Online Minimum Spanning Trees with Weight Predictions

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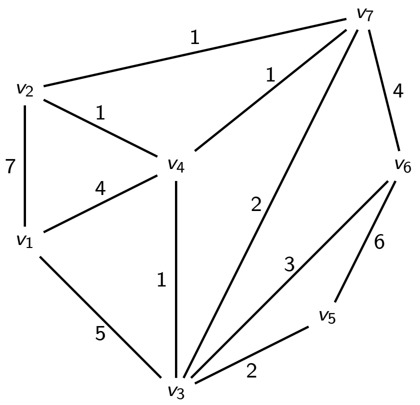
The Minimum Spanning Tree Problem

An instance: weighted graph $G = (V, E, w)$, where $w : E \to \mathbb{R}^+$.
Objective: Construct spanning tree of minimum cost.



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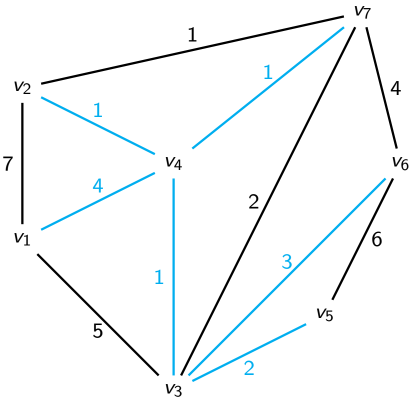
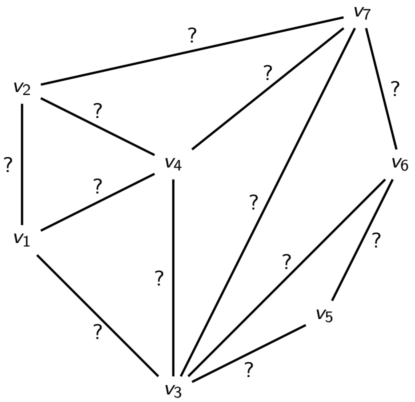


In this case, we have that $\text{OPT}(G) = 12$.

Online MST Problem - Weight Arrival Model (WMST)

An instance:

- $G_u = (V, E)$
- Sequence of $(w(e), e)$



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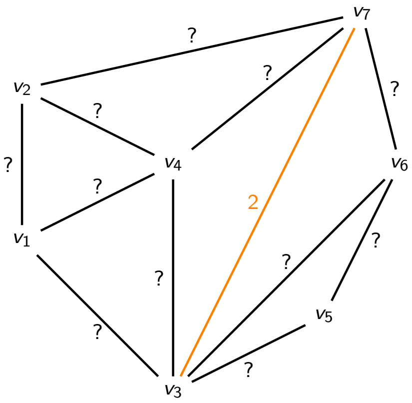

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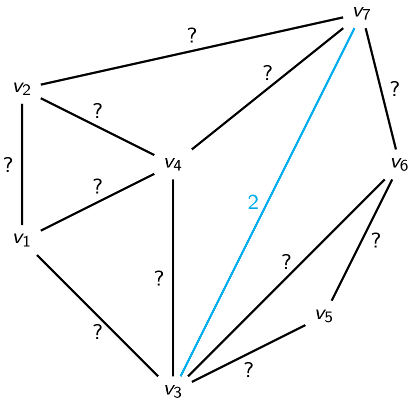

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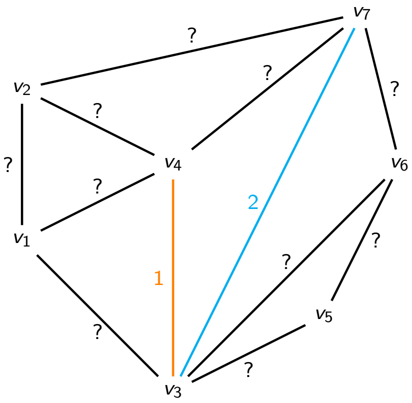

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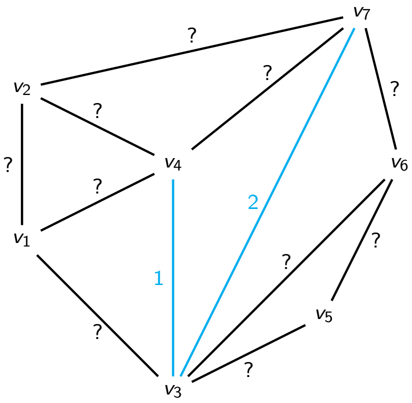

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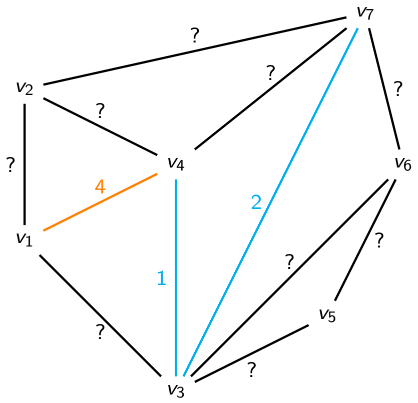

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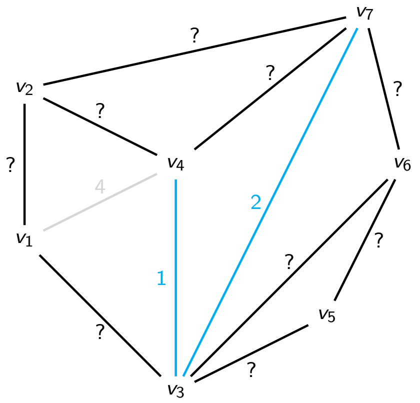

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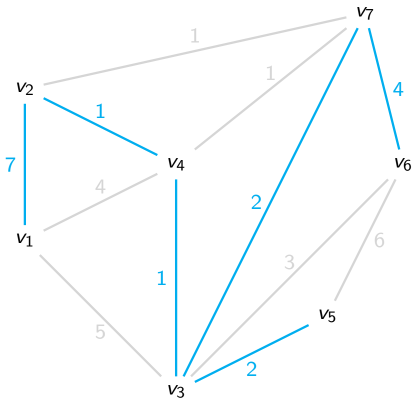

In this case $\text{ALG}(G) = 17$, whereas $\text{OPT}(G) = 12$.

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Definition

An online algorithm, $\textsc{Alg}$, for a minimization problem Π is said to be *c-competitive* if there exists a constant b such that for all instances I of Π:

$$\textsc{Alg}(I) \leqslant c \cdot \textsc{Opt}(I) + b.$$

The *competitive ratio* of $\textsc{Alg}$ is then

$$\textsc{cr}_{\textsc{Alg}} = \inf\{c \mid \textsc{Alg} \text{ is } c\text{-competitive}\}.$$

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For the WMST problem, no online algorithm is competitive.

Online Algorithms with Predictions

- Competitive analysis: Optimize for worst case.
- Machine Learning: Optimize for common cases.
- Question is: can we combine the best of both worlds?

In recent years, a lot of work has been done on *Online Algorithms with Predictions*.

The idea is to assume that the online algorithms can access some predictions providing (unreliable) information about the instance.

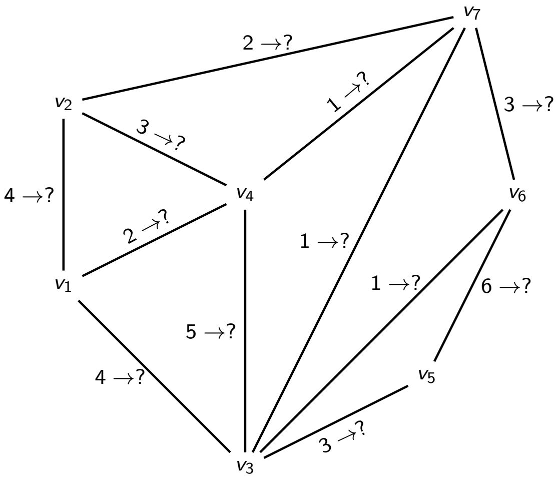
Formally, these predictions need not be Machine Learned.

Our playground

An instance:

$G = (V, E, \hat{w})$, where $\hat{w}\colon E \to \mathbb{R}^+$ is a prediction for the edge weights.

Sequence of $(w(e), e)$.



Details of this framework

Define error measure η for quantifying the quality of the predictions. In our case, we sum the $n-1$ greatest prediction errors, where $n = |V(G)|$.

With this, we aim to describe the cost, and competitive ratio, of an algorithm, $\textsc{Alg}$, as a function of η, and $\varepsilon = \frac{\eta}{\textsc{Opt}}$, respectively.

Definition

$\textsc{Alg}$ is said to be *β-consistent*, if $\textsc{cr}_{\textsc{Alg}}(0) = \beta$

Definition

$\textsc{Alg}$ is said to be *f-smooth*, if $\textsc{cr}_{\textsc{Alg}}(\varepsilon) \leqslant f(\varepsilon)$, for all $\varepsilon \geqslant 0$.

Definition

$\textsc{Alg}$ is said to be *γ-robust*, if $\textsc{cr}_{\textsc{Alg}}(\varepsilon) \leqslant \gamma$, for all $\varepsilon \geqslant 0$.

Since no online algorithm for the WMST problem can be competitive, the robustness of any online algorithm with predictions, is as good as the competitive ratio of any online algorithm.

Follow-the-predictions

Algorithm 1 FtP

1: **Input:** A WMST-instance $(G, \hat{w})$
2: Let $\hat{T}$ be a MST of G w.r.t. $\hat{w}$
3: **while** receiving inputs $(w(e_i), e_i)$ **do**
4:     **if** $e_i \in \hat{T}$ **then**
5:         Accept e_i ▷ Add e_i to the solution

Greedy-FTP

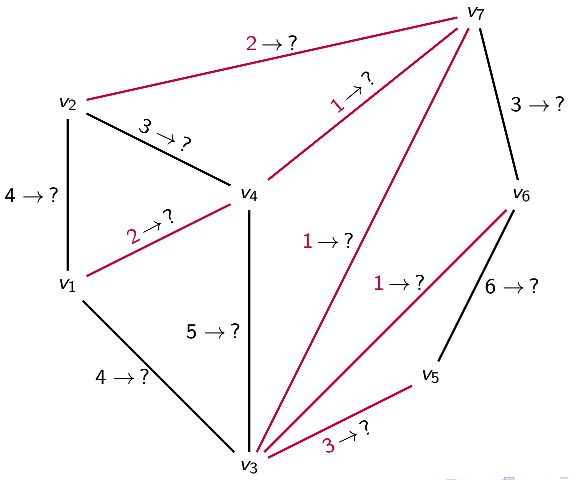
Algorithm 2 GFTP

Input: A WMST-instance $(G, \hat{w})$
Let T_{G} be a MST of G w.r.t. $\hat{w}$
$U = E(G)$ ▷ U contains the *unseen* edges
while receiving inputs $(w(e_i), e_i)$ **do**
  $U = U \setminus \{e_i\}$
  if $e_i \in T_{\mathrm{G}}$ **then**
    Accept e_i ▷ Add e_i to the solution
  else if $e_i \notin T_{\mathrm{G}}$ **then**
    C is the cycle e_i introduces in T_{G}
    $C_U = U \cap C$
    if $C_U \neq \emptyset$ **then**
      $e_{\max} = \arg\max_{e_j \in C_U} \{\hat{w}(e_j)\}$
      if $w(e_i) \leqslant \hat{w}(e_{\max})$ **then**
        $T_{\mathrm{G}} = (T_{\mathrm{G}} \setminus \{e_{\max}\}) \cup \{e_i\}$ ▷ Update T_{G}
        Accept e_i ▷ Add e_i to the solution

Running GFTP on our example graph.

Color codes:

- T
- Just revealed
- Accepted by GFTP
- Rejected by GFTP



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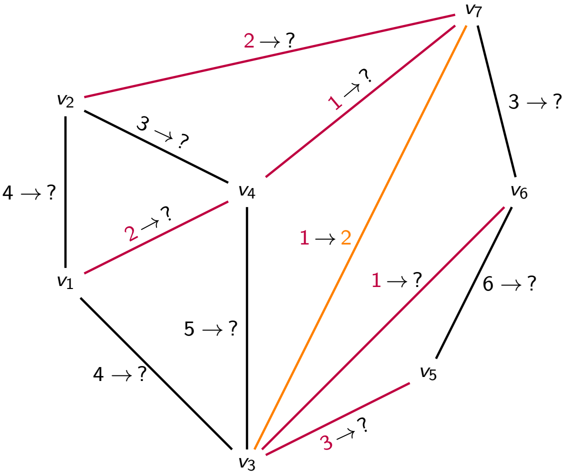

Running GFtP on our example graph.

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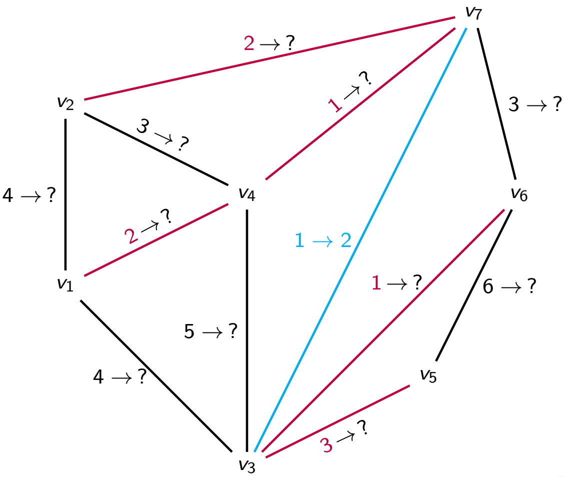

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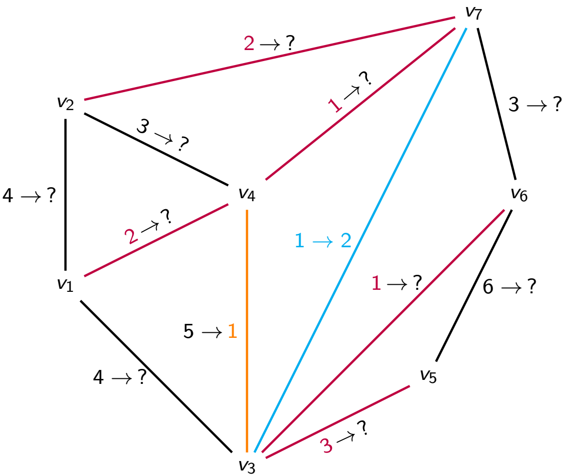

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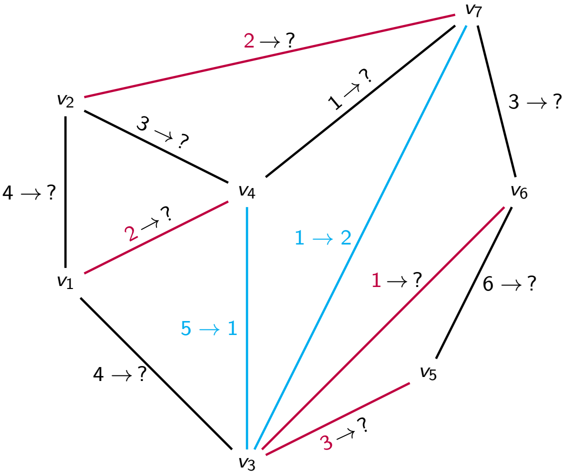

Cannot distinguish using competitive analysis

Theorem

$\text{CR}_{\text{FtP}}(\varepsilon) = 1 + 2\varepsilon$

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$\text{CR}_{\text{GFtP}}(\varepsilon) = 1 + 2\varepsilon$

Theorem

For $\varepsilon = \frac{1}{2}$*, and any online algorithm with predictions* ALG, $\text{CR}_{\text{ALG}}(\varepsilon) \geqslant 1 + 2\varepsilon$.

Random Order Analysis

A weakening of the adversary:

Definition

Let ALG be an online algorithm for a minimization problem Π, and let $I = \langle r_1, r_2, \ldots, r_m \rangle$ be an instance of Π. Then, a permutation σ of $\{1, 2, \ldots, m\}$ is chosen uniformly at random, and $\sigma(I)$ is presented to ALG. The random order ratio of ALG is

$$\text{ROR}_{\text{ALG}} = \inf\{c \mid \exists b : \forall I : \mathbb{E}_\sigma[\text{ALG}(\sigma(I))] \leqslant c\text{OPT}(\sigma(I)) + b\}$$

As competitive ratio, we describe the random order ratio of ALG as a function of ε.

This is the first time random order analysis has been used in online algorithms with predictions.

Separation by Random Order Analysis

This analysis separates $\textsc{FtP}$ and $\textsc{GFtP}$:

Theorem

$\textsc{ror}_{\textsc{FtP}}(\varepsilon) = 1 + 2\varepsilon$.

Theorem

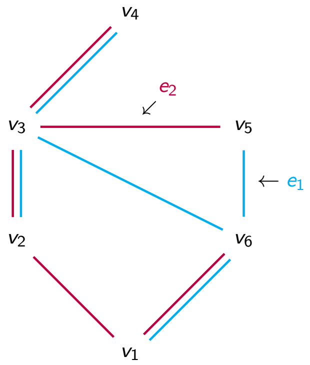
$\textsc{ror}_{\textsc{GFtP}}(\varepsilon) \leqslant 1 + (1 + \ln(2))\varepsilon$.

The idea behind this separation...

Random Order Analysis

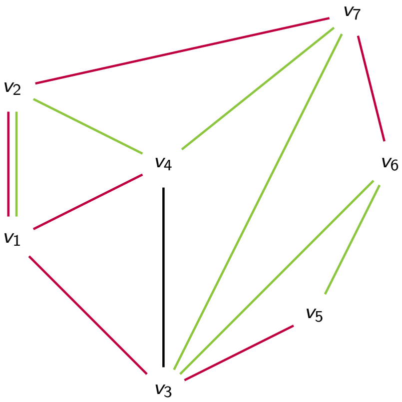
Lemma

Let G be a graph, and let T_1 and T_2 be two spanning trees of G. Then, for any edge $e_1 \in T_1 \setminus T_2$, there exists an edge $e_2 \in T_2 \setminus T_1$ such that e_2 introduces a cycle into T_1 that contains e_1, and e_1 introduces a cycle into T_2 that contains e_2.



How we use this Lemma

Dominate the “random variable” $\textsc{GFtP}(G, \hat{w}) - \textsc{Opt}(G)$ online.



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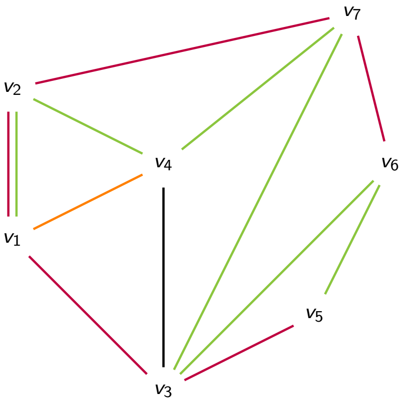

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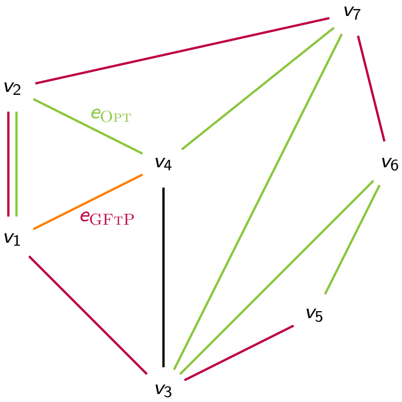

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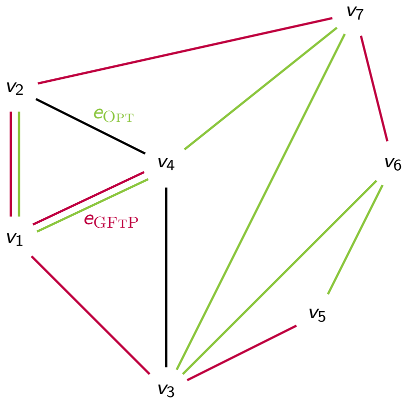

- $w(e_{\textsc{GFtP}}) - w(e_{\textsc{Opt}}) \leqslant |\hat{w}(e_{\textsc{GFtP}}) - w(e_{\textsc{GFtP}})| + |\hat{w}(e_{\textsc{Opt}}) - w(e_{\textsc{Opt}})|$

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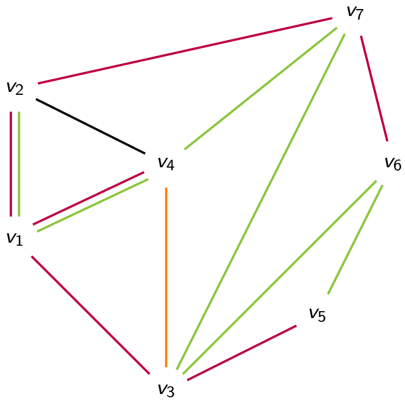

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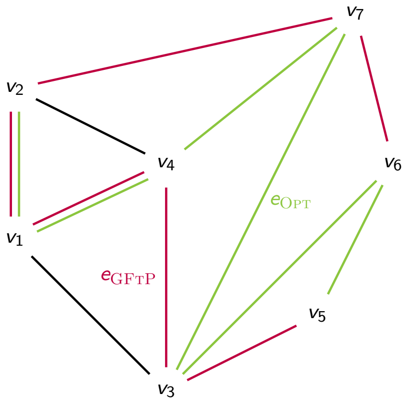

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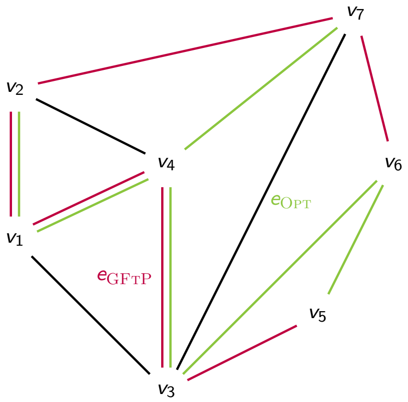

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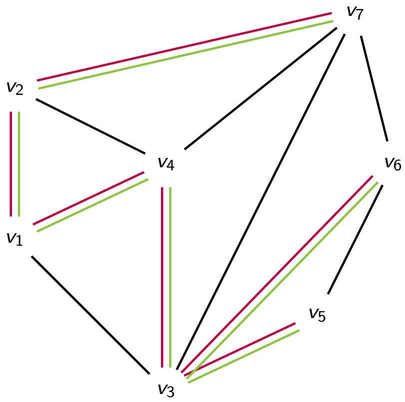

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- $\mathbb{E}[\#\text{dominating edges}] \leqslant (1 + \ln(2))(n-1)$, and all distinct.

Thank you for your attention!