Improving Local Search Algorithms via Probabilistic Configuration Checking

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HCP Report of AAAI 2022 Paper

Content

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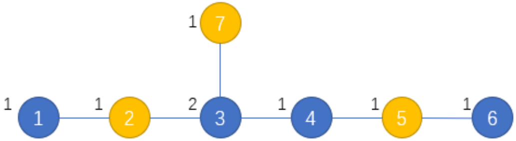
Definition of Problem

Combinatorial optimization problems (COPs)

- Minimum weight dominating set problem (MWDS)



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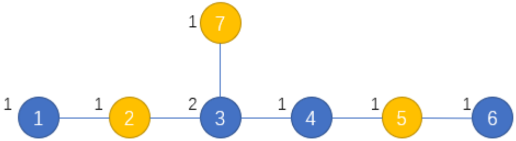

Figure 1: Example for MWDS.

- Maximum weight clique problem (MWCP)

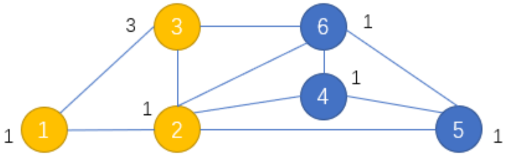

Figure 2: Example for MWCP.

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- Configuration checking (CC)[3]: alleviate the *cycling problem* for COPs

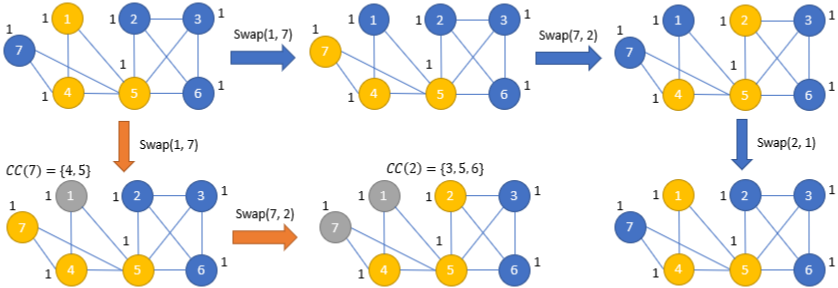

Figure 3: CC for MWCP.

Related Work

The variants of CC

- Redefinition of configuration (What we focus)
  - 1-level neighborhoods: [1,2,10]
  - 2-level neighborhoods: [8,11]
- Multi-value CC
- Changes of CC rules

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- When removing a vertex u from the candidate solution S
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What about 3-, 4-, or larger-level neighborhoods?

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Neighborhoods with more than two levels can have an impact on a vertex and should be considered in the configuration.

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Table 1: CC^{2}FS vs. CC^{2}FS-H.

Instances	CC^{2}FS			CC^{2}FS-H		
	min	avg	time	min	avg	time (s)
frb30-15-1	212	214.2	2.59	212	**212.0**	**0.11**
frb30-15-2	242	242.0	8.81	242	242.0	**0.18**
frb30-15-3	175	175.0	**0.01**	175	175.0	0.03
frb30-15-4	166	168.6	0.19	166	**166.0**	**0.08**
frb30-15-5	160	160.0	**0.01**	160	160.0	0.02
frb35-17-1	274	274.9	0.57	274	**274.0**	**0.11**
frb35-17-2	208	208.3	67.44	208	**208.0**	**0.29**
frb35-17-3	201	201.0	0.38	201	201.0	**0.10**
frb35-17-4	286	286.8	0.73	286	**286.0**	**0.45**
frb35-17-5	295	295.7	5.60	295	**295.0**	**0.11**
frb40-19-1	262	262.0	1.99	262	262.0	**0.14**
frb40-19-2	243	243.9	0.66	243	**243.0**	**0.18**
frb40-19-3	250	251.8	102.43	250	**250.0**	**3.88**
frb40-19-4	250	250.0	0.07	**249**	**249.0**	95.82
frb40-19-5	272	282.3	0.31	272	**277.6**	82.50
frb45-21-1	328	328.3	7.82	328	**328.0**	**0.64**
frb45-21-2	259	261.7	46.82	259	**259.1**	**1.39**
frb45-21-3	233	233.9	9.19	233	**233.0**	**0.89**
frb45-21-4	399	399.2	22.67	399	**399.0**	**0.95**
frb45-21-5	312	318.8	128.19	312	**312.0**	**1.82**
frb50-23-1	261	264.7	90.71	261	**261.0**	**8.97**
frb50-23-2	277	277.0	**0.01**	277	277.0	0.17
frb50-23-3	299	301.9	1.21	**281**	**292.2**	31.13
frb50-23-4	265	265.0	3.04	265	265.0	**0.47**
frb50-23-5	410	418.8	128.09	410	**411.1**	158.96
frb53-24-1	229	230.0	95.41	229	**229.0**	**2.35**
frb53-24-2	298	298.0	1.04	298	298.0	**0.38**
frb53-24-3	182	182.1	0.01	182	**182.0**	0.26
frb53-24-4	189	189.0	**0.02**	189	189.0	0.27
frb53-24-5	204	204.0	**0.01**	204	204.0	0.29
frb56-25-1	229	229.2	0.32	229	**229.0**	0.41
frb56-25-2	319	319.5	25.27	319	**319.0**	**3.46**
frb56-25-3	336	338.7	30.21	336	**336.0**	38.80
frb56-25-4	268	268.0	**0.21**	268	268.0	0.41
frb56-25-5	425	427.6	103.13	425	**425.0**	**1.83**
frb59-26-1	262	264.0	1.62	262	**262.0**	25.31
frb59-26-2	383	391.1	97.04	383	**383.0**	**5.64**
frb59-26-3	248	248.0	1.13	**246**	**246.0**	14.24
frb59-26-4	248	248.9	47.47	248	**248.0**	**0.62**
frb59-26-5	288	288.8	195.62	288	**288.0**	**3.26**
frb100-40	350	350.0	**2.04**	350	350.0	9.70
#win	0	0	7	**3**	**29**	**25**

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1. Is there a general way to define the configuration of a vertex?
2. How does the new configuration lead to a further improvement of the CC strategy?

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Definition 1 (i-th-level Neighborhoods)

For a vertex v, we define its i-th-level neighborhoods as $N_i(v) = \{u \in V \mid dist(u, v) = i\}$, i-level neighborhoods as $N_{\leq i}(v) = \bigcup_{j=1}^{i} N_j(v)$, and its i^+-level neighborhoods as $N_{>i}(v) = \bigcup_{j=i+1} N_j(v)$, particularly, $N_1(v) = N_{\leq 1}(v) = N(v)$.

Probabilistic Configuration

Definition 2 (Probabilistic Configuration (PC))

Given an undirected graph $G = (V, E)$ and a candidate solution S, the probabilistic configuration (PC) of a vertex $v \in V$ is a vector consisting of the states of all vertices in $(\bigcup_{i=1}^{2}(N_i(v))^{p_i}) \cup (N_{>2}(v))^{p_3}$, where $p_i \in [0, 1]$, $i = 1, 2, 3$, and $\{*\}^{p_i}$ is randomly chosen vertices from the set $\{*\}$ with the size of $\lceil |\{*\}| \cdot p_i \rceil$.

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Existing configurations are *special cases* of the PC.

Table 2: Configurations in the form of PC.

Configuration	Probabilistic configuration form
$N_1(v)$	$(N_1(v))^{1.0} \cup (N_2(v))^{0.0} \cup (N_{>2}(v))^{0.0}$
$N_1(v) \cup N_2(v)$	$\bigcup_{i=1}^{2}(N_i(v))^{1.0} \cup (N_{>2}(v))^{0.0}$

Probabilistic Configuration Checking

Probabilistic Configuration Checking (PCC)

1. At beginning, compute the 1st-, 2nd-, and 2^+-level neighborhoods for each vertex
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   - only needs to be run once
2. In each search step, for the operated vertex v, select vertices from $N_1(v)$, $N_2(v)$ and $N_{>2}(v)$ to form its configuration

Algorithm 2 SelectConf(v, $N_1(v)$, $N_2(v)$, $N_{>2}(v)$, P)

Input: a vertex v and $N_1(v)$, $N_2(v)$, $N_{>2}(v)$, $P = \{p_1, p_2, p_3\}$ a set of probabilities.
Output: the configuration $Conf$.

1: $Q_1 \leftarrow$ randomly choose $\lceil |N_1(v)| \cdot p_1 \rceil$ vertices from $N_1(v)$;
2: $Q_2 \leftarrow$ randomly choose $\lceil |N_2(v)| \cdot p_2 \rceil$ vertices from $N_2(v)$;
3: $Q_3 \leftarrow$ randomly choose $\lceil |N_{>2}(v)| \cdot p_3 \rceil$ vertices from $N_{>2}(v)$;
4: $Conf(v) \leftarrow Q_1 \cup Q_2 \cup Q_3$;
5: **return** $Conf(v)$;

Example of PC and PCC

Example 1

PC: $p_1 = p_2 = p_3 = 0.5$
For $v = 3$, $N_1(3) = \{2, 4, 7\}$, $N_2(3) = \{1, 5\}$, $N_{>2}(3) = \{6\}$.
Calculate $Conf[3]$ according to Algorithm 1.
Assume $Q_1 \leftarrow \{4, 7\}$, $Q_2 \leftarrow \{1\}$, $Q_3 \leftarrow \{6\}$.
$Conf[3] \leftarrow Q_1 \cup Q_2 \cup Q_3 = \{1, 4, 6, 7\}$.

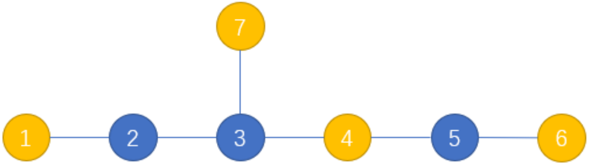

Figure 4: Example for vertex 3.

A PCC Strategy for MWDS

When removing a vertex u from the candidate solution S

- $confCh[u] := 0$;
- calculate $Conf[u]$ according to Algorithm 1;
- for each vertex $w \in Conf[u]$, $confCh[w]$ is set to 1.

When adding a vertex v to the candidate solution S

- calculate $Conf[v]$ according to Algorithm 1;
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A PCC Strategy for MWCP

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- $confCh[u] := 0;$

When adding a vertex v to the candidate solution S

- calculate $Conf[v]$ according to Algorithm 1;
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When swapping a vertex u from the candidate solution S with a vertex v

- $confCh[u] := 0;$
- calculate $Conf[v]$ according to Algorithm 1;
- for each vertex $w \in Conf[v]$, $confCh[w]$ is set to 1.

Complexity Analysis

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  - Time-consuming
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The complexity of PCC is roughly comparable with CC.

Automatic Configuration Process

Three parameters in the definition of PC: p_1, p_2, and p_3

- configurator: like SMAC[5]

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Training set

COP	Benchmarks	Instances	t.t.(s)
MWDS	T1	1000_1000_1, 1000_5000_3, 1000_10000_6, 1000_15000_6, 1000_20000_1	2
	T2	1000_1000_4, 1000_5000_6, 1000_10000_2, 1000_15000_6, 1000_20000_1	2
	UDG	S3N800U150, S0N800U200, S7N1000U150, S6N1000U200	10
	BHSOLIB	50-23-1.mis, 53-24-3.mis, 56-25-3.mis, 59-26-4.mis	30
	DIMACS	brock800_4.mis, C4000.5.mis, DSJC1000.5.mis, gen400_p0.9_75.mis, hamming10-4.mis, keller6.mis, MANN_a81.mis, p_hat1500-3.mis	10
MWCP	BHSOLIB	50-23-5.clq, 53-24-4.clq, 56-25-3.clq, 59-26-1.clq	30
	DIMACS	brock800_4.clq, C4000.5.clq, DSJC1000.5.clq, gen400_p0.9_75.clq, hamming10-4.clq, keller6.clq, MANN_a81.clq, p_hat1500-3.clq	10

Table 3: The detail about the training set, where 't.t.' means the evaluation time of each instance during training.

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MWDS	BHSOLIB	50-23-1.mis, 53-24-3.mis, 56-25-3.mis, 59-26-4.mis	30
MWDS	DIMACS	brock800_4.mis, C4000.5.mis, DSJC1000.5.mis, gen400_p0.9_75.mis, hamming10-4.mis, keller6.mis, MANN_a81.mis, p_hat1500-3.mis	10
MWCP	BHSOLIB	50-23-5.clq, 53-24-4.clq, 56-25-3.clq, 59-26-1.clq	30
MWCP	DIMACS	brock800_4.clq, C4000.5.clq, DSJC1000.5.clq, gen400_p0.9_75.clq, hamming10-4.clq, keller6.clq, MANN_a81.clq, p_hat1500-3.clq	10

Table 3: The detail about the training set, where 't.t.' means the evaluation time of each instance during training.

Training

- average scores of the training set as the evaluate metric
- 24 hours for the entire configuration process

Content

Setting

Benchmarks

- MWDS: T1[7], T2[7], UDG[7], BHOSLIB[12], DIMACS[6]
- MWCP: BHOSLIB[12], DIMACS[6]

Setting

Benchmarks

- MWDS: T1[7], T2[7], UDG[7], BHOSLIB[12], DIMACS[6]
- MWCP: BHOSLIB[12], DIMACS[6]

Competitors

- MWDS
  - CC^2FS[11]
  - CC^2FS-P (ours, one PC for each COP)
  - CC^2FS-SP (ours, one PC for each benchmark)
- MWCP
  - LSCC[10]
  - LSCC-P (ours, one PC for each COP)
  - LSCC-SP(ours, one PC for each benchmark)

Comparison PCC with CC in MWDS

Table 4: Comparison results of CC^{2}FS and CC^{2}FS-P on 7 benchmarks. We also report the sum of difference ('sum of diff') between CC^{2}FS-P and CC^{2}FS in 'min' and 'avg'. The smaller the difference, the better for CC^{2}FS-P.

	Benchmarks	#inst.	CC^{2}FS		CC^{2}FS-P		sum of diff	
			#w.m.	#w.a.	#w.m.	#w.a.	min	avg
train	T1	5	0	0	**5**	**5**	**-167**	**-167.0**
train	T2	5	0	0	**3**	**3**	**-49**	**-49.0**
train	UDG	4	**4**	**4**	0	0	30	30.0
train	BHOSLIB	4	0	0	**1**	**4**	**-1**	**-8.4**
train	DIMACS	8	0	0	0	0	0	0.0
test	T1	525	10	10	**152**	**152**	**-2129**	**-2129.0**
test	T2	525	0	0	**57**	**57**	**-697**	**-697.0**
test	UDG	116	**81**	**81**	16	16	541	541.0
test	BHOSLIB	37	0	0	**6**	**26**	**-52**	**-105.1**
test	DIMACS	29	0	0	**2**	**9**	**-4**	**-27.2**
Total		1258	95	95	**242**	**272**	**-2528**	**-2611.7**

- CC^{2}FS-P is the better solver (except the UDG)
- CC^{2}FS-P performs worse even in the training set for UDG

Comparison PCC with CC in MWDS

Table 4: Comparison results of CC^{2}FS and CC^{2}FS-P on 7 benchmarks. We also report the sum of difference ('sum of diff') between CC^{2}FS-P and CC^{2}FS in 'min' and 'avg'. The smaller the difference, the better for CC^{2}FS-P.

	Benchmarks	#inst.	CC^{2}FS #w.m.	CC^{2}FS #w.a.	CC^{2}FS-P #w.m.	CC^{2}FS-P #w.a.	sum of diff min	sum of diff avg
train	T1	5	0	0	**5**	**5**	**-167**	**-167.0**
train	T2	5	0	0	**3**	**3**	**-49**	**-49.0**
train	UDG	4	**4**	**4**	0	0	30	30.0
train	BHOSLIB	4	0	0	**1**	**4**	**-1**	**-8.4**
train	DIMACS	8	0	0	0	0	0	0.0
test	T1	525	10	10	**152**	**152**	**-2129**	**-2129.0**
test	T2	525	0	0	**57**	**57**	**-697**	**-697.0**
test	UDG	116	**81**	**81**	16	16	541	541.0
test	BHOSLIB	37	0	0	**6**	**26**	**-52**	**-105.1**
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Total		1258	95	95	**242**	**272**	**-2528**	**-2611.7**

- CC^{2}FS-P is the better solver (except the UDG)
- CC^{2}FS-P performs worse even in the training set for UDG

the adverse bias generated from training data from other benchmarks

Comparison PCC with CC in MWCP

Table 5: Experimental results of LSCC and LSCC-P on DIMACS and BHOSLIB benchmarks. We report the sum of difference between LSCC-P and LSCC in 'min' and 'avg'. The larger the difference, the better for LSCC-P.

	Benchmarks	#inst.	LSCC #w.m.	LSCC #w.a.	LSCC-P #w.m.	LSCC-P #w.a.	sum of diff min	sum of diff avg
train	BHOSLIB	4	1	0	**2**	**4**	**13**	**67**
train	DIMACS	8	0	1	**3**	**3**	**124**	**166.8**
test	BHOSLIB	37	2	3	**14**	**26**	**315**	**462.7**
test	DIMACS	29	**2**	2	0	2	-19	**52.9**
Total		78	5	6	**19**	**35**	**433**	**749.4**

- LSCC-P achieves better performance than LSCC in BHOSLIB
- LSCC-P achieves comparable performance with LSCC in DIMACS

Discussion About the Bias of Training in MWDS

Table 6: Comparison results of CC^{2}FS and CC^{2}FS-SP.

	Benchmarks	#inst.	CC^{2}FS #w.m.	CC^{2}FS #w.a.	CC^{2}FS-SP #w.m.	CC^{2}FS-SP #w.a.	sum of diff min	sum of diff avg
train	T1	5	0	0	**5**	**5**	**-184**	**-184.0**
train	T2	5	0	0	**3**	**3**	**-49**	**-49.0**
train	UDG	4	1	1	**2**	**2**	**-8**	**-8.0**
train	BHOSLIB	4	0	0	**1**	**4**	**-1**	**-8.4**
train	DIMACS	8	0	0	0	0	0	0.0
test	T1	525	10	10	**154**	**154**	**-2205**	**-2205.0**
test	T2	525	0	0	**58**	**58**	**-697**	**-697.0**
test	UDG	116	**47**	**47**	41	41	**-14**	**-14.0**
test	BHOSLIB	37	0	0	**6**	**26**	**-52**	**-109.1**
test	DIMACS	29	0	0	**2**	**9**	**-4**	**-27.1**
Total		1258	58	58	**272**	**302**	**-3214**	**-3301.6**

Table 7: Comparison results of CC^{2}FS-P and CC^{2}FS-SP.

	Benchmarks	#inst.	CC^{2}FS-P #w.m.	CC^{2}FS-P #w.a.	CC^{2}FS-SP #w.m.	CC^{2}FS-SP #w.a.	sum of diff min	sum of diff avg
train	T1	5	0	0	**2**	**2**	**-17**	**-17.0**
train	T2	5	0	0	0	0	0	0.0
train	UDG	4	0	0	**4**	**4**	**-38**	**-38.0**
train	BHOSLIB	4	0	0	0	0	0	0.0
train	DIMACS	8	0	0	0	0	0	0.0
test	T1	525	17	17	**36**	**36**	**-76**	**-76.0**
test	T2	525	1	1	1	1	0	0.0
test	UDG	116	22	22	**82**	**82**	**-555**	**-555.0**
test	BHOSLIB	37	0	0	0	**1**	0	**-4.0**
test	DIMACS	29	0	**1**	0	0	0	0.1
Total		1258	40	41	**125**	**126**	**-686**	**-689.9**

- CC^{2}FS-SP achieves a better performance than CC^{2}FS-P
- CC^{2}FS-SP and CC^{2}FS are comparable in UDG

Discussion About the Bias of Training in MWCP

Table 8: Comparison results of LSCC and LSCC-SP.

	Benchmarks	#inst.	LSCC #w.m.	LSCC #w.a.	LSCC-SP #w.m.	LSCC-SP #w.a.	sum of diff max	sum of diff avg
train	BHOSLIB	4	1	0	**2**	**4**	**8**	**69.4**
train	DIMACS	8	0	1	**3**	**3**	**124**	**166.8**
test	BHOSLIB	37	2	2	**14**	**27**	**371**	**502.3**
test	DIMACS	29	**2**	2	0	2	-19	**52.9**
Total		78	5	5	**19**	**36**	**484**	**791.4**

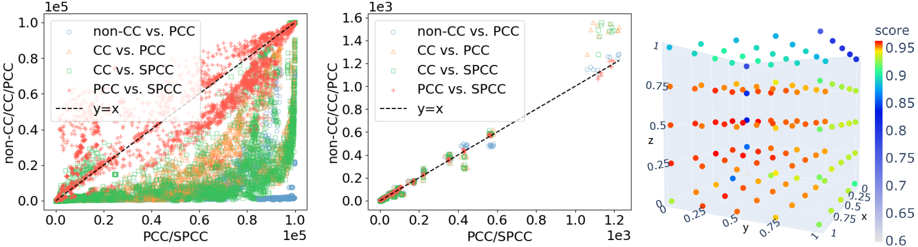
Table 9: Comparison results of LSCC-P and LSCC-SP.

	Benchmarks	#inst.	LSCC-P #w.m.	LSCC-P #w.a.	LSCC-SP #w.m.	LSCC-SP #w.a.	sum of diff max	sum of diff avg
train	BHOSLIB	4	1	2	**2**	2	-5	**2.4**
train	DIMACS	8	0	0	0	0	0	0
test	BHOSLIB	37	**9**	8	6	**15**	**56**	**39.6**
test	DIMACS	29	0	0	0	0	0	0
Total		78	**10**	10	8	**17**	**51**	**42**

- specially PC for each benchmark can improve the performance
- in DIMACS, LSCC-SP and LSCC-P are the same because they share the same PC

Performance on Reducing the Cycling Problem

Figure 5: (a) Comparison of the number of different candidate solutions of non-CC, CC, PCC, SPCC. (b) Comparison of CPU time. (c) The scores of CC^{2}FS-P with different configurations on MWDS benchmark. The X-axis, Y-axis, and Z-axis represent p_1, p_2, and p_3 respectively.



(a) (b) (c)

- not have much more time consumption
- potentially alleviates the cycling problem
- necessary to tune for an optimal PC

Content

Conclusion and Future Work

Conclusion:

1. We observe that neighborhoods with different levels should have different contributions to alleviate the cycling problem.
2. We expand the configuration with probability, i.e., probabilistic configuration (PC), to capture the contributions of vertices at different levels, resulting in the probabilistic configuration checking (PCC) strategy.
3. Our experimental results confirm that the PC can improve existing local search algorithms in two classic COPs, i.e., MWDS and MWCP, due to alleviating the cycling problem.

Conclusion and Future Work

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Future work:

1. making the method suitable for massive graphs.
2. extending our approach to other COPs.

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Thank you for your listening!