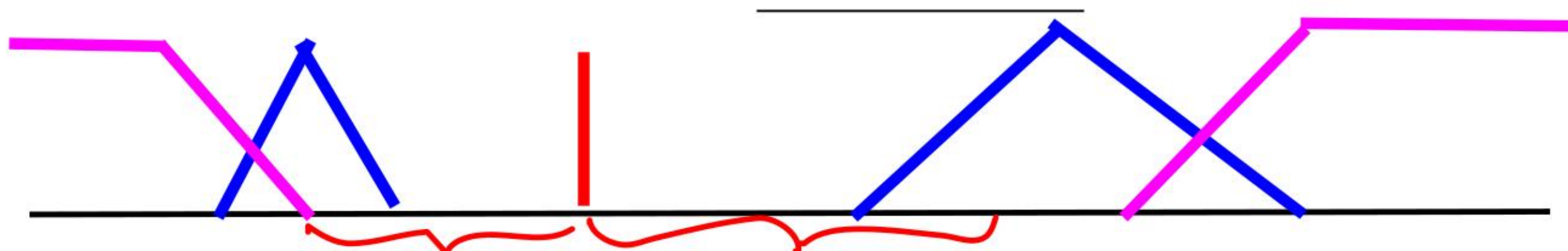
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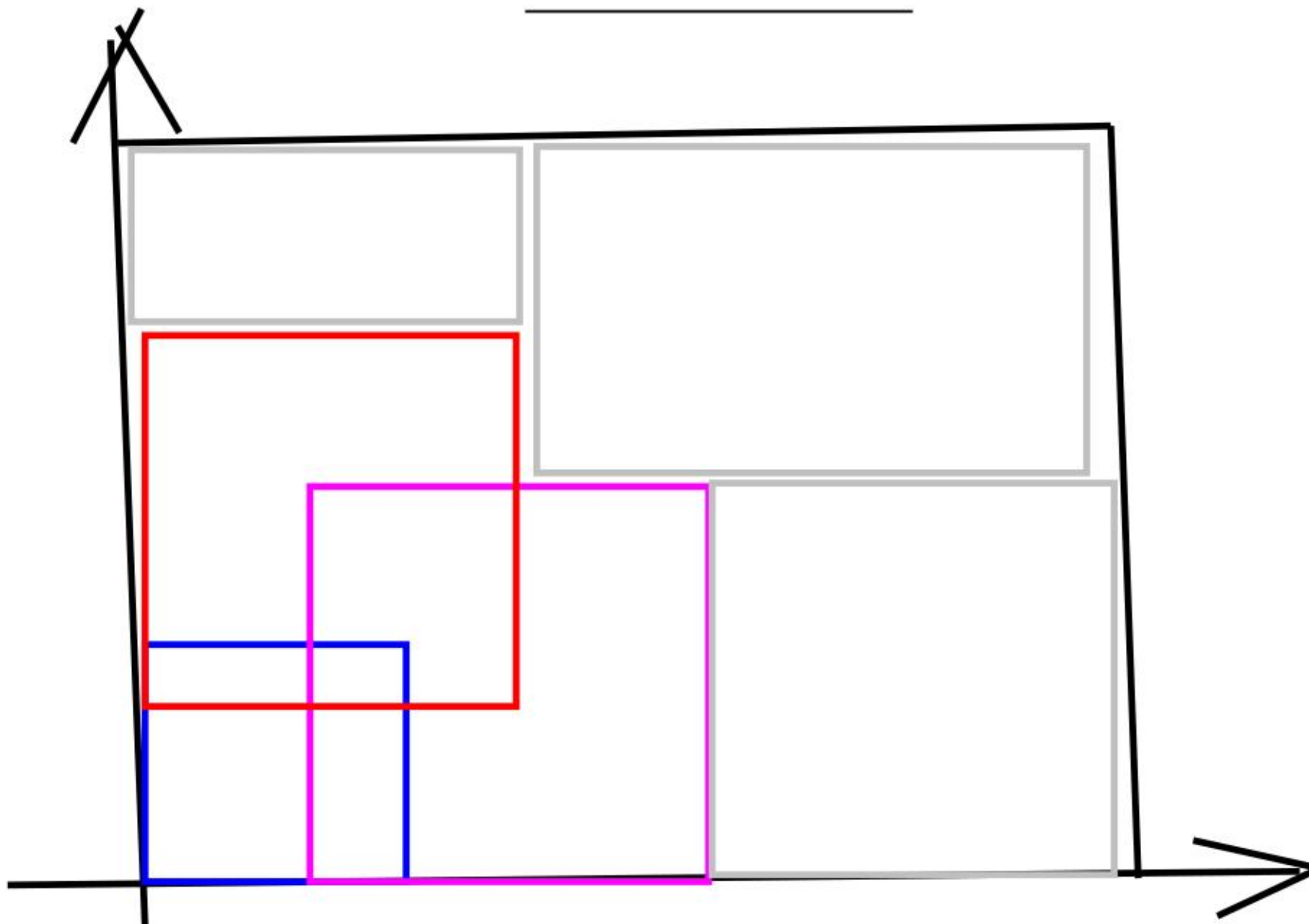


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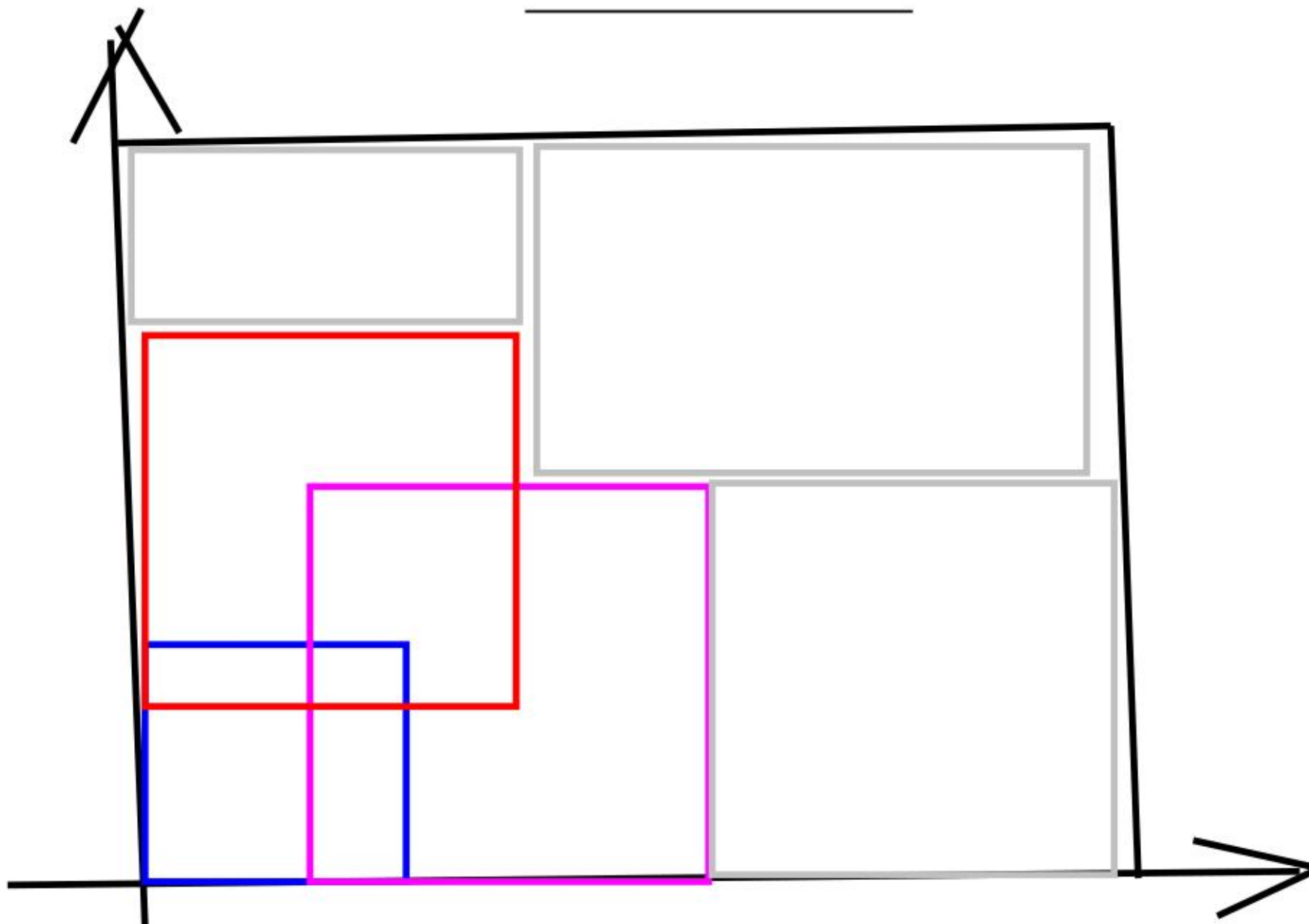


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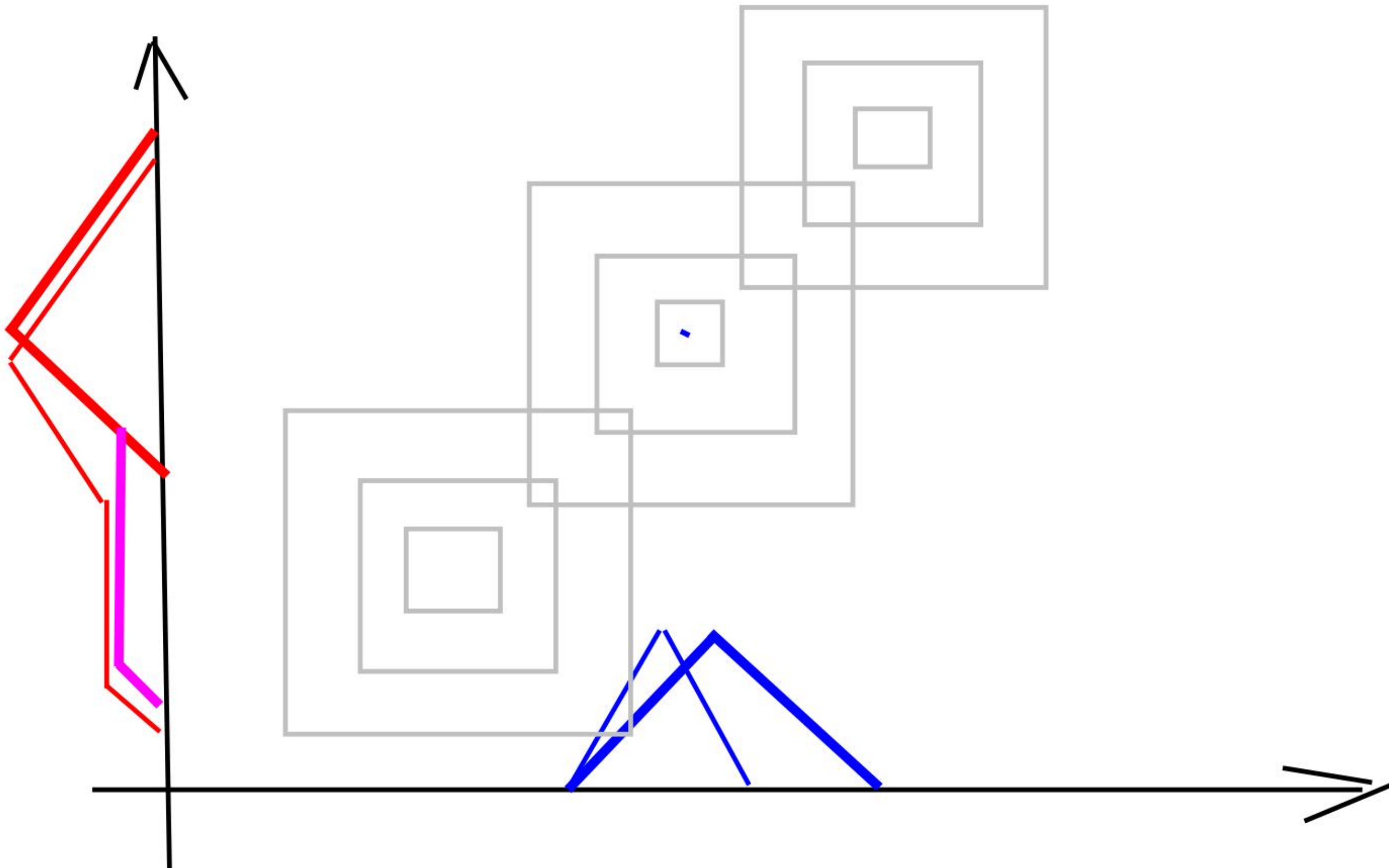
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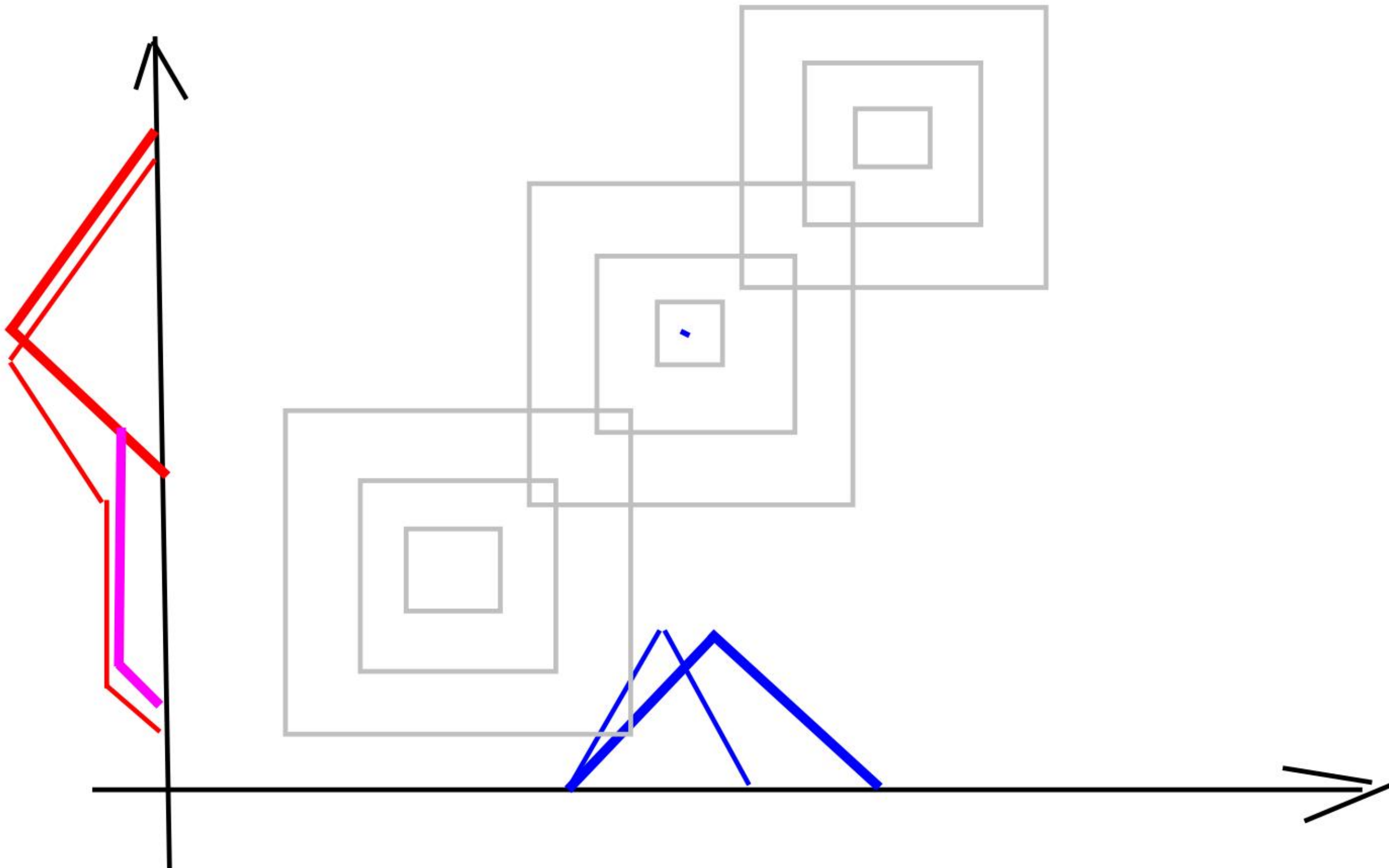
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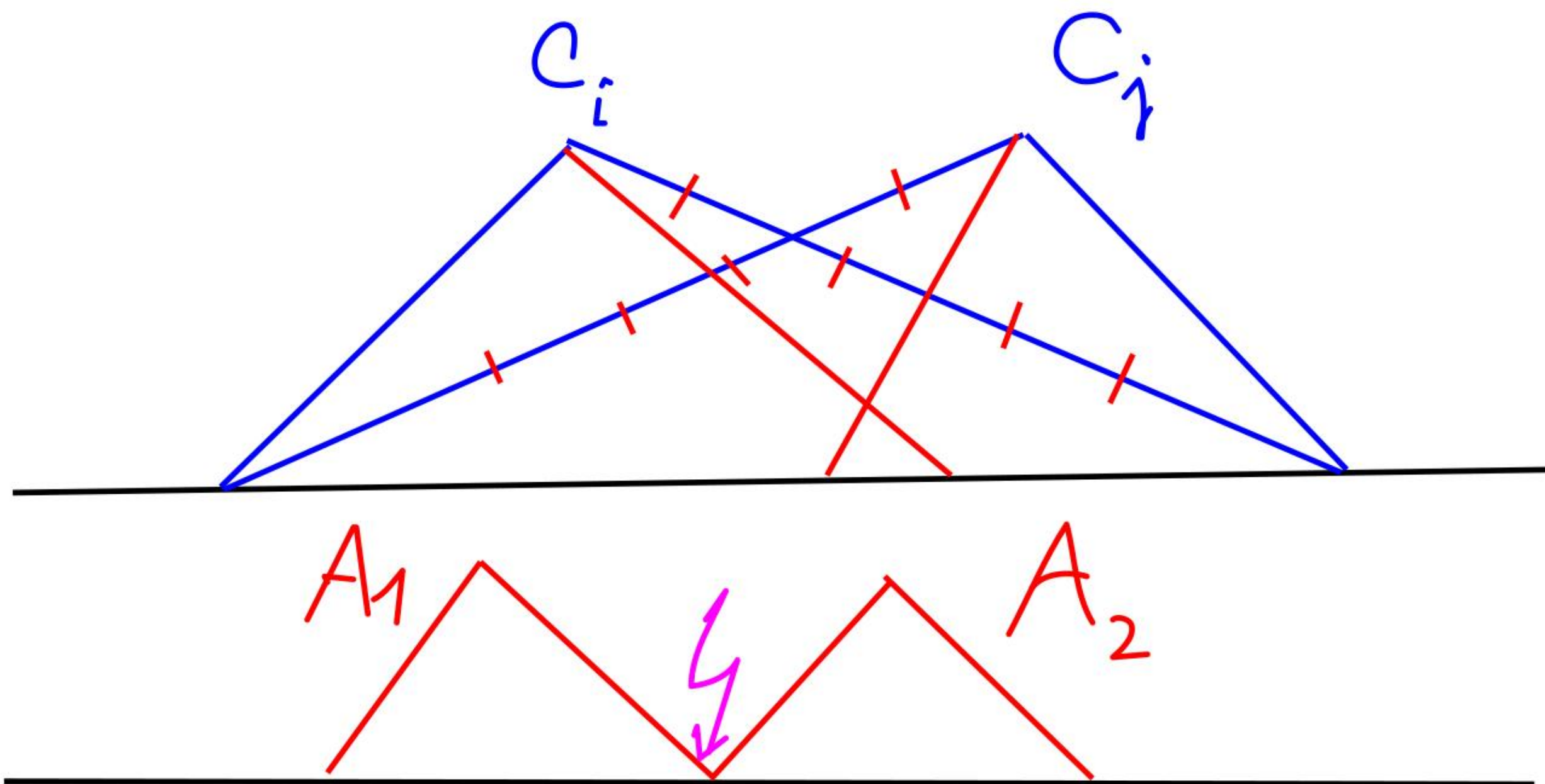
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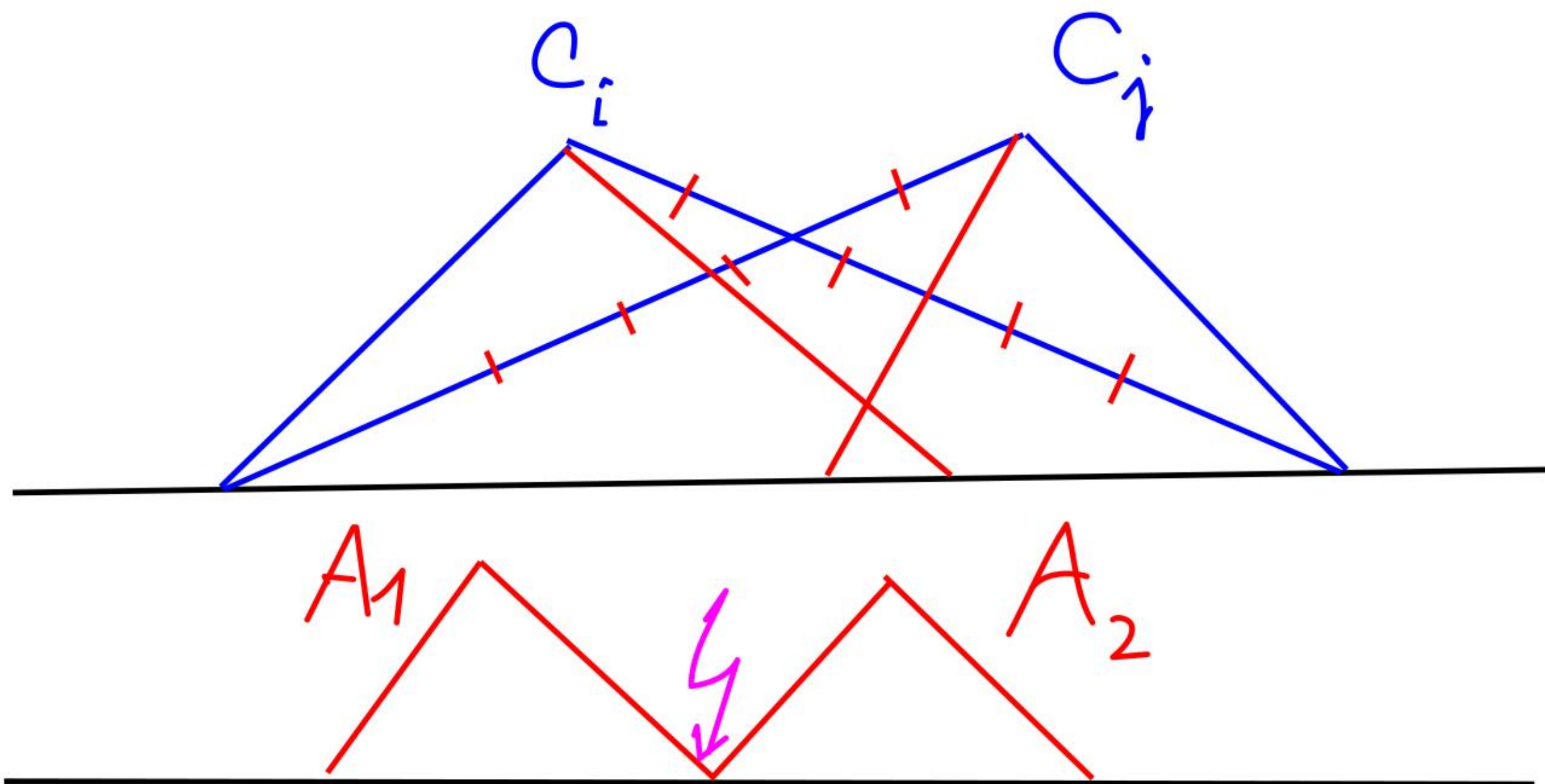


Correctness of Mamdani–Assilian controller

[Moser, Navara 1999]

If $\wedge$ has no zero divisors (e.g., the minimum or product), then $\mathcal{D}(A_i, A_j) \leq \mathcal{E}(C_i, C_j)$ is satisfied in two situations:

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However, this choice may easily violate the strong completeness [Moser, Navara 1999].

Correctness of residuum-based controller

Theorem: $\forall j : \Phi_{\text{RES}}(A_j) \leq C_j$.

Proof: $X := A_j$,

$$\begin{aligned} \Phi_{\text{RES}}(A_j)(y) &= \sup_x (A_j(x) \wedge \min_i (A_i(x) \rightarrow C_i(y))) \\ &\leq \sup_x (A_j(x) \wedge (A_j(x) \rightarrow C_j(y))) \leq C_j(y). \end{aligned}$$

Theorem: If there is a fuzzy relation R such that $\forall j : A_j \circ R = C_j$, then also R_{RES} satisfies these equalities (and it is the largest solution).

Proof: $\forall j \forall x \forall y :$

$$\begin{aligned} A_j(x) \wedge R(x, y) &\leq C_j(y) \\ R(x, y) &\leq A_j(x) \rightarrow C_j(y) \\ R(x, y) &\leq \min_i (A_i(x) \rightarrow C_i(y)) = R_{\text{RES}}(x, y), \end{aligned}$$

$$C_j = A_j \circ R \leq A_j \circ R_{\text{RES}} \leq C_j.$$



What happens if correctness is violated?

Nothing serious, this is usually accepted and possibly compensated during the tuning.

However, it causes a distorted interpretation of (possibly good) control rules.

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An alternative: **CFR (Controller with conditionally firing rules)** [Moser, Navara 2002]

1st generalization of Mamdani–Assilian controller:

$\varrho: [0, 1] \rightarrow [0, 1]$... increasing bijection, e.g., $\varrho(t) = t^r$, $r > 1$, or piecewise linear.
Transformation of membership degrees in the input space $\mathcal{X}$.

The degrees of overlapping, $\mathcal{D}(A_i \circ \varrho, A_j \circ \varrho)$, may be made arbitrarily small.

2nd generalization of Mamdani–Assilian controller:

$\sigma: [0, 1] \rightarrow [c, 1]$... increasing bijection
($0 < c < 1$).

Transformation of membership degrees in the output space $\mathcal{Y}$.

Output $Y \circ \sigma$ has to be transformed back by $\sigma^{[-1]}$,

so the inference rule is not compositional

(however, the computational complexity remains of the same order).

The degrees of equality, $\mathcal{E}(C_i \circ \sigma, C_j \circ \sigma)$, may be made arbitrarily large.

We may satisfy $\mathcal{D}(A_i \circ \varrho, A_j \circ \varrho) \leq \mathcal{E}(C_i \circ \sigma, C_j \circ \sigma)$.

Problem 1: $\mathcal{D}(X \circ \varrho, A_i \circ \varrho)$ becomes also small, causing “irrelevant outputs” and violating strong completeness.

Problem 2: Correctness and strong completeness are “almost contradictory” for the Mamdani–Assilian controller; sometimes they cannot be satisfied simultaneously for any compositional inference rule.

An alternative: CFR (Controller with conditionally firing rules)

So far, we obtained a special case of the generalized FATI inference rule, where $\pi_i(a, b) = \varrho(a) \wedge \sigma(b)$, $\beta = \max$, $\kappa(a, b) = \varrho(a) \wedge b$, $Q = \sup \circ \sigma^{[-1]}$.

However, we need:

3rd generalization of Mamdani–Assilian controller:

For the **degree of firing** in the inference rule, replace the **degree of overlapping** $\mathcal{D}(X, A_i)$ with the normalized value — **degree of conditional firing**

$$\mathcal{C}_i(X) = \frac{\mathcal{D}(X, A_i)}{\max_j \mathcal{D}(X, A_j)}.$$

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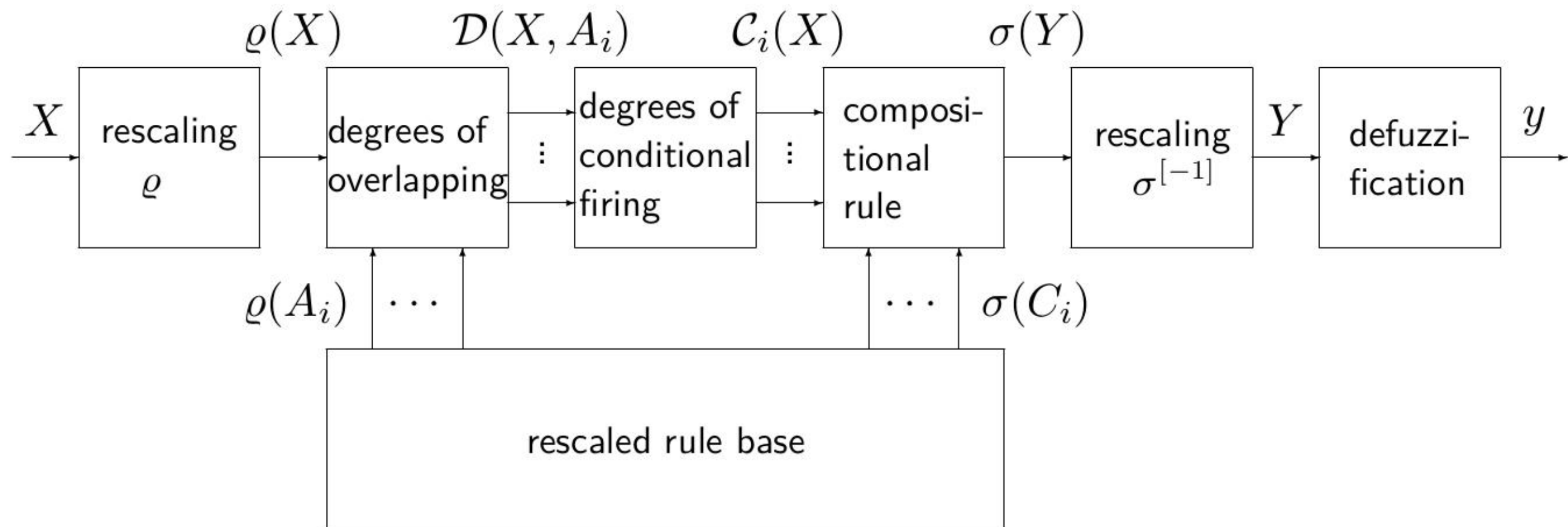
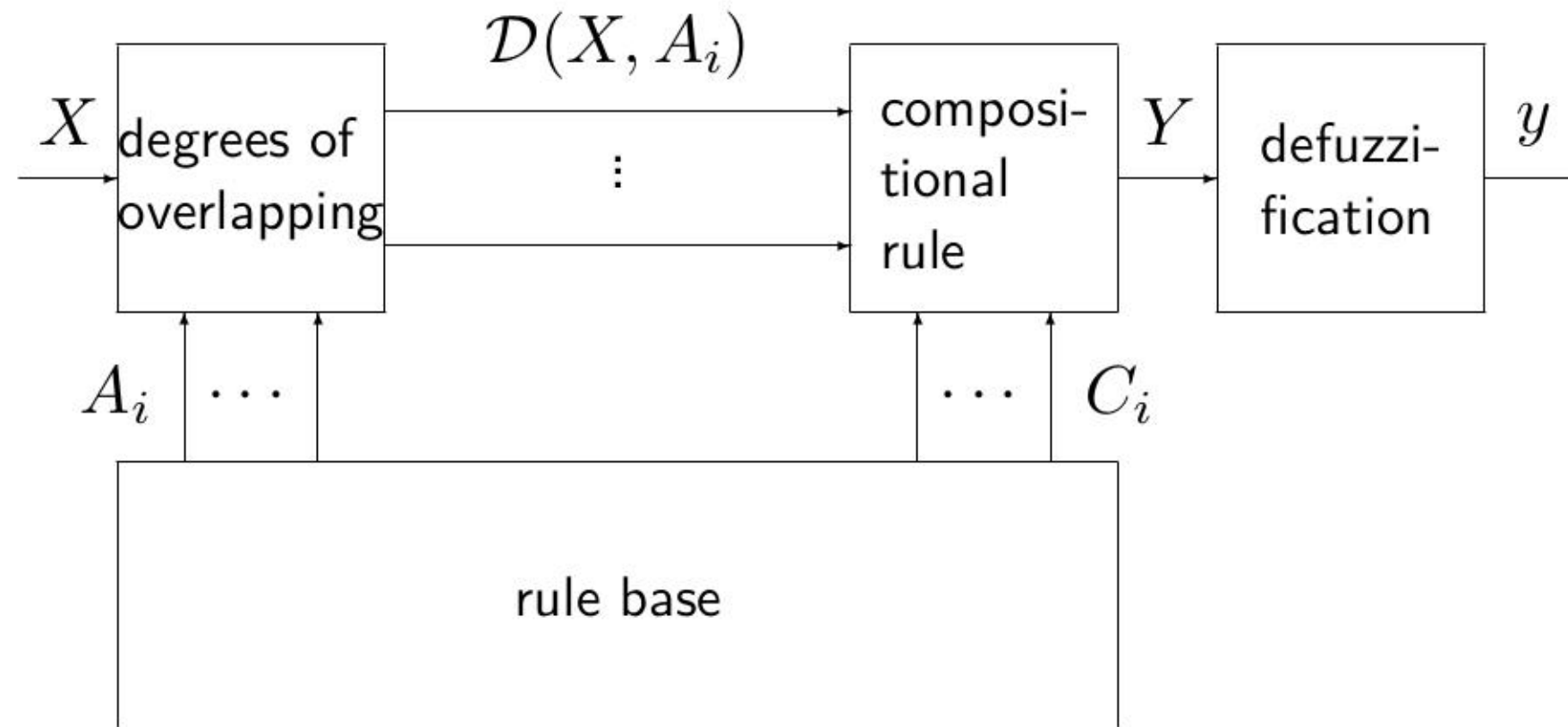
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- [C1] Each antecedent is normal.
 - [C2] Each point of the input space belongs to the support of some antecedent.
 - [C3] No consequent is covered by the maximum all other consequents.
 - [C4] “Weak disjointness of antecedents”: $\exists c < 1 : A_i(x) \wedge A_j(x) < c$ whenever $i \neq j$.
-

Comparison of Mamdani–Assilian and CFR controller — block diagrams



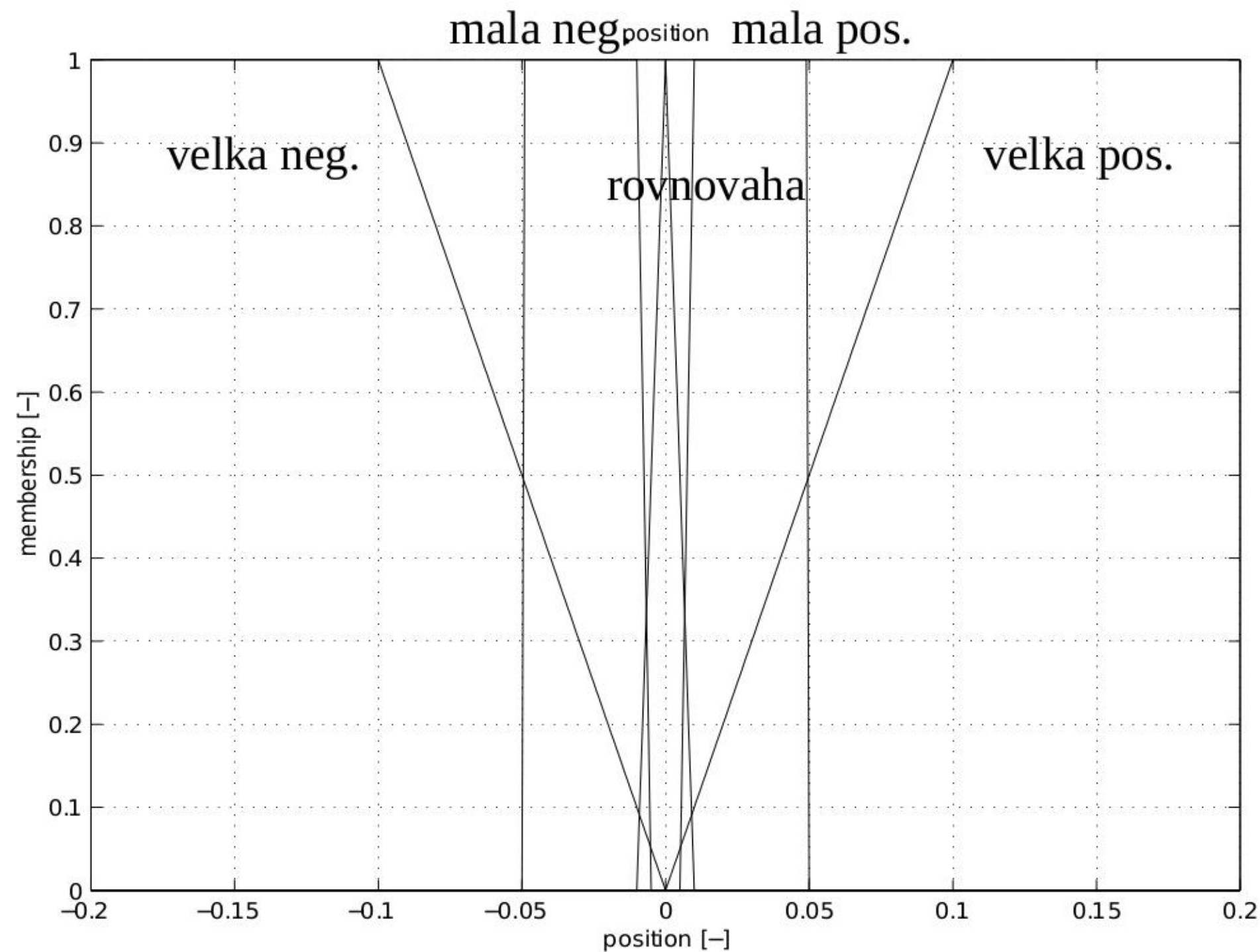
Sample problem: ball on beam (ball on plate)

We want to stabilize a position of a ball by leaning a plate on which it lies.

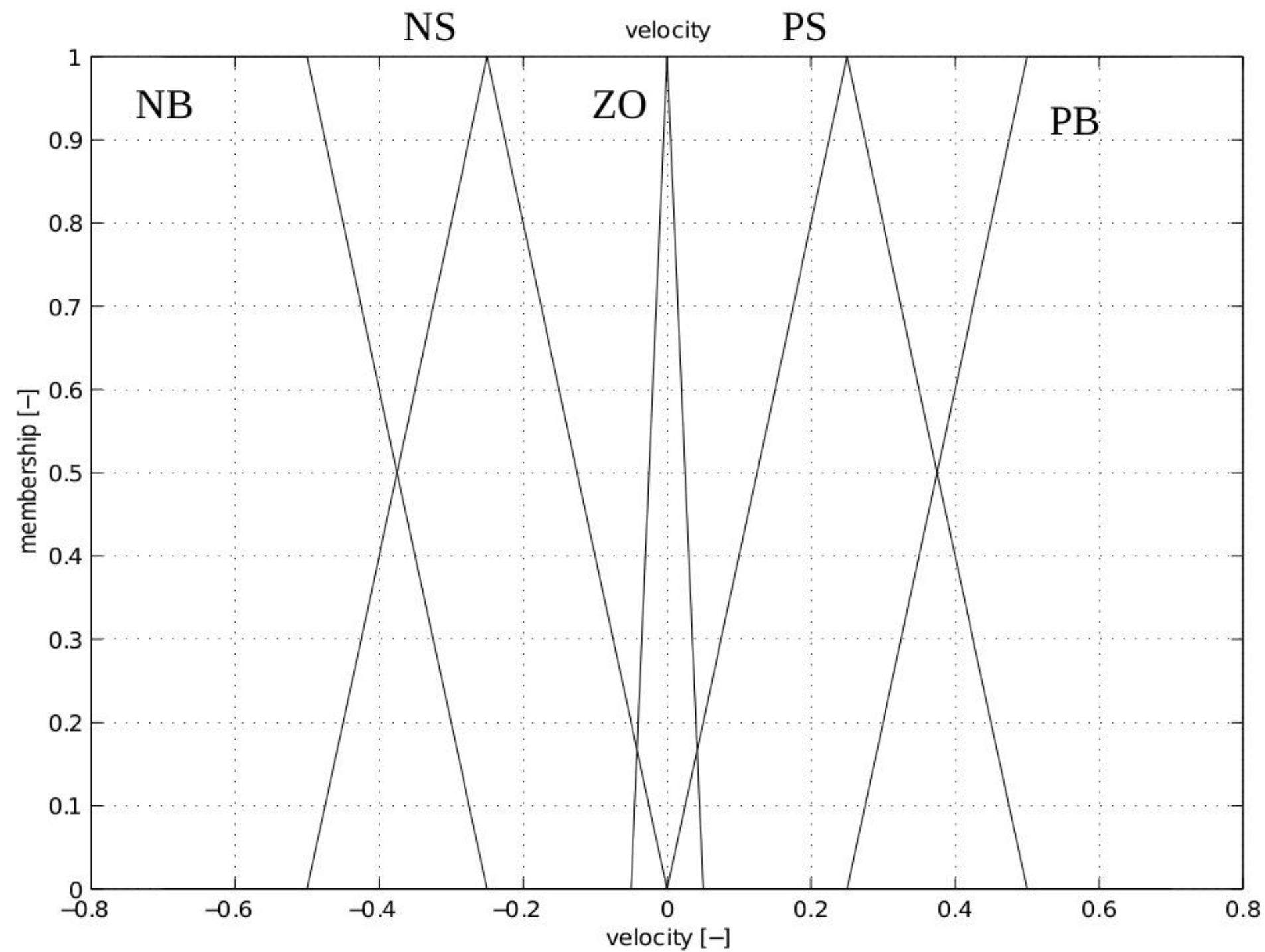
Static friction is considered ($\Rightarrow$ non-linearity).

Solution due to [Št'astný 2001].

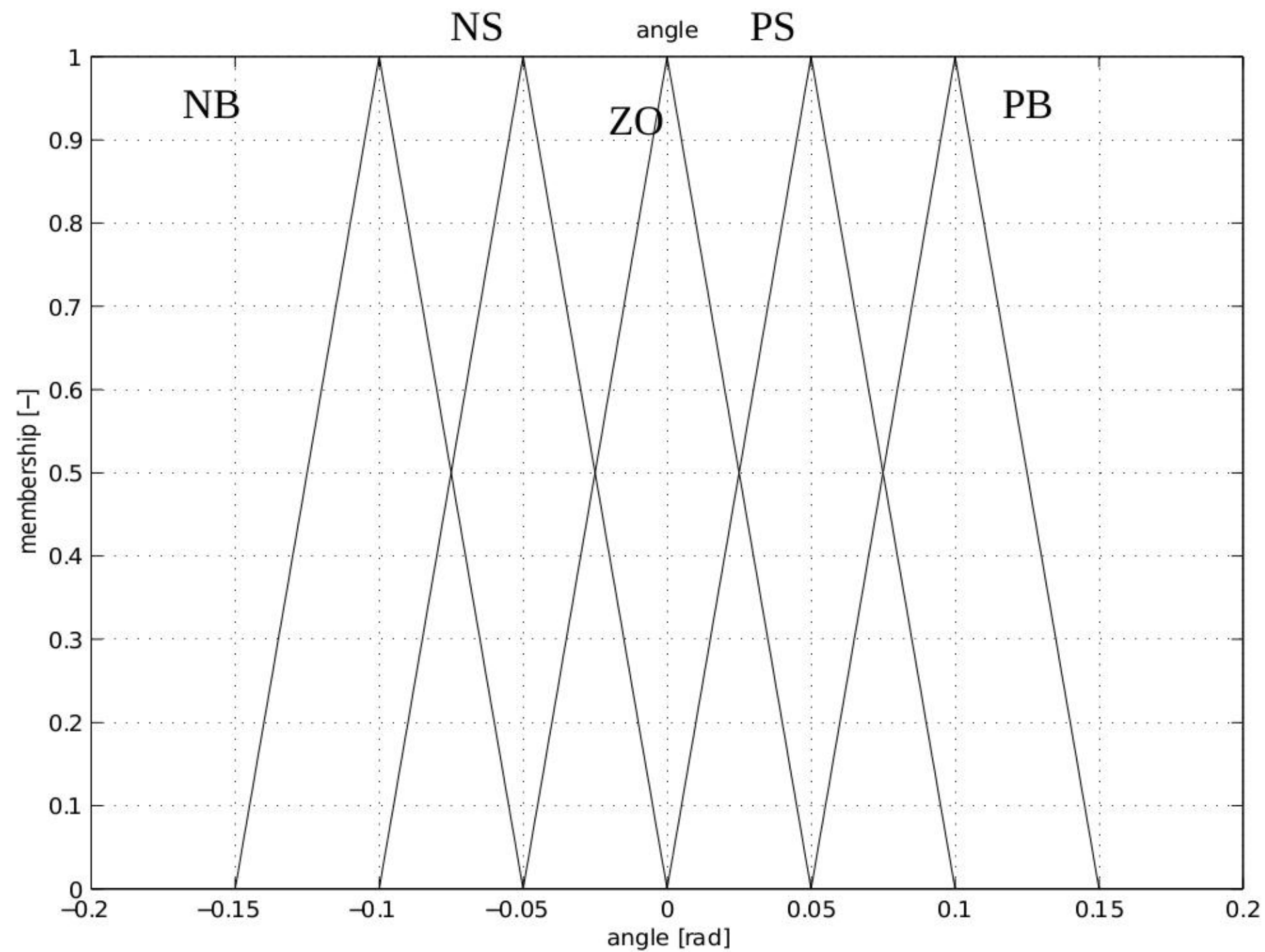
Example: Comparison of Mamdani–Assilian and CFR controller — position (premises)



Example: Comparison of Mamdani–Assilian and CFR controller — velocity (premises)



Example: Comparison of Mamdani–Assilian and CFR controller — angle (consequents)



Example: Comparison of Mamdani–Assilian and CFR controller — rules

Angle:

position velocity	NB	NS	ZO	PS	PB
NB	PB	PB	PB	PB	PS
NS	PB	PS	PS	PS	ZO
ZO	PB	PB	ZO	NB	NB
PS	ZO	NS	NS	NS	NB
PB	NS	NB	NB	NB	NB

Example: Comparison of Mamdani–Assilian and CFR controller — quality of control

criterion	Mam. controller	CFR controller
maximum overshoot [m] σ	-	-
asymptotic value [m] y_∞	-0.0021	0.0012
number of extremes [-]	-	-
transient time [s]	3.56	3.05
cumulative quadratic error [ms]	0.0552	0.0569

Ball on plate, **initial position +0.25**, simulation time 5 s — till steady state. Smaller values – better control. $T_{OUT} = 100\text{ ms}$.

criterion	Mam. controller	CFR controller
maximum overshoot [m] σ	-	-
asymptotic value [m] y_∞	-0.0052	-0.0006
number of extremes [-]	-	-
transient time [s]	18.06	17.22
cumulative quadratic error [ms]	23.12	22.34

Ball on plate, **initial position +2.00**, simulation time 20 s — till steady state. Smaller values – better control. $T_{OUT} = 100\text{ ms}$.

Example: Comparison of Mamdani–Assilian and CFR controller — quality of control

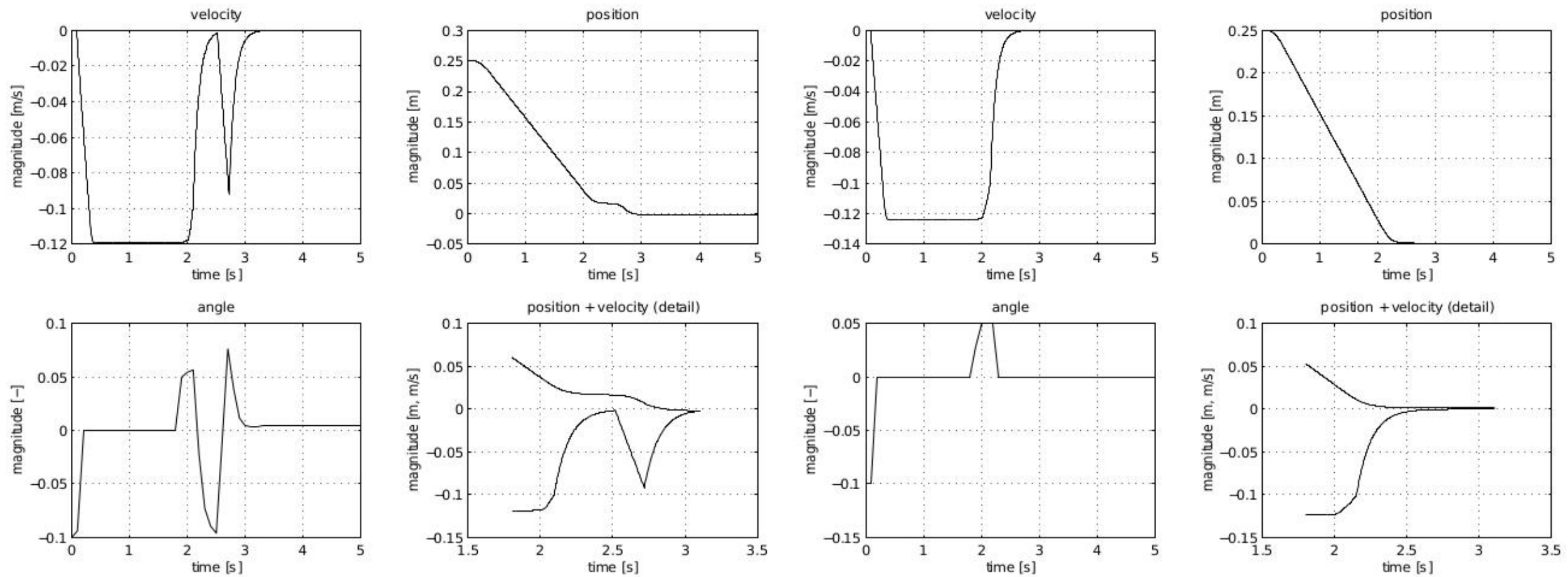
criterion	Mam. controller	CFR controller
maximum overshoot [m] σ	0.35	0.35
asymptotic value [m] y_∞	-0.0032	-0.0041
number of extremes [-]	1	1
transient time [s]	13.49	11.39
cumulative quadratic error [ms]	0.523	0.474

Ball on plate, **initial speed $0.5ms^{-1}$** , simulation time $15\,s$ — till steady state. Smaller values – better control. $T_{OUT} = 50\,ms$.

criterion	Mam. controller	CFR controller
maximum overshoot [m] σ	0.346	0.346
asymptotic value [m] y_∞	0.0051	0.0034
number of extremes [-]	1	1
transient time [s]	14.8	11.1
cumulative quadratic error [ms]	0.583	0.441

Ball on plate, **initial speed $0.5ms^{-1}$** , simulation time $15\,s$ — till steady state. Smaller values – better control. $T_{OUT} = 5\,ms$.

Example: Comparison of Mamdani–Assilian and CFR controller — outputs



Typical outputs of Mamdani–Assilian controller (left) and CFR controller (right).

Problems of implementation of CFR controller

Software implementation: only three new blocks requiring a few lines of source code. The computational complexity slightly increases, but its order remains unchanged.

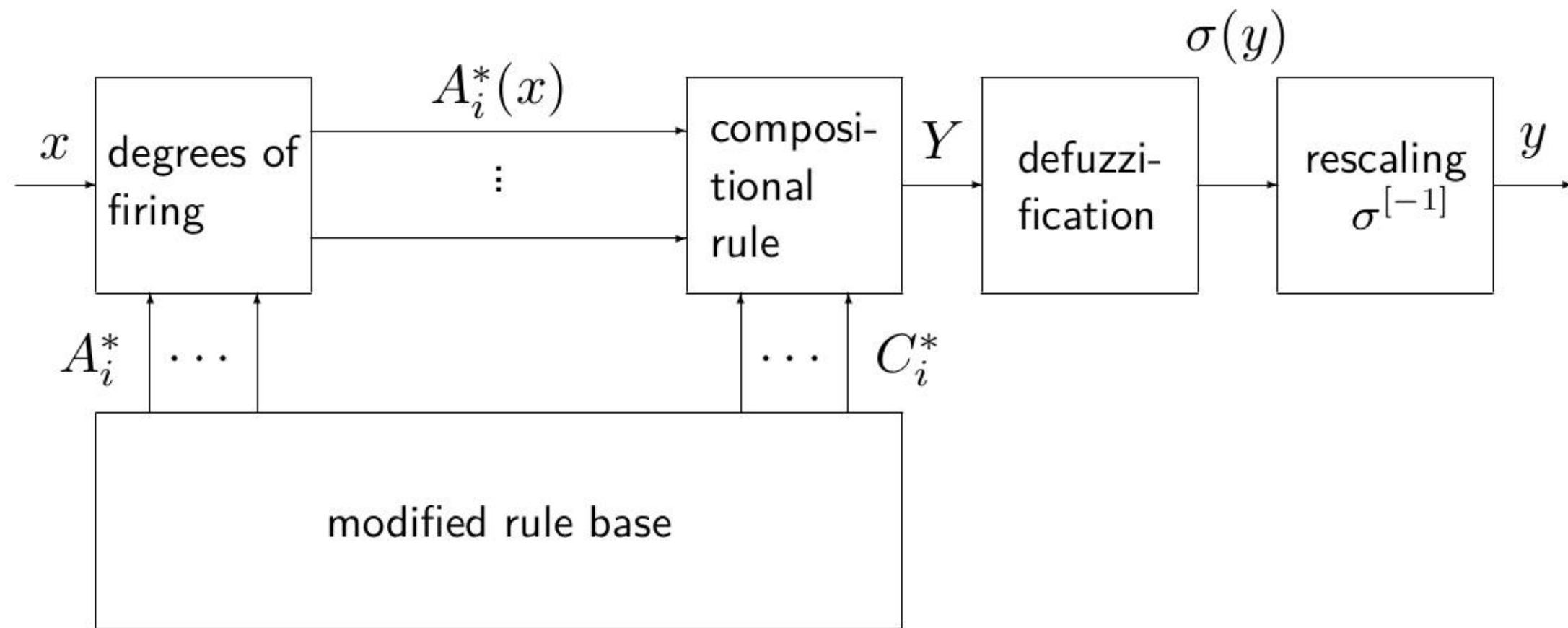
Hardware implementation: Requires to add an additional block inside the current structure, thus a totally new design of an integrated circuit - **expensive!**

Looking for a possibility to achieve the same control action using current fuzzy hardware and a **modified rule base**, we have found [Amato, Di Nola, Navara 2003]:

1. it is not possible to substitute the CFR controller in its full generality, but
2. this is possible for crisp input variables.

This case is still of much importance, because it covers most of applications; in fact, current fuzzy hardware works only with crisp inputs.

Hardware implementation of CFR controller



Conclusion

- ◆ We formulated well motivated axioms for fuzzy controllers (approximators). They cannot be satisfied by any controller using the classical compositional rule of inference (including the Mamdani–Assilian controller). Our generalized controller satisfies them under very general conditions.
 - ◆ Practical experiments show that our controller allows to achieve better results with the same rule database.
 - ◆ The computational efficiency is basically the same as that of the Mamdani–Assilian controller.
 - ◆ New results allow to transform the rule base (automatically) so that the current fuzzy hardware could be used to implementation of our controller, although its performance could not be achieved by the original Mamdani–Assilian controller.
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