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Abstract. In this paper, we revisit the famous heuristic called nearest neighbor (NN) for the traveling salesman problem under maximization and minimization goal. We deal with variants where the edge costs belong to interval [a; ta] for a > 0 and t > 1, which certainly corresponds to practical cases of these problems. We prove that NN is a (t + 1)/2t-approximation for Max TSP[a; ta] and a 2/(t + 1)-approximation for Min TSP[a; ta] under the standard performance ratio. Moreover, we show that these ratios are tight for some instances.

Keywords: Approximate algorithms; Performance ratio; Analysis of Algorithms; Traveling salesman problem.

The classical traveling salesman problem can be formulated as follows: given $K_n$, a complete graph on $n$ vertices with non-negative integer costs on its edges, the traveling salesman problem under minimization version, called Min TSP (resp. maximization, called Max TSP) consists of minimizing (resp. maximizing) the cost of a Hamiltonian cycle, the cost of such cycle is the sum of its edge’s costs. Moreover, when the edge-weights are in the set \{a, a + 1, ..., b − 1, b\}, we will call of TSP[a; b] problem. Several restrictions of this problem have often being studied in the literature, like Euclidean, metric or 1,2 cases and very elegant positive or negative approximation results have been produced by Arora [1], Christofides [2], Papadimitriou and Yannakakis [7], Engebretsen and Karpiniski [3], Papadimitriou and Vempala [6]. There are no special study about this heuristic when edge-weights are in the set \{a, a + 1, ..., b − 1, b\}.

In this paper, we revisit some approximation results for Nearest Neighbor algorithm (noted NN) described the first time by Karg and Thompson [5], also called the next best method in some sequencing jobs to a single production facility. This very simple heuristic has already mainly studied by Fisher et al. [4] for Max TSP and by Rosenkrantz et al. [8] for Min metric − TSP and consist in starting from any vertex and keep visiting the nearest vertex that has not been visited. In [4], the authors present several polynomial-time approximation algorithms, among which Nearest Neighbor achieving approximation ratio 1/2 for the maximization version whereas in [8], the results are less optimistic since they produce a $\theta(1/\log n)$-approximation for minimization metric version, by using an approximation measure, called performance ratio, defined as:

$$\rho[\pi]_A(I) = \min \{ \frac{A(I)}{OPT(I)}, \frac{OPT(I)}{A(I)} \}$$

where $A(I)$ is the value of algorithm $A$ and OPT(I) is the value of an optimal solution on the instance $I$ of a combinatorial problem $\pi$.

The performance ratio is a number less than or equal to 1, and is equal to 1 when $A(I) = OPT(I)$. Remark that, compared to some definitions, we have inverted the performance ratio in the case of minimization problems. Hence, we will always consider the ratio value as being between 0 and 1. We say that $A$ is an $r$-approximation if for any instance $I$, we have $\rho_A(I) \geq r$. 


A case that seems to be very common in practical situations appears when $d_{\text{max}}/d_{\text{min}}$ is upper bounded by a constant. We prove that, when edge-costs belongs to the interval $[a;ta]$, Nearest Neighbor is a $(t+1)/2t$-approximation for the maximization problem and yields a $2/(t+1)$-approximation for the minimization version.

The previous guaranteed performances on theses heuristics are strengthened by our results in both versions. Moreover, we show that ratios are tight.

1. The Nearest Neighbor algorithm

This algorithm depends on the goal of the traveling salesman problem, so when we study maximization case, we replace goal by Max else goal by Min.

\[ [NN_{\text{goal}}] \]

**input:** $I = (K_n, d)$ instance of goal TSP;

**output:** An acyclic permutation $p$ of $I$;

Take arbitrarily $x_1 \in V$;

Set $S = \{x_1\}$ and $z = x_1$;

While $S \neq V$ do

Take $y \notin S$ such that $d(z, y) = \text{goal} \{d(z, w) | w \notin S\}$ (line a);

Set $y = p(z)$ and $z = y$;

End while;

$p(y) = x_1$ ;

return $p$ ;

We assume that when there are ties in different steps of algorithm, it can be broken by taking the vertex with minimum index, so in particular we always start with vertex $x_1$. This algorithm yields an Hamilton cycle since an acyclic permutation describes a feasible solution by the set $\{(x, p(x)) | x \in V\}$ (where $p$ points out the successor of $x$ in the cycle) and its complexity-time is $O(n^2)$.

The authors of [4] have proved by linear programming method that Max TSP is 1/2-approximable, whereas we prove by a combinatorial technic that more generally Max TSP$[a;ta]$ is $(t + 1)/2t$-approximable for all $t > 1$.

**Theorem 1.1.** The algorithm $[NN_{\text{max}}]$ is a $\frac{t+1}{2t}$-approximation for Max TSP$[a;ta]$ and this ratio is tight.

**Proof:** Let $I = (K_n, d)$ be an instance on $n$ vertices, such that $a \leq d(e) \leq ta$ for all edge $e$ and let $p^*$ (resp. $p$) be an acyclic permutation describing an optimal solution of $I$ (resp. the solution returned by $NN$). We split $V$ into $V_1 = \{x \in V | d(x, p(x)) < d(x, p^*(x))\}$ and $V_2 = \{x \in V | d(x, p(x)) \geq d(x, p^*(x))\}$. Remark that $V_2 \neq \emptyset$ since by construction $x_1 \in V_2$. Moreover, if $V_1 = \emptyset$ then the nearest neighbor heuristic is optimal and we have the main key following result:

\begin{equation}
\forall x \in V_1, \quad d(p^*(x), p \circ p^*(x)) \geq d(x, p^*(x))
\end{equation}

Indeed, let $x \in V_1$; by construction $p^*(x)$ correspond to a previous step of algorithm than $x$ (else $x \in V_2$) and then at the step $p^*(x)$, we have $x \notin S$ and the expected result.

Finally, we obtain

\[ 2NN_{\text{max}}(I) = \sum_{x \in V} d(x, p(x)) + \sum_{x \in V} d(p^*(x), p \circ p^*(x)) \]

\[ \geq \sum_{x \in V} d(x, p(x)) + \sum_{x \in V_1} d(p^*(x), p \circ p^*(x)) + a|V_1| + a|V_2| \]

\[ \geq \sum_{x \in V} d(x, p^*(x)) + \sum_{x \in V_1} d(x, p^*(x)) + an \]

\[ \geq OPT_{\text{max}}(I) + \frac{1}{7}OPT_{\text{max}}(I) \]

We now show that this ratio is tight. Let $J_n = (K_n, d)$ be an instance defined by: $V = \{x_i | 1 \leq i \leq 2n\}$ and for all $i, j$ such that $1 \leq i < j \leq 2n$, we have $d(x_i, x_{j-n}) = d(x_i, x_j) = ta$ and $d(x_i, x_j) = a$. 

...
The nearest neighbor solution is described by \( \forall i \leq 2n - 1, p(x_i) = x_{i+1} \) and \( p(x_{2n}) = x_1 \) and an optimal solution by \( \forall i \leq n - 1, p^*(x_i) = x_{n+i}, p^*(x_{n+i}) = x_{i+1} \) and \( p^*(x_n) = x_{2n}, p^*(x_{2n}) = x_1 \). Finally, we obtain:

\[
\rho_{NN_{\text{max}}}(J_n) = \frac{a(n + 1)(t + 1) - 2a}{2atn} \to \frac{t + 1}{2t} \]

\( \Box \)

In order to study the behavior of \( NN_{\text{min}} \), we will establish a mathematical relation between respective solutions returned by algorithm on two instances linked by reduction. Moreover, we show that this relation remains true for \( OPT_{\text{max}} \) and \( OPT_{\text{min}} \).

**Theorem 1.2.** The algorithm \([NN_{\text{min}}]\) is a \( \frac{2}{t+1} \)-approximation for \( \text{Min} - \text{TSP}[a; \tau a] \) and this ratio is tight.

**Proof:** Let \( I = (K_n, d) \) be an instance on \( n \) vertices of \( \text{Min} - \text{TSP}[a; \tau a] \), set \( d_{\text{max}} = \max_{e \in E} d(e) \) and \( d_{\text{min}} = \min_{e \in E} d(e) \). We transform instance \( I \) into instance \( \propto (I) = (K_n, d') \) just by changing the weight of edges by \( d'(e) = d_{\text{max}} + d_{\text{min}} - d(e) \). It is clear that \( \propto (I) \) is still an instance verifying \( a \leq d'(e) \leq \tau a \), so we can apply nearest neighbor algorithm on \( \propto (I) \) and we have:

\[
(1.2) \quad NN_{\text{min}}(I) = n(d_{\text{max}} + d_{\text{min}}) - NN_{\text{max}}(\propto (I))
\]

We show this equality by an inductive proof. Note \( p_{min} \) (resp. \( p_{max} \)) the solution produces by \( NN_{\text{min}} \) (resp. \( NN_{\text{max}} \)) on the instance \( I \) (resp. \( \propto (I) \)). For an arbitrate step \( x \) (we identify current step with last vertex visited) if we have \( y = p_{min}(x) \) then \( \forall z \not\in S, d(x, y) \leq d(x, z) \) and \( \forall z \not\in S, d'(x, y) = d_{\text{max}} + d_{\text{min}} - d(x, z) = d'(x, z) \), thus we have \( y = p_{max}(x) \) and more generally for any vertex \( x, p_{min}(x) = p_{max}(x) \).

Moreover, this equality also holds for the respective optimal solution of \( I \) and \( \propto (I) \):

\[
(1.3) \quad OPT_{\text{max}}(\propto (I)) = n(d_{\text{max}} + d_{\text{min}}) - OPT_{\text{min}}(I)
\]

Let \( p_{min}^{*} \) be an optimal solution of \( I \), it is an feasible solution of \( \propto (I) \), thus we have \( OPT_{\text{min}}(I) \geq n(d_{\text{max}} + d_{\text{min}}) - OPT_{\text{min}}(\propto (I)) \). Conversely since \( \propto (I) \propto (I) = I \), we also have \( OPT_{\text{min}}(I) \leq n(d_{\text{max}} + d_{\text{min}}) - OPT_{\text{max}}(\propto (I)) \).

Thanks the equality (1.3) and since \( OPT_{\text{min}}(I) \geq d_{\text{min}}n \), we also obtain:

\[
(1.4) \quad OPT_{\text{max}}(\propto (I)) \leq n(d_{\text{min}} + d_{\text{min}}) - OPT_{\text{min}}(I) \leq tOPT_{\text{min}}(I)
\]

Finally, add equality (1.2) to (1.3) and thanks to previous theorem and inequality (1.4), we have:

\[
NN_{\text{min}}(I) - OPT_{\text{min}}(I) = OPT_{\text{max}}(\propto (I)) - NN_{\text{max}}(\propto (I)) \leq \frac{t+1}{t}OPT_{\text{max}}(\propto (I)) \leq \frac{t+1}{t}OPT_{\text{min}}(I) \leq \frac{t+1}{t}OPT_{\text{min}}(I)
\]

and the expected result holds.

We show that this ratio is tight by considering the instances \( \propto (J_n) = (K_n, d') \) where \( J_n = (K_n, d) \) is defined as in the previous theorem. Thus, we obtain:

\[
\rho_{NN_{\text{max}}}(\propto (J_n)) = \frac{2an}{a(n + 1) + at(n - 1)} \to \frac{2}{t+1}
\]

We give another proof of this theorem by a straightforward analysis of this heuristic in the special case where the edge-costs are only \( a \) and \( \tau a \). We split \( V \) into \( V_1 = \{ x \in V | |d(x, p(x)) = a \} \) and \( V_2 = \{ x \in V | |d(x, p(x)) = \tau a \} \) and we have that \( V_1 \) (resp. \( V_2 \)) is isomorphic to the edge set of cost \( a \) (resp. \( \tau a \)) taken by the heuristic, so we have:

\[
(1.5) \quad NN_{\text{min}}(I) = a|V_1| + at|V_2| = an + a(t - 1)|V_2|
\]
We do the same partition for an optimal solution \( p^* \); so we split \( V \) into \( V_1^* = \{ x \in V | d(x, p^*(x)) = a \} \) and \( V_2^* = \{ x \in V | d(x, p^*(x)) = ta \} \). We also have the following result:

\[
OPT_{\min}(I) = an + a(t-1)|V_2^*|
\]

Moreover, the key following result establishes one relationship between sets \( V_i, \ i = 1,2 \) thanks to optimal acyclic permutation \( p^* \):

\[
p^*(V_2 \cap V_1^*) \subseteq V_1
\]

Indeed, this mathematical relation shows that for each mistake of algorithm (i.e., \( x \in V_2 \cap V_1^* \)), we can find a step for which the heuristic works well (i.e., \( y \in V_1 \)). The proof is not presented here. Finally, since \( p^* \) is a permutation, we have:

\[
2a(t-1)|V_2| = a(t-1)|V_2 \cap V_2^*| + a(t-1)|V_2 \cap V_1^*| + a(t-1)|V_2|
\]

\[
= a(t-1)|V_2 \cap V_2^*| + a(t-1)|p^*(V_2 \cap V_1^*)| + a(t-1)|V_2|
\]

\[
\leq a(t-1)|V_2 \cap V_2^*| + a(t-1)(|V_1| + |V_2|)
\]

\[
\leq (an + a(t-1)|V_2 \cap V_2^*|) + atn - 2an
\]

\[
\leq OPT_{\min}(I) + atn - 2an
\]

Thus, we obtain:

\[
NN_{\min}(I) = an + a(t-1)|V_2|
\]

\[
\leq \frac{1}{2}OPT_{\min}(I) + \frac{atn}{2}
\]

\[
\leq \frac{t+1}{2}OPT_{\min}(I)
\]

and the expected result holds.

Finally let us notice we could show that this algorithm gives the same performance ratio for the two versions of Hamiltonian path problem (with or without a specified endpoint) through a slight modification of line a of algorithm. Nevertheless for the version where the two endpoints are specified, this heuristic yields no constant approximation ratio when \( d_{\max}/d_{\min} \) is not upper bounded by a constant.

References