A Comparative Synthesis Approach to Optimal Network Designs with Indeterminate Objectives

Yanjun Wang
Purdue University
West Lafayette, IN, USA
wang3204@purdue.edu

Zixuan Li
Purdue University
West Lafayette, IN, USA
li3566@purdue.edu

Chuan Jiang
Purdue University
West Lafayette, IN, USA
jiang486@purdue.edu

Xiaokang Qiu
Purdue University
West Lafayette, IN, USA
xkqiu@purdue.edu

Sanjay G. Rao
Purdue University
West Lafayette, IN, USA
sanjay@ecn.purdue.edu

Abstract
When managing wide-area networks, network architects must decide how to balance multiple conflicting metrics, and ensure fair allocations to competing traffic while prioritizing critical traffic. The state of practice poses challenges since architects must precisely encode their (somewhat fuzzy) intent into formal optimization models using abstract notions such as utility functions, and ad-hoc manually tuned knobs. In this paper, we present the first effort to synthesize network designs with indeterminate objectives using an interactive program-synthesis-based approach. We make three contributions. First, we present a novel framework in which a user’s design objective, and the synthesis of a program (network design) that optimizes that objective are done in tandem. Second, we develop a novel algorithm for our framework in which a voting-guided learner makes two kinds of queries (Propose and Compare) to the user, with the aim of minimizing the number of queries. We present theoretical analysis of the convergence rate of the algorithm. Third, we implemented Net10Q, a system based on our approach, and demonstrate its effectiveness on four real-world network case studies using black-box oracles and simulation experiments, as well as a pilot user study comprising network researchers and practitioners. Both theoretical and experimental results show the promise of our approach.

1 Introduction
Synthesizing wide-area computer network designs typically involves solving multi-objective optimization problems. For instance, consider the task of managing the traffic of a wide-area network — deciding the best routes and allocating bandwidth for them — the architect must consider myriad considerations. She must choose from different routing approaches — e.g., shortest path routing [15], and routing along pre-specified paths [23, 34]. The traffic may correspond to different classes of applications — e.g., latency-sensitive applications such as Web search and video conferencing, and elastic applications such as video streaming, and file transfer applications [23, 25, 31]. The architect may need to decide how much traffic to admit for each class of applications. It is desirable to make decisions that can ensure high throughput, low latency, and fairness across different applications, yet not all these goals may be simultaneously achievable. Likewise, a network must not only perform acceptably under normal conditions, but also under failures — however, providing guaranteed performance under failures may require being sacrificing normal performance [29, 34].

While traffic engineering has seen over two decades of research in the networking community [15, 25, 29, 31, 54], the primary focus of all this work has been on determining an optimal design given precisely specified objectives. However, it is challenging for architects to precisely state the objectives in the first place. Even the simplest objective function may involve several knobs to capture the relative importance of different criteria (e.g., throughput, latency, and fairness, performance under normal conditions vs. failures). These knobs must be manually tuned by the architect in a “trial and error” fashion to result in a desired design. Further, many optimization problems (e.g., [31]) require architects to use abstract functions that capture the utility an application sees if a given design is deployed. Utility functions are often non-linear (e.g., logarithmic) and may involve weights none of which are intuitive for a designer to specify in practice [48]. Finally, objectives are often chosen in a manner to ensure tractability, rather than necessarily reflecting the true intent of the architect.

This paper presents one of the first attempts to learn optimal network designs with indeterminate objectives. Our work adopts an interactive, program-synthesis-based approach based on the key insight that when a user has difficulty in providing a concrete objective function, it is relatively easy and natural to give preferences between pairs of concrete candidates. The approach may be viewed as a new variant of programming-by-example (PBE), where preference pairs are used as “examples” instead of input-output pairs in traditional PBE systems.

In this paper, we make the following contributions:
We present a rigorous formulation of a synthesis framework which we refer to as comparative synthesis. As Fig 1 shows, the framework consists of two major components: a comparative learner and a teacher (a user or a black-box oracle). The learner takes as input a clearly defined qualitative synthesis problem (including a parameterized program and a specification), a metric group and an objective function space, and is tasked to find a near-optimal program w.r.t. the teacher’s quantitative intent through two kinds of queries — Propose and Compare.

The notion of comparative synthesis stems from a recent position paper [53]. The preliminary work lacks formal foundation and query selection guidance, and may involve impractically many rounds of user interaction (see §2). In contrast, the formalism of our framework enables the design and analysis of learning algorithms that strive to minimize the number of queries, and are amenable for real user interaction.

**Novel algorithm for comparative synthesis (§4).** We develop a novel voting-guided learning algorithm, which maintains a running best solution and makes queries to the teacher, with the aim of minimizing the number of queries. The key insight behind the algorithm is that objective learning and program search are mutually beneficial and should be done in tandem. The idea of the algorithm is to search over a special, unified search space we call Pareto candidate set, and to pick the most informative query in each iteration using a voting-guided estimation.

We analyze the convergence of voting-guided algorithm, i.e., how fast the solution approaches the real optimal as more queries are made. We prove that the algorithm guarantees the median quality of solutions to converge logarithmically to the optimal. When the objective function space is sortable, which covers a commonly seen class of problems, a better convergence rate can be achieved — the median quality of solutions converges linearly to the optimal.

**Evaluations on network case studies and pilot user study (§5).** We developed Net10Q, an interactive network optimization system based on our general approach. We evaluated Net10Q on four real-world scenarios using oracle-based evaluation. Experiments show that Net10Q only makes half or less queries than the baseline system to achieve the same solution quality, and robustly produces high-quality solutions with inconsistent teachers. We conducted a pilot study with Net10Q among networking researchers and practitioners. Our study shows that user policies are diverse, and Net10Q is effective in finding allocations meeting the diverse policy goals in an interactive fashion.

Overall, our work develops the foundations of comparative synthesis, and shows the value and viability of the approach in network synthesis. The challenge of indeterminate objectives is also commonly seen in many quantitative synthesis problems beyond the networking domain. For example, the default ranker for the FlashFill synthesizer is manually designed and highly tuned by experts [20]. In quantitative syntax-guided synthesis (qSyGuS) [24], the objective should be provided as a weighted grammar, which is nontrivial for average programmers. We believe the advances we make in this paper can also help in these other domains.

2 Motivation

In this section, we present background on network design, how it may be formulated as a program synthesis problem, and discuss challenges that we propose to tackle.

Network design background. In designing Wide-Area Networks (WANs), Internet Service Providers (ISPs) and cloud providers must decide how to provision their networks, and route traffic so their traffic engineering goals are met. Typically WANs carry multiple classes of traffic (e.g., higher priority latency sensitive traffic, and lower priority elastic traffic). Traffic is usually specified as a matrix with cell $(i, j)$ indicating the total traffic which enters the network at router $i$ and that exits the network at router $j$. We refer to each pair $(i, j)$ as a flow, or a source-destination pair. It is typical to predecide a set of tunnels (paths) for each flow, with traffic split across these tunnels in a manner decided by the architect, though traffic may also be routed along a routing algorithm that determines shortest paths (§5.1).

Given constraints on link capacities, it may not be feasible to meet the requirements of all traffic of all flows. An architect must decide how to allocate bandwidth to different flows of different classes and how to route traffic (split each flow’s traffic across it paths) so desired objectives are met. In doing so, an architect must reconcile multiple metrics including...
struct Topology {
    int n_nodes; int n_links; int n_flows;
    bit[n_nodes][n_nodes] links;
    /* every link has a capacity and a weight, every flow consists
       of multiple links and has a demand */
    float[n_links] capacity; int[n_links] wght;
    bit[n_links][n_flows] l_in_f; float[n_flows] demand; ...
} Topology abilene = new Topology(n_nodes=11, n_links=...);
float[] allocate(Topology T) {
    float[T.n_flows] bw = ???; // generate bandwidth allocation
    /* assert that every flow's demand is satisfied and every
       link's bandwidth is not exceeded */
    assert \( \sum_i b[i] \leq T.demand[i] \);
    assert \( \sum_j \left( \sum_i l_{i,j} \right) \cdot wght[j] : 0 \) \leq T.capacity[j];
    return bw; }
float[] main() {
    float[] alloc = allocate(abilene);
    /* compute the throughput and weighted latency */
    float throughput = \( \sum_i alloc[i] \);
    float latency = \( \sum_j \left( \sum_i l_{i,j} \right) \cdot wght[j] : 0 \);
    return [throughput, latency];
}

Figure 2. MCF allocation encoded as a program sketch.

throughput, latency, and link utilizations [23, 25, 32, 50],
ensure fairness across flows [9, 31, 48], and consider performance
under failures [4, 7, 29, 34, 54].

Network Design as Program Synthesis Problems. Consider
a variant of the classical multi-commodity flow problem
used in Microsoft’s Software Defined Networking Controller
SWAN [23], which we refer to as MCF. MCF allocates traffic
to tunnels optimally trading off the total throughput seen by
all flows with the weighted average flow latency [23]. We
consider a single class (see §5.1 for multiple classes).

Fig 2 shows how the task may be described as a sketch-based synthesis problem, in which the programmer specifies
a sketch — a program that contains unknowns to be solved for,
and assertions to constrain the choice of unknowns. The
Topology struct represents the network topology (we use the
Abilene topology [30] with 11 nodes, 14 links and 220
flows as a running example). The allocate function should
determine the bandwidth allocation (denoted by ??), which
is missing and should be generated by the synthesizer. The
function also serves as a test harness and checks that the
synthesized allocation is valid, satisfying all demand and
capacity constraints (lines 11–12). Finally, the main function
takes the generated allocation, and computes and returns the
total throughput and weighted latency.

Why synthesis with indeterminate objectives? While
Fig 2 has encoded all hard constraints, the architect has to
provide an objective function which maps each possible solution
to a numerical value indicating the preference. Given a well-specified objective function, the bandwidth allocation problem becomes a quantitative synthesis problem and can be solved using existing techniques from both synthesis and optimization communities. E.g., in Fig 2, one can explicitly add an objective function \( O_{\text{real}} \) and use the minimize construct (cf. Sketch manual [46]) to find the optimal solution.

Unfortunately, in practice, it is hard for network architects
to precisely express their true intentions using objective functions. For example, to capture the intuition that once
the throughput (resp. latency) reaches a certain level, the
marginal benefit (resp. penalty) may be smaller (resp. larger),
an architect may need to use an objective function like below:

\[
O_{\text{real}}(\text{throughput}, \text{latency}) \overset{\text{def}}{=} 2 \cdot \text{throughput} - 9 \cdot \text{latency} - \max(\text{throughput} - 350, 0) - 10 \cdot \max(\text{latency} - 28, 0) \tag{2.1}\]

More generally, the marginal reward in obtaining a higher
bandwidth allocation is smaller capturing which may require
an objective of the form \( O(\text{throughput}, \text{latency}) \overset{\text{def}}{=} 1 \cdot \log_{\text{real}}(\text{throughput}/\text{imax} + 1) + 5 \cdot \log_{\text{real}}(\text{limin}/\text{latency} + 1) \) where \( \text{imax} \) is the maximum possible throughput and \( \text{limin} \) is the minimum possible latency. Expressing such abstract
objective functions is not trivial, let alone the parameters
associated with the functions. We present several other examples in §5.1.

Naïve objective synthesis is not enough. A preliminary
work [53] argued for synthesizing objective functions by
having the learner (synthesizer) iteratively query the
teacher (user) on its preference between two concrete net-
work designs. In each iteration, any pair of designs may be
considered as long as there exist two objective functions that
(i) disagree on how they rate these designs, and (ii) both satis-
fy preferences expressed by the teacher in prior iterations.

The process continues until no disagreeing objectives are
found. However, this work only discusses objective learning
and does not explicitly consider design synthesis. Moreover,
it does not address how to generate good preference pairs
to minimize queries. These limitations make this naïve approach not amenable for real user interaction. Fig 3 shows the
performance of a design optimal for an objective function
synthesized using this procedure if it were terminated after
a given number of queries. The resulting designs achieve an
objective value only 60% of the true optimal design under the
ground truth (Eq 2.1), and there is hardly any performance
improvement in the first 100 queries.

3 Comparative Synthesis, Formally

In this section, we provide a formal foundation for the com-
parative synthesis framework, based on which we design
and analyze learning algorithms. We first define quantita-
tive synthesis in a purely semantical way based on metric
We next discuss the quantitative aspect of a synthesis problem. We semantically describe the quantitative specification of a synthesis problem.

**Definition 3.7** (Metric ranking). Given a \( d \)-dimensional metric group \( M \), a metric ranking for \( M \) is a total preorder \( \leq_M \) over \( \mathbb{Z}^d \). In other words, \( \leq_M \) satisfies the following properties: for any \( u, v \in \mathbb{Z}^d \), \( u \leq_M u \) (reflexivity); for any three vectors \( u, v, w \in \mathbb{Z}^d \), if \( u \leq_M v \) and \( v \leq_M w \), then \( u \leq_M w \) (transitivity); for any two vectors \( u, v \in \mathbb{Z}^d \), \( u \leq_M v \) or \( v \leq_M u \) (connectivity).

We write \( u \sim_M v \) if \( u \leq_M v \) and \( v \leq_M u \). In this paper, we also flexibly write \( u \preceq_M v \), \( u \prec_M v \), and \( u \succ_M v \) with the expected meaning. Moreover, we also abuse other derived symbols we just described as relations between programs: when the metric group \( M \) is clear from the context, for any two program parameters \( c_1, c_2 \in \text{dom}(M) \), we write \( c_1 \preceq_M c_2 \) to indicate that \( M(c_1) \preceq_M M(c_2) \).

**Definition 3.8** (Quantitative synthesis problem). A quantitative synthesis problem is represented as a tuple \( \mathcal{Z} = (\mathcal{P}, \mathcal{Q}, M, \leq_M) \) where \( \mathcal{P} \) is a parameterized program, \( \mathcal{Q} \) is the space of parameters for \( \mathcal{P} \), and \( M \) is a metric group w.r.t. \( \leq_M \) which includes \( 2^2 \) bandwidth values of the Abilene network. \( \Phi_{\text{abilene}} \) is the verification condition, taking a candidate solution \( c \in \mathbb{R}^{220} \) as input and checking whether \( \mathcal{P}_{\text{abilene}}[c] \) satisfies all assertions in Fig 2.

**Definition 3.9** With the metric group \( M_{\text{MCF}} \) defined in Example 3.6, the function \( O_{\text{real}} \) defined in Equation 2.1 is a 2-dimensional objective function and implicitly defines a metric ranking \( \leq_{O_{\text{real}}} \). Then the quantitative synthesis problem \( \mathcal{Z}_{\text{MCF}} = (\mathcal{P}_{\text{abilene}}, \mathbb{R}^{220}, \Phi_{\text{abilene}}) \) can be extended to a quantitative synthesis problem

\[
\mathcal{Z}_{\text{MCF}} \overset{\text{def}}{=} (\mathcal{P}_{\text{abilene}}, \mathbb{R}^{220}, \Phi_{\text{abilene}}, M_{\text{MCF}}, \leq_{O_{\text{real}}})
\]
framework special is that the learner can make queries about the metric ranking—queries that compare two metric value vectors, check whether a candidate program is better than the best known solution, or just ask the teacher to provide a better metric value vector.

Let us fix a parameterized program $P$ and a metric group $M$. In this paper, we assume the interactive synthesis process maintains a running best candidate and the learner and the teacher interact using two types of queries:

- **Compare**$(c_1, c_2)$ query: The learner provides two concrete programs $P[c_1]$ and $P[c_2]$, and asks “Which one is better under the target metric ranking $\leq M$?” The teacher responds with $<$ or $>$ if one is strictly better than the other, or $=$ if $P[c_1]$ and $P[c_2]$ are considered equally good.

- **Propose**$(c)$ query: The learner proposes a candidate program $P[c]$ and asks “Is $P[c]$ better than the running best candidate $r_{\text{best}}$?” If the teacher finds that $P[c]$ is not better than the running best, she can respond with $\perp$. Otherwise, the teacher considers that $P[c]$ is better and responds with $\top$; in that case, the running best will be updated to $P[c]$.

Now in comparative synthesis, the specification (a metric ranking $R$) is hidden to the learner. Instead, the learner can approximate/guess the specifications by making queries to the teacher. Ideally, the teacher should be perfect, i.e., the responses she makes to queries are always consistent and satisfiable. Formally,

**Definition 3.10** (Perfect teacher). A teacher $T$ is perfect if there exists a metric ranking $\leq M$ such that: 1) for any query Compare$(v_1, v_2)$, the response is “$<$” if $v_1 \leq M v_2$ and $v_2 \not\leq M v_1$, or “$>$” if $v_1 \not\leq M v_2$ and $v_2 \leq M v_1$, or “$=$” if $v_1 \leq M v_2$ and $v_2 \leq M v_1$; 2) for any query Propose$(c)$ with the current running best $r_{\text{best}}$, the response is “$\top$” if $c > M r_{\text{best}}$; or “$\perp$” otherwise.

We denote the perfect teacher w.r.t. $\leq M$ as $T_{\text{SM}}$. We also denote the metric ranking $\leq M$ represented by a perfect teacher $T$ as $\leq T$. A perfect teacher guarantees that an optimal solution exists among all candidates. For now, let us assume that the teacher is perfect, i.e., consistent and able to answer all queries; but in the real world, a human teacher may be inconsistent and responds incorrectly. We do consider imperfect teachers in our evaluation (see §5.3).

### 3.3 The Comparative Synthesis Problem

Now we are ready to formally define the comparative synthesis problem. Intuitively, the goal of the learner is to approximate the quantitative objective, through a budgeted number of queries, and to produce a program close enough to the real optimal program, from the perspective of the learner. We give the formal definition below.

**Definition 3.11** (Comparative synthesis problem). A comparative synthesis problem is represented as a tuple $\mathcal{C} = (P, C, \Phi, M, T)$ where $P$ is a parameterized program, $C$ is the space of parameters for $P$, $\Phi$ is a verification condition for $P$, $M$ is a metric group w.r.t. $P$ and $T$ is a perfect teacher, such that $(P, C, \Phi, M, \leq T)$ forms a quantitative synthesis problem, which is denoted as $\mathcal{C}_{\text{quan}}$. The synthesis problem is to find, by making a sequence of Compare and Propose queries to the teacher $T$, a likely solution $\text{ctr}$ to $\mathcal{C}_{\text{quan}}$.

We believe our framework can be extended in the future to support more types of queries.

Note that Propose$(c)$ can be viewed as a special Compare query between $c$ and $r_{\text{best}}$, the goal of the query is slightly different: Propose$(c)$ intends to beat the running best using $c$, while Compare$(c_1, c_2)$ intends to distinguish very close solutions $c_1$ and $c_2$ to learn the teacher’s intent.

Note that the goal of a comparative synthesis problem is to find a likely optimal solution, because the learner has no means to determine whether a solution is indeed the optimal one, i.e., a solution to $\mathcal{C}_{\text{quan}}$. The teacher only provides preferences between concrete solutions—even for a Propose query, she only determines whether the proposed solution is better than the running best. Therefore, we formally define the quality of solutions, which determines how good a solution relatively is to other solutions.

**Definition 3.12** (Quality of solution). Let $\mathcal{C} = (P, C, \Phi, M, T)$ be a comparative synthesis problem. The quality of a solution $\text{ctr}$ to $\mathcal{C}$ is defined as $\text{Quality}_{\mathcal{C}}(\text{ctr}) \equiv P(\text{ctr} \geq_T X^M_{\mathcal{C}})$ where $X^M_{\mathcal{C}}$ is a variable randomly sampled from the uniform distribution for Solutions$(\mathcal{C}_{\text{quan}})$.

Intuitively, the quality of solution is the cumulative distribution function for the set of all solutions of $\mathcal{C}_{\text{quan}}$ ordered by $\geq_T$. In particular, when $\text{Quality}_{\mathcal{C}}(c) = 1$, $c$ is better than or equal to all other possible solutions, i.e., is the optimal solution under the teacher’s preference.

**Example 3.13**. A comparative synthesis problem $\mathcal{C}_{\text{MCF}}$ can be defined such that the corresponding $\mathcal{C}_{\text{quan}}$ is just $\mathcal{C}_{\text{MCF}}$ in Example 3.9, and the corresponding teacher is $T_{\text{real}}$. Table 1 illustrates how the comparative synthesis process works on $\mathcal{C}_{\text{MCF}}$. A voting-guided learning algorithm (which we present later in §4) serves as the comparative learner. An oracle serves as the perfect teacher and answers queries based on the objective function in Equation 2.1. In the first iteration, the learner solves the synthesis problem in Fig 2 and gets a first mediocre allocation $P_0$ and presents it to the architect, using query Propose$(P_0)$. The teacher accepts the proposal as this is the first running best. In the sixth iteration, the learner presents two programs $P_6$ and $P_7$ to the teacher and asks her to compare them. Based on the feedback that the architect prefers $P_6$ to $P_7$, the learner proposes $P_8$ which is confirmed by the teacher to be the best program so far. After all of seven queries, the running best is already very close to the optimal under the real objective (Quality of this solution has already achieved 97.8%). If the teacher wishes to answer more queries, the solution quality can be further improved.
Table 1. A Comparative Synthesis run for Example 3.13

| Iter | Candidate Allocation | Query       | R | B | Quality |
|------|----------------------|-------------|---|---|---------|
| 1    | P₀ (thrpt = 205.2, latency = 10.3) | Propose (P₀) | T | P₀ | 32.8%   |
| 2    | P₁ (thrpt = 479.2, latency = 33.0) | Propose (P₁) | T | P₁ | 73.6%   |
| 3    | P₂ (thrpt = 385.2, latency = 24.5) | Propose (P₂) | T | P₂ | 92.8%   |
| ...  | ...                  | ...         | ...| ...| ...     |
| 6    | P₆ (thrpt = 405.4, latency = 26.5) | Compare (P₀, P₁) | P₀ | P₁ | 92.8%   |
| 7    | P₇ (thrpt = 392.9, latency = 25.3) | Propose (P₇) | T | P₇ | 97.8%   |

R—Response of teacher. B—Running best.

4 Voting-Guided Learning Algorithm

In this section, we focus on the learner side of the framework and propose a voting-guided learning algorithm that can play the role of the comparative learner and interact with an arbitrary teacher. Below we propose a novel search space combining the program search and objective learning, then present an estimation of query informativeness, based on which our voting-guided algorithm is designed. We discuss the convergence of the algorithm at last.

4.1 A Unified Search Space

A syntactical and natural means to describing quantitative specification is objective functions (in contrast to the semantically defined metric ranking in Def 3.7). Now to solve a comparative synthesis problem efficiently, an explicit task of the learner is program search: the goal is to minimize human interaction (i.e., the number of queries) and maximize the quality of the solution (see Def 3.12) proposed through propose queries. Another implicit task of the learner is objective learning: to steer program search faster to the optimal and minimize the query count, the learner should make comparative queries to learn an objective function that fits the teacher’s preferences and approximates the teacher’s metric ranking \( \leq r \).

The key insight is that the two tasks are inherently tangled and better be done together. On one hand, the quantitative simulation task needs to be guided by an appropriate objective function; otherwise the search is blind and unlikely to steer to those candidates satisfying the user. On the other hand, learning the real objective involves user interaction and can be extremely expensive and unnecessary — even an inaccurate objective function may guide the program search.

We formally define objective function spaces and discuss its relationship with metric ranking in Appendix A of supplemental material. In short, multiple objective functions may have the same metric ranking, hence an ideal objective function space should be a rich yet easy-to-search class of functions. For example, the conditional linear integer arithmetic (CLIA) space \( O_{CLIA}^{d} \) (Example A.4 in supplemental material) is general enough for arbitrary metric group, but it can be too large to be efficiently searched. For many concrete metric groups, more compact objective function spaces usually exist.

Example 4.1 For our running example, a commonly used function to quantify this trade-off is the multi-commodity flow functions used in software-driven WAN [23]. The \( O_{real} \) function (Equation 2.1) in our running example is an instance of the generalized, two-segment MCF function space, which can be described in the following form:

\[
O(\text{throughput, latency}) \defeq \text{throughput} \star ?? - \max(\text{throughput} - ??, 0) \star ??
- \text{latency} \star ?? - \max(\text{latency} - ??, 0) \star ??
\]

where ?? can be arbitrary weights or thresholds. Note that the two-segment template is insufficient to characterize arbitrary finite metric ranking. In that case, the template may be extended to more segments. We call the whole objective function space \( O_{MCF} \).

Now as the learner’s task is to search two spaces — one for programs and one for objective functions — we merge the two tasks into a single one, searching over a unified search space which we call Pareto candidate set:

Definition 4.2 (Pareto candidate set). Let \( \mathcal{D} = (\mathcal{P}, C, \Phi, M, \leq_{M} \) ) be a quantitative synthesis problem and \( O \) be an objective function space w.r.t. \( M \). A Pareto candidate set (PCS) with respect to \( \mathcal{D} \) and \( O \) is a finite partial mapping \( \mathcal{G}: \mathcal{P} \rightarrow C \) from an space of objective function \( O \) to a space of program parameters \( C \), such that for any \( O \in O \), \( \mathcal{G}(O) \) is the effectively optimal solution to \( \mathcal{D}^{\text{final}} \), i.e., a solution \( c \in C \) such that \( c >_{O} \mathcal{G}(O) \), if exists, cannot be effectively found. Specifically, for any other \( O' \in O \), \( \mathcal{G}(O') \preceq_{O} \mathcal{G}(O) \).

Intuitively, a Pareto candidate set (PCS) \( \mathcal{G} \) maintains a set of candidate objective functions, a set of candidate programs, and a mapping between the two sets, and guarantees that every candidate objective function \( O \) is mapped to the best candidate program under \( O \).

4.2 Query Informativeness

Now with the unified search space — PCS in Def 4.2 — comparative synthesis becomes a game between the learner and the teacher: a PCS \( \mathcal{G} \) is maintained as the current search space; and in each iteration, the learner makes a query and the teacher gives her response, based on which \( \mathcal{G} \) is shrunked. The learner’s goal should be, in each iteration, to pick the most informative query in the sense that it can reduce the size of \( \mathcal{G} \) as fast as possible. From the perspective of active learning [42], the key question is how to evaluate the informativeness of a query.

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\[^3\]Note that in general, the best candidate program under \( O \) is not necessarily unique. To break the tie and make \( \mathcal{G} \) uniquely determined by the component sets of objective functions and programs, when two candidate programs \( c_{1} \) and \( c_{2} \) both get the highest reward under \( O \), we assume \( \mathcal{G}(O) = c_{1} \) if \( M(c_{1}) \) is smaller than \( M(c_{2}) \) in lexicographical order, or \( c_{2} \) otherwise.
In this paper, we develop a greedy strategy which evaluates the informativeness by computing how many candidate programs from \( \mathcal{G} \) can be removed immediately with the teacher’s response. As the teacher’s response can be arbitrary, our evaluation considers all possible responses and take the minimum number among all cases. The formulation is shown in Fig 4 and explained below.

- **Compare query**: Given a query \( \text{COMPARE}(c_1, c_2) \), the teacher may prefer \( \mathcal{P}[c_1] \) to \( \mathcal{P}[c_2] \), or vice versa, or consider the two programs equally good (corresponding to the three responses: <, > and =). For the first case, one can remove all those candidates of the form \( \mathcal{G}(O) \) such that \( \mathcal{O} \) considers \( \mathcal{P}[c_1] \) is at least as good as \( \mathcal{P}[c_2] \); the number of removed candidates is denoted as \#\text{RemNEQ}(c_1, c_2). Similarly, for the second case, \#\text{RemNEQ}(c_2, c_1) candidates will be removed. And for the last case, the set of candidates considering \( \mathcal{P}[c_1] \) and \( \mathcal{P}[c_2] \) not equally good, which is of size \#\text{RemEQ}(c_2, c_1), will be removed. The overall informativeness is just the minimum of the three cases.

- **Propose query**: Given a query \( \text{PROPOSE}(c) \), the teacher may confirm that \( \mathcal{P}[c] \) is indeed better than the running best \( \mathcal{P}[r_{\text{best}}] \) (response \( \top \)), or keep the current running best (response \( \bot \)). For the former case, one can remove all those candidates of the form \( \mathcal{G}(O) \) such that \( \mathcal{O} \) considers \( \mathcal{P}[r_{\text{best}}] \) is at least as good as \( \mathcal{P}[c] \). In addition, a \( \mathcal{G}(O) \) can also be removed if it is equally good to \( \mathcal{P}[c] \) under \( \mathcal{O} \), i.e., even if \( \mathcal{O} \) is the real objective function, \( \mathcal{G}(O) \) will not be able to improve the running best. The total number of removed candidates is \#\text{RemNewBest}(c). For the latter case, for any objective function \( \mathcal{O} \) that prefers \( c \) to \( r_{\text{best}} \), \( \mathcal{G}(O) \) will be removed; the total number is \#\text{RemOldBest}(c). The overall informativeness is just the minimum of the two cases.

Figure 4. Informativeness of queries (with \( \mathcal{G} \) the current Pareto candidate set, and \( r_{\text{best}} \) the running best program).

4.3 The Algorithm

With the search space PCS and the query informativeness estimation we set forth above, our learning algorithm is almost straightforward: for each iteration, compute the informativeness of every possible query and make the most informative query. The remaining issue is that it is not realistic to keep a PCS that contains all possible candidates, because the number of candidates is usually very large, if not infinite. For example, \( \mathcal{L}_{MCF} \) in Example 3.2 has infinitely many Pareto optimal solutions, ranging in the continuous spectrum from maximizing throughput to minimizing latency. To this end, our voting-guided algorithm maintains a moderate-sized PCS, from which queries are generated and selected based on their informativeness. The algorithm is akin to the query-by-committee [43] in active learning — the PCS serves as a committee and votes for the most informative query.

Algorithm 1 illustrates the voting-guided algorithm. The algorithm takes as input a comparative synthesis problem \( \mathcal{G} \) and an objective function space \( \mathcal{O} \), and maintains a PCS \( \mathcal{G} \) w.r.t. \( \mathcal{O} \) and \( \mathcal{O} \) and set of preferences \( \mathcal{K} \), both empty initially. In each iteration, the algorithm computes the quality of all possible queries that can be made about the current candidates image(\( \mathcal{G} \)), and picks the highest-quality query according to the computation presented in Fig 4 (line 7). After the query is made and the response is received, an update subroutine is invoked to update \( \mathcal{G} \) and remove all candidates violating the preference (lines 11–15). Moreover, the algorithm also checks at the beginning of every iteration the size of \( \mathcal{G} \); if image(\( \mathcal{G} \)) is below a fixed Thresh, the algorithm attempts to extend \( \mathcal{G} \) using a generate-more subroutine. The algorithm terminates and returns the current running best when at least NQuery queries have been made and \( \mathcal{G} \) becomes 0 (line 17).

The subroutines involved in the algorithm are shown as Algorithm 2 in Appendix B.1 in supplementary material (in the interest of space). The update subroutine is straightforward, taking a new preference pair and shrinking \( \mathcal{G} \) accordingly. The generate-more subroutine is tasked to expand \( \mathcal{G} \) as much as possible within a time limit. Each time, it tries to find a pair \( (O, c) \) such that \( O \) satisfies all existing preferences and prefers \( \mathcal{P}[c] \) to \( \mathcal{P}[r_{\text{best}}] \), and \( \mathcal{P}[c] \) is effectively optimal under \( O \). Note that this subroutine delegates several heavy-lifting tasks to off-the-shelf, domain-specific procedures, e.g., quantitative synthesis and objective synthesis.

4.4 Convergence

In the rest of the section, we discuss the convergence of the algorithm. Recall that our algorithm only produces quasi-optimal programs as the ground-truth objective function is not present. Therefore, the algorithm should be evaluated on the rate of convergence [18], i.e., how fast the median quality \(^4\) of solutions (see Def 3.12) approaches 1 as more queries

\(^4\)The algorithm involves random sampling and results we prove below are for the median quality of output solutions; the proofs can be easily adapted to get similar results for the mean quality of solutions.
are made. Our first result is that the algorithm guarantees a logarithmic rate of convergence.

**Theorem 4.3.** Given a comparative synthesis problem $E$ and an objective function space $O$ as input, if Algorithm 1 terminates after $n$ queries, the median quality of the output solutions is at least $2^{-\frac{n}{\ln 2}}$.

**Proof:** Note that every query will discard at least one candidate program from the PCS, regardless of the query type. In other words, the final output $c$ must be the optimal among at least $(n+1)$ randomly selected candidates from the uniform distribution. Therefore, the quality of $c$ is at least the $(n+1)$-th order statistic of the uniform distribution, which is a beta distribution $Beta(n+1, 1)$, whose median is $2^{-\frac{n}{\ln 2}}$. □

The proved lower-bound in the theorem above is tight only when each query only removes one candidate from the PCS $\mathcal{G}$. Unfortunately, the following lemma shows that in general, this scenario is always realizable:

**Theorem 4.4.** The bound in Theorem 4.3 is tight.

**Proof:** See Appendix B.2 in supplementary material. □

### 4.5 Better Convergence Rate with Sortability

We next show a class of comparative synthesis problems on which our algorithm converges faster. Our main result here is that our algorithm guarantees the median quality of solutions converges linearly when it searches from a sortable objective function space. Intuitively, the sortability makes sure that the candidate programs in the PCS can be ordered appropriately such that every objective function with corresponding candidate $c$ always prefers nearer neighbors of $c$ to farther neighbors of $c$.

**Definition 4.5** (Sortability). A PCS $\mathcal{G}$ is sortable if there exists a total order $\prec$ over $\text{image}(\mathcal{G})$ such that for any objective functions $O, P, Q \in \text{dom}(\mathcal{G})$ such that $\mathcal{G}(O) < \mathcal{G}(P) < \mathcal{G}(Q)$, the following two conditions hold: $\mathcal{G}(P) \succ O \mathcal{G}(Q)$, and $\mathcal{G}(P) \succ Q \mathcal{G}(Q)$. An objective function space $O$ is sortable with respect to a qualitative synthesis problem $\mathcal{F}$ if any PCS $\mathcal{G}$ w.r.t. $\mathcal{F}$ and $O$ is sortable.

**Theorem 4.6.** Given a comparative synthesis problem $E$ with metric group $M$ and a sortable objective function space $O$ w.r.t. $E^{\text{qual}}$ as input, if Algorithm 1 terminates after $n$ queries, the median quality of the output solutions is at least $1 - \frac{1}{\Omega(1.5^n)}$.

**Proof:** See Appendix B.3 in supplementary material. □

We conclude this section by identifying a subclass of comparative synthesis problems which guarantees the sortability and hence the convergence result of Theorem 4.6 applies. The subclass relies on the convexity of the comparative synthesis problem and the concavity of the objective function space, which we define below.

**Definition 4.7** (Convexity of comparative synthesis problem). A comparative synthesis problem $E$ with metric group $M$ is convex if for any two solutions $c_1, c_2 \in E^{\text{qual}}$ and any $\alpha \in [0, 1]$, a solution $c_\alpha$ to $E^{\text{qual}}$ can be effectively found such that $M(c_\alpha) \geq \alpha \cdot M(c_1) + (1 - \alpha) \cdot M(c_2)$.

**Definition 4.8** (Concavity of objective function space). Let $O$ be an objective function space w.r.t. a $d$-dimensional metric group $M$. $O$ is concave if for any $O \in O$, for any $v_1, v_2 \in \mathbb{R}^d$ and any $\alpha \in [0, 1]$,

$$O(\alpha \cdot v_1 + (1 - \alpha) \cdot v_2) \geq \max(O(v_1), O(v_2)).$$

**Example 4.9.** Our running example falls in this subclass. The comparative synthesis problem $E_{\text{MCB}}$ in Example 3.13 is convex. As shown in Fig 2, both throughput and latency are weighted sum of allocations to every link. Therefore given any two solutions $c_1$ and $c_2$, their convex combination is still feasible, and the metric vector is also the corresponding convex combination of $M(c_1)$ and $M(c_2)$. Moreover, it is not hard to verify that the objective function space $O_{\text{MCB}}$ in Example 4.1 is concave, as both the weights of throughput and latency decrease when their values are good enough and exceed a threshold.
Theorem 4.10. Let $\mathcal{C}$ be a convex comparative synthesis problem with a 2-dimensional metric group $M$ and $O$ be a concave objective function space w.r.t. $M$, then $O$ is sortable w.r.t. $\mathcal{C}^{qual}$.

Proof: See Appendix B.4 in supplementary material. □

5 Evaluation

We have prototyped the comparative synthesis framework and the voting-guided learning algorithm as Net10Q — an interactive system that produces near-optimal network design by asking 10 questions to the user — through which we evaluate the effectiveness and efficiency of our approach. We selected four real-world network design scenarios and conducted experiments with both oracles and human users. Our evaluations were conducted on seven real-world, large-scale internet backbone topologies obtained from [25, 30] (sizes summarized in Table 2).

5.1 Network Optimization Problems

We summarize the four optimization scenarios in Table 3, including their metric groups, objective function spaces and sortability. We present some details below.

Balancing throughput and latency (MCF). This is our running example based on [23] described throughout the paper. This bandwidth allocation problem focuses on a single traffic class and considers balancing the throughput and latency in the network.

Utility maximization with multiple traffic classes (BW). We model an optimization problem for maximizing utility when allocating bandwidth to traffic of different classes [19, 31, 48]. Many applications such as file transfer have concave utility functions which indicate that as more traffic is received, the marginal utility in obtaining a higher allocation is smaller. A common concave utility function which is widely used is a logarithmic utility function, where a flow that receives a bandwidth allocation of $x$ gets a utility of $\log x$. Consider $N$ flows, and $K$ classes. Each flow belongs to one of the classes with $F^k$ denoting the set of flows belonging to class $k$. The weight of class $k$ is denoted by $w_k$ and is a knob manually tuned today to control the priority of the class, which we treat as an unknown in our framework.

Performance with and without failures (NF). Resilient routing mechanisms guarantee the network does not experience congestion on failures [4, 7, 29, 34, 54] by solving robust optimization problems that conservatively allocate bandwidth to flows while planning for an desired set of failures. We consider the model presented in [34] to determine how to allocating bandwidth to flows while being robust to single link failure scenarios. We consider an objective with (unknown) knobs $\omega_i$ and $\omega_f$ that trade off performance under normal conditions and failures tuned differently for each group of flows $i$.

Balancing latency and link utilization (OSPF). Open Shortest Path First (OSPF) is a widely used link-state routing protocol for intra-domain internet and the traffic flows are routed on shortest paths [15]. A variant of OSPF routing protocol assigns a weight to each link in the network topology and traffic is sent on paths with the shortest weight and equally split if multiple shortest paths with same weight exist. By configuring the link weights, network architect can tune the traffic routes to meet network demands and optimize the network on different metrics [15]. We consider a version of the OSPF problem where link weights must be tuned to ensure utilizations on links are small while still ensuring low latency paths [22]. Intuitively, when utilization is higher than a threshold, it becomes the primary metric to optimize, and when lower than a threshold, minimizing latency is the primary goal. In between the thresholds, both latency and utilization are important, and can be scaled in a manner chosen by the network architect. We treat the thresholds and the scale factors as unknowns in the objective.

5.2 Implementation

Note that in Net10Q, once the scenario and the topology are fixed, we can pre-compute a large pool of objective-program pairs, from which the PCS is generated. For each scenario-topology combination, we used the templates shown in Table 3 to generate a pool of random objective functions. Then for all scenarios except for OSPF, we generate their corresponding optimal allocations using Gurobi [21], a state-of-the-art solver for linear and mixed-integer programming problems. For OSPF, as we are not aware of any existing tools that can symbolically solve the optimization problem, we used traditional synthesis approaches (cf. Fig 2) to generate numerous feasible link weight assignments. The pre-computed objective functions and allocations are paired to form a large PCS serving as the candidate pool.

When the teacher is an imperfect oracle or a human user, inconsistent answers may potentially result in the algorithm unable to determine objectives that meet all user preferences. To ensure Net10Q robust to an imperfect oracle, inspired by the ensemble methods [10], we implemented Net10Q as a multi-threaded application where a primary thread accepts all inputs and the backup threads run the same algorithm but randomly discard some user inputs. In case no objective could satisfy all user preferences, a backup thread with the largest satisfiable subset of user inputs would take over.

5.3 Oracle-Based Evaluation

We used Net10Q to solve all scenario-topology combinations described above, through interaction with (both perfect and imperfect) oracles who answer queries based on their internal objectives. As a first-of-its-kind system, Net10Q does not have any similar systems to compare with. Therefore, we developed a variant of Net10Q which adopts a simple but aggressive strategy: repeatedly proposing optimal candidates
generating from randomly picked objective functions. We call this baseline algorithm Net10Q-NoPrune, as the teacher’s preference is not used to prune extra candidates from the search space. As a solution’s real quality (per Def 3.12) is not practically computable, we approximate its quality using its rank in our pre-computed candidate pool. Moreover, as Net10Q involves random sampling, we ran each synthesis task 301 times and reported the median of the (approximated) solution quality achieved after every query.

**Evaluation on perfect teacher.** We built an oracle to play the role of a perfect teacher who answers all queries correctly based on a ground truth objective function. For each scenario, we as experts manually crafted an objective function that fits the template and reflects practical domain knowledge.

We present the performance of Net10Q and Net10Q-NoPrune on solving four network optimization problems (cf. Table 3) on seven different topologies (cf. Table 2). Our key observation is that Net10Q performed constantly better than Net10Q-NoPrune in every scenario-topology combination. In the interest of space, we collected the quality of solutions achieved over all seven topologies for each optimization scenario and presented the median (shown as dots) and the range from max to min (shown as bars). As Fig 5 shows, our voting-guided query selection is very effective. Net10Q always needs 5 or fewer queries to obtain a solution quality achieved by Net10Q-NoPrune in 10 queries. We note that although the all-topology range for Net10Q sometimes overlaps with the corresponding range for Net10Q-NoPrune (primarily for the NF scenario), Net10Q still outperformed Net10Q-NoPrune for every topology. We leave the topology-wise results for NF in Appendix C.1. Further, in all the cases where we could compute the optimal under the ground truth objective function, we confirmed that programs recommended by Net10Q achieved at least 99% of the optimal.

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**Table 2. Summary of topologies.**

| Topology         | #nodes | #links |
|------------------|--------|--------|
| Abilene          | 11     | 14     |
| B4               | 12     | 19     |
| CIVIX            | 21     | 26     |
| BTNorthAmerica   | 36     | 76     |
| Timnet           | 48     | 84     |
| Delacom          | 103    | 151    |
| Ion              | 114    | 135    |

**Table 3. Summary of optimization scenarios.**

| Scenario | Metric group | Objective function space | Sortable? |
|----------|--------------|--------------------------|-----------|
| BW       | (throughput, -latency) | \( \sum_{k=1}^{K} w_k \log(a_{yk}) \) (\( w_k > 0 \)) | No        |
| MCF      | (traffic demand, -utilization) | throughput \( \times ?? \) - max(throughput - ??, 0) \( \times ?? \) - latency \( \times ?? \) - max(latency - ??, 0) \( \times ?? \) | Yes       |
| OSPF     | (-latency, -utilization) | utilization \( \times ?? \) + utilization \( \times ?? \) \( ?? < \) utilization \( ?? \) | Yes       |
| NF       | (\( z_{ni}, z_{fi} \): guaranteed fraction of traffic demand of group \( i \) under normal conditions and failures respectively) | \( \sum_{i} w_n z_{ni} + w_f z_{fi} \) (\( w_n, w_f > 0 \)) | No        |

**Evaluation on imperfect teacher.** We also adapt the oracle to simulate imperfect teachers whose responses are potentially inconsistent, based on an error model described below. When an allocation candidate is presented, the imperfect oracle assigns a random reward that is sampled from a normal distribution, whose expectation is the true reward under corresponding ground truth objective function. The standard deviation is \( p \) percentage of the distance between average reward and optimal reward under ground truth objective.

Fig 6 shows our experimental results with imperfect teacher on BW with the CWIX topology. In the interest of space, we defer results of other scenarios to Appendix C.2, from which we see similar trend. Fig 6a compares Net10Q with Net10Q-NoPrune under the inconsistency level \( p = 10 \). Net10Q continues to outperform Net10Q-NoPrune. Fig 6b presents the sensitivity of Net10Q on the inconsistency level (\( p = 0, 5, 10, 20 \)). Although the solution quality degrades with higher inconsistency \( p \), Net10Q achieves relatively high solution quality even when \( p \) is as high as 20. The results show that Net10Q tends to be able to handle moderate feedback inconsistency from an imperfect teacher, although investigating ways to achieve even higher robustness is an interesting area for future work.

**Online query time.** For every synthesis task mentioned above, and across all topologies, the average running time spent by Net10Q for each interactive user query is less than 0.15 seconds.

**Offline pool creation time and sensitivity to pool size.** When creating a pool, the solving time for a single optimization problem is under a second for most topologies on all scenarios on a 2.6 GHz 6-Core Intel Core i7 laptop with 16 GB memory, and we used a pool size of 1000 objectives. The only exception was the NF on the two largest topologies, Deltacom and Ion, which took 11.8 and 15.5 seconds respectively, and we used a smaller pool size in these cases to limit the pool generation time. Note that the pool creation occurs offline. Further, it involves solving multiple distinct optimization problems, and is trivially parallelizable.

To examine sensitivity to pool size, we first generated 5000 objective-program pairs and then randomly sampled a given...
number of objective-program pairs to form a candidate pool. Evaluating on candidate pools of size ranging from 10 to 5000, we found that pools with 300 objective-program pairs are sufficient for Net10Q to achieve over 99% optimal after 10 iterations. Please find details in Appendix C.3.

### 5.4 Pilot User Study

We next report on a small-scale study involving 17 users. The primary goal of the user study is to evaluate Net10Q when the real objective is arbitrarily chosen by the user, and even the actual shape is unknown to Net10Q. This is in contrast to the oracle experiments where the ground truth objectives are drawn from a template (with only the parameters unknown to Net10Q). Further, like with imperfect oracles, users may not always correctly express relative preferences.

The user study was conducted online using an IRB-approved protocol. Participants were recruited with a minimal qualifying requirement being they should have taken a university course in computer networking. 88% of them are computer networking researchers or practitioners. 53% of users have more than 2 years of experience managing networks (details in Appendix C.4).

The algorithm implemented in the user study was an earlier version of Algorithm 1 and did not contain all the optimizations. Specifically, the preference pairs were generated on the fly rather than pre-generated (see Appendix C.4).

The study focused on the BW scenario (with four classes of traffic) and the Abilene topology. The user was free to choose any policy on how bandwidth allocations were to be made, and answer queries based on their policy. In each iteration, the user was asked to choose between two different bandwidth allocations generated by Net10Q. The user could either pick which allocation was better, or indicate it was too hard to call if the decisions were close. The study terminated after the user answered 10 questions, or when the user indicated she was ready to terminate the study.

Based on a post-study questionnaire (see Appendix C.4), a majority of users wished to achieve higher allocations for a higher priority while not starving lower priority classes – however, they differed considerably in terms of where they lay in the spectrum based on their qualitative comments.

**Results.** Fig 7a summarizes how well the recommended allocations generated by Net10Q met user policy goals. 82% of the users indicated that the final recommendation is consistent, or somewhat consistent with their policies. The remaining 18% of the users took the study before we explicitly added an objective question to ask users to rate how well the recommended policy met their goals. However, the qualitative feedback provided by these users indicated Net10Q produced allocations consistent with user goals. For instance, one expert user said: “The study was well done in my opinion.”
It put the engineer/architect in a position to make a qualified decision to try and chose the most reasonable outcome."

Figure 7b shows that 94% of users indicated the response time with Net10Q was usually acceptable, while 6% indicated the time was sometimes acceptable. We also collected additional data which indicated the time taken by Net10Q was hardly a second, and much smaller than the user think time which varied from 8 to 12 seconds, indicating Net10Q can be used interactively.

Across all users, Net10Q was always able to find a satisfiable objective that met all of the user’s preferences (it never needed to invoke the fallback approach (§5.2) of only considering a subset of user preferences). This indicates users express their preferences in a relatively consistent fashion in practice. Inconsistent responses may still allow for satisfiable objectives, however we are unable to characterize this in the absence of the exact ground truth objective function.

Overall, the results show the promise of a comparative synthesis approach even when dealing with complex user chosen objectives of unknown shape. We believe there is potential for further improvements with all the optimizations in Algorithm 1, and other future enhancements.

6 Related Work

Network verification/synthesis. As we discussed in §2, the naïve approach to comparative synthesis proposed in [53] is preliminary and may involve prohibitively many queries. In contrast, we generalize and formalize the framework, design the first synthesis algorithm with the explicit goal of minimizing queries, present formal convergence results, and conduct extensive evaluations including a user study.

Much recent work applies program languages techniques to networking. Several works focus on synthesizing forwarding tables or router configurations based on predefined rules [13, 14, 38, 39, 47, 51, 55]. Much research focuses on verifying network configurations and dataplanes [2, 49, 50], and does not consider synthesis. Recent works mine network specification from configurations [3], generate code for programmable switches from program sketches[16, 45], or focus on generating network classification programs from raw network traces[44]. In contrast to these works, we focus on synthesizing network designs to meet quantitative objectives, with the objectives themselves not fully specified.

Optimal synthesis. There is a rich literature on synthesizing optimal programs with respect to a fixed or user-provided quantitative objective. Some of these techniques aims to solve optimal syntax-guided synthesis problems by minimizing given cost functions [5, 24]. Other approaches either generate optimal parameter holes in a program through probabilistic reasoning [8] or solve SMT-based optimization problems [33], under specific objective functions. In example-based synthesis, the examples as a specification can be insufficient or incompatible. Hence quantitative objectives can be used to determine to which extent a program satisfies the specification or whether some extra properties hold. Gulwani et al. [20] and Drosos et al. [12] defined the problem of quantitative PBE (qPBE) for synthesizing string-manipulating programs that satisfy input-output examples as well as minimizing a given quantitative cost function.

Our work is different from all optimal synthesis work mentioned above as in our setting, the objective is unknown and automatically learnt/approximated from queries.

Human interaction. Many novel human interaction techniques have been developed for synthesizing string-manipulating programs. A line of work focuses on proposing user interaction models to help resolve ambiguity in the examples [35] and/or accelerate program synthesis [11, 37]. Using interactive approaches to solve multiobjective optimization problems has been studied by the optimization community for decades (as surveyed by Miettinen et al. [36]). Our novelty on the interaction method is to proactively ask comparative queries, with the aim of minimizing the number of queries and maximizing the desirability of the found solution. The comparison of concrete candidates is easier than asking the user to provide rank scale, marginal rates of substitution or aspiration level, which is done by most existing approaches. The objective functions we target to learn for network design also involve guard conditions, which is beyond what most existing methods can handle.

Oracle-guided synthesis. The learner-teacher interaction paradigm we use in the paper is referred to as active learning and systematically studied in the community of machine learning theory [1, 42]. This paradigm has been studied in the context of programming-by-example (PBE), aiming at minimizing the sequence of queries. Jha et al. [26] presented an oracle-based learning approach to automatic synthesis of bit-manipulating programs and malware deobfuscation over a given set of components. Their synthesizer generates inputs that distinguishes between candidate programs and then queries to the oracle for corresponding outputs. Ji et al. [28] followed up and studied how to minimize the sequence of queries. This line of work allows input-output queries only ("what is the output for this input?") to distinguish different programs. If two programs are distinguishable, they consider them equivalent or a ranking function is given. In invariant synthesis, Garg et al. [17] followed this paradigm and synthesized inductive invariants by checking hypothes- es (equivalent to Propose queries in our setting) with the teacher. Jha and Seshia [27] proposed a theoretical framework, called oracle-guided inductive synthesis (OGIS) for inductive synthesis. The framework OGIS captures a class of synthesis techniques that operate via a set of queries to an oracle. Our comparative synthesis can be viewed as a new instantiation of the OGIS framework.
7 Conclusions
In this paper, we have presented the first effort at synthesizing network designs with indeterminate objectives, and we have made three contributions. First, we have developed a new formal framework for comparative synthesis through iterative interactions with users. Second, we have developed a novel algorithm for our framework that combines program search and objective learning, and seeks to achieve high solution quality with relatively few queries. We proved that the algorithm guarantees the median quality of solutions converges logarithmically to the optimal, or even linearly when the objective function space is sortable (a property satisfied by two of our case studies). Third, we have developed Nett10Q, a system implementing our approach. Experiments show that Nett10Q only makes half or less queries than the baseline system to achieve the same solution quality, and robustly produces high-quality solutions with inconsistent teachers. A pilot user study with network practitioners and researchers shows Nett10Q is effective in finding allocations that meet diverse user policy goals in an interactive fashion. Overall, the results show the promise of our framework, which we believe can help in domains beyond networking in the future.

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A Objective Function Space

Definition A.1 (Objective function). Given a metric group $M$, an objective function with respect to $M$ is a computable function $\mathbb{R}^{|M|} \to \mathbb{R}$.

Objective functions and metric rankings are closely related. Every objective function implicitly determines a metric ranking, as formally defined below:

Definition A.2. Given an objective function $O$ w.r.t. a $d$-dimensional metric group $M$, the corresponding metric ranking $\leq_O \subseteq \mathbb{Z}^d \times \mathbb{Z}^d$ is defined as follows: for any two program parameters $c_1, c_2 \in \text{dom}(M)$, $c_1 \leq_O c_2$ if and only if $O(M(c_1)) \leq O(M(c_2))$. It can be easily verified that $\leq_O$ is indeed a metric ranking.

Note that multiple objective functions may have the same metric ranking. For example, any objective functions $O$ and $O'$ such that $O'(v) = 2 \cdot O(v)$ for any $v \in \mathbb{Z}^{|M|}$ have the same metric ranking. On the other hand, some metric ranking does not correspond to any objective function, e.g., one can define a metric ranking $\leq$ between integer metric values such that $n_1 \leq n_2$ if and only if the $n_1$-th digit of $\Omega$ is less than or equal to the $n_2$-th digit of $\Omega$, where $\Omega$ is a Chaitin’s constant [6] representing the probability that a randomly generated program halts. However, it is usually possible to define an objective function space which is large enough to match any metric ranking restricted to a finite subset, e.g., allowing the arbitrarily many if-then-else operators in the expression. We define such objective function spaces formally below.

Definition A.3 (Objective function space). An objective function space $O$ is a set of objective functions $O$ with respect to a $d$-dimensional metric group $M$ such that for any metric ranking $\leq_M \subseteq \mathbb{Z}^d \times \mathbb{Z}^d$ and any finite subset $S \subseteq \mathbb{Z}^d$, there exists an objective function $O \in O$ such that for any $u, v \in S$, $u \leq_M v$ if and only if $O(u) \leq O(v)$.

Example A.4. The class of conditional linear integer arithmetic (CLIA) functions forms an objective function space. A CLIA objective function, intuitively, uses linear conditions over metrics to divide the domain into multiple regions, and defines in each region as a linear combination of metric values. Formally, for any $d$-dimensional metric group $M$, an objective function space $O_{\text{CLIA}}^d$ can be defined as the class of expressions derived from the nonterminal $T$ of the following grammar:

$$
T ::= E \mid \text{if } B \text{ then } T \text{ else } T \\
B ::= E \geq 0 \mid B \land B \mid B \lor B \\
E ::= v_1 \mid \ldots \mid v_d \mid c \mid E + E \mid E - E
$$

where $c \in \mathbb{Z}$ is a constant integer, and $v_i$ is the $i$-th value of the metric vector. It is not hard to see that $O_{\text{CLIA}}^d$ is indeed an objective function space, because with arbitrarily many conditionals, one function can be constructed to fit any finite subset of any metric ranking.

input : Two program metric vectors $m, n$ and their comparison result $\text{response}$

modifies : The current metric vector preferences $R$ and the current Pareto candidate set $\mathcal{G}$

def update $(m, n, \text{response})$

if $\text{response} = (>)$

$R \leftarrow R \land m > n$

else if $\text{response} = (<)$

$R \leftarrow R \land n > m$

else:

$R \leftarrow R \land m = n$

$\mathcal{G} \leftarrow \mathcal{G} \cup \{O | O \models R\}$

return

input : A parameterized program $\mathcal{P}$, a metric group $M$, current metric vector preferences $R$ and current running best $r_{\text{best}}$

modifies : The Pareto candidate set $\mathcal{G}$

def generate-more $(\mathcal{P}, M, R, r_{\text{best}}, \mathcal{G})$

repeat

$c \leftarrow \text{SYNPROG}(\mathcal{P}, M)$ ; // synthesize an arbitrary (Pareto optimal) program

$O \leftarrow \text{SYNOBJ}(R \land M(\mathcal{P}[c]) > M(\mathcal{P}[r_{\text{best}}]))$ ; // synthesize an objective that prefers the

$\text{new } c \text{ over } r_{\text{best}}$

if $O \neq \top$

$c \leftarrow \text{IMPROVE}(O, \mathcal{P}, M, c)$ ; // this is optional: try to improve $\mathcal{P}[c]$

else:

$O \leftarrow \text{SYNOBJ}(R)$ ; // synthesize an arbitrary objective satisfying $R$

$c \leftarrow \text{IMPROVE}(O, \mathcal{P}, M, r_{\text{best}})$ ; // synthesize a best possible program

under $O$, but at least better than $r_{\text{best}}$

$\mathcal{G} \leftarrow \mathcal{G} \cup \{O, c\}$

until timeout;

Algorithm 2: The subroutines involved in the voting-guided learning algorithm.

B Subroutines and Proofs

B.1 Subroutines for Algorithm 1

The subroutines involved in Algorithm 1 are shown in Algorithm 2. Note that this subroutine delegates several heavy-lifting tasks to off-the-shelf, domain-specific procedures: SYNPROG for qualitative synthesis, SYNOBJ for objective synthesis, and IMPROVE for optimization under a known objective.

B.2 Proof of Theorem 4.4

The PCS constructed for the following lemma serves as a witness of the bound tightness:

Lemma B.1. Let $\mathcal{G} = (\mathcal{P}, C, \Phi)$ be a qualitative synthesis problem with infinitely many solutions and $O$ be an objective function space. For any integer $n > 0$, there exist a PCS $\mathcal{G} : O \rightarrow C$ and a parameter $r_{\text{best}} \in C$ such that:
We first prove the following lemma which shows that if a random sampling. Therefore, if a query cuts the size of cur-

Proof: As $G$ has infinitely many solution, we can pick arbitrary $n$ solutions, say $c_1, \ldots, c_n$. For each $1 \leq i \leq n$, one can construct a total order $\leq_i$ such that $c_n \leq_i \cdots \leq_i c_{i+1} \leq_i c_i$. According to the definition of objective function space (Def A.3), there exists an objective function $O_i$ that fits $\leq_i$. Now we can construct $G$ such that $\text{dom}(G) = \{O_1, \ldots, O_n\}$, and $G(O_i) = c_i$ for each $i$. It can be verified $G$ is a Pareto candidate set satisfying the required conditions.

B.3 Proof of Theorem 4.6

We first prove the following lemma which shows that if a PCS is sortable, one can make a query to cut at least half of the candidates, no matter what the teacher’s response is.

Lemma B.2. If a Pareto candidate set $G$ is finite and sortable, then there exists a query whose quality for $G$ as computed in Fig 4 is $\frac{\lfloor |\text{image}(G)| \rfloor}{2}$.

Proof: Let $n = |\text{image}(G)|$ and $m = \lfloor |\text{image}(G)| \rfloor / 2$. As $G$ is sortable, by Def 4.5, there exists a total order $G(O_1) < \cdots < G(O_n)$. Now we claim that

$$\text{Info}(\text{COMPARE}(G(O_m), G(O_{m+1}))) = m$$

By Def 4.5, for any $1 \leq i \leq m$, $G(O_m) \gg O_i$, $G(O_{m+1})$, and for any $m+1 \leq j \leq n$, $G(O_m) \ll G(O_{m+1})$. Then according to the query quality estimation described in Fig 4, both #RemNEQ($G(O_m)$, $G(O_{m+1})$) and #RemNEQ($G(O_{m+1})$, $G(O_m)$) are at least $m$. Therefore, $\text{Info}(\text{COMPARE}(G(O_m), G(O_{m+1}))) = m$, which is $\frac{\lfloor |\text{image}(G)| \rfloor}{2}$.

With the lower bound of removed candidates guaranteed by Lemma B.2, we are ready to prove Theorem 4.6. Note that Algorithm 1 generates candidates for the Pareto candidate set $G$ (through the generate-more subroutine) by random sampling. Therefore, if a query cuts the size of current candidate pool ($G$ and the running best) by a ratio of $r$, the search space (those candidates satisfying all preferences in $R$) by an equal or higher ratio in that iteration (extra candidates may be discarded by generate-more, before the query). Now as $G$ is sortable, by Lemma B.2, after the highest-quality query, the number of candidates remaining in $G$ is at most $\frac{\lfloor |\text{image}(G)| \rfloor}{2}$. In other words, the query reduces the size of $G$ by a ratio of at least $\frac{2}{3}$ (when $|\text{image}(G)| = 2$, the total number of candidates including the running best, reduces from 3 to 2), except for the last query. Therefore, the output is the best among $O(1.5^n)$ randomly selected candidates, which is Beta($1.5^n$, 1)-distributed. Hence by Def 3.12, the median of the quality of the output is $\frac{1}{2(1.5^n)}$, which is asymptotically equivalent to $(1 - \frac{1}{\Omega(1.5^n)})$.

B.4 Proof of Theorem 4.10

We shall show the sortability of any Pareto candidate set $G$ w.r.t. $G_{\text{qual}}$ and $O$. We claim that the lexicographic order $\ll_{\text{lex}}$ over $Z^2$ (i.e., $(a_1, a_2) \ll_{\text{lex}} (b_1, b_2)$ if and only if $a_1 < b_1$ or $a_1 = b_1$ and $a_2 < b_2$) witnesses the sortability. Per Def 4.5, for any objective functions $O, P, Q \in \text{dom}(G)$ such that $G(O) \ll_{\text{lex}} G(P) \ll_{\text{lex}} G(Q)$, we shall show $G(P) \gg G(O)$ below. It can be similarly proved that $G(P) \gg G(Q)$.

Let $M(G(O)) = (o_1, o_2), M(G(P)) = (p_1, p_2)$, and $M(G(Q)) = (q_1, q_2)$. Note that by Def 4.2, each of $G(O), G(P)$ and $G(Q)$ is optimal under a distinct objective function, therefore $M(G(O)), M(G(P))$, and $M(G(Q))$ are pairwise incomparable, i.e., $\{o_1, p_1, q_1\}$ and $\{o_2, p_2, q_2\}$ are all distinct values. Due to the lexicographic order $\ll_{\text{lex}}$, we have $o_1 < p_1 < q_1$ and $o_2 > p_2 > q_2$.

Now by Def 4.7, one can effectively find a solution $c$ such that

$$M(c) = \left( \frac{(q_1 - p_1) \cdot o_2 + (p_1 - o_1) \cdot q_2}{q_1 - o_1}, \frac{(q_1 - p_1) \cdot o_2 + (p_1 - o_1) \cdot q_2}{q_1 - o_1} \right)$$

Then by Def 4.2, $G(P)$ is at least as good as $c$ and $p_2 \geq \frac{(q_1 - p_1) \cdot o_2 + (p_1 - o_1) \cdot q_2}{q_1 - o_1}$. Finally, by Def 4.8, we have

$$O((p_1, p_2)) \geq O((q_1, q_2))$$

In other words, $G(P) \gg G(Q)$.

C Additional Experimental Results

C.1 Evaluation on Perfect Oracle

The range of solution quality achieved by Net10Q sometimes overlaps with Net10Q-NoPrune in Fig 5c – however Net10Q outperformed Net10Q-NoPrune in every scenario-topology combination. To demonstrate this for the NF scenario which saw the most overlap in Fig 5c, consider Fig 8 which presents a detailed breakdown of results by topology, and clearly illustrates Net10Q’s out-performance.

C.2 Evaluation on Imperfect Oracle

Fig 6a showed Net10Q outperforms Net10Q-NoPrune for BW on CWIX. Fig 9 shows the performance of Net10Q and Net10Q-NoPrune when $p = 10$ for the other three scenarios, namely, MCF, NF and OSPF. Net10Q outperforms in these scenarios as well. Fig 10 presents the performance of Net10Q on CWIX when $p = 0, 5, 10, 20$ for MCF, NF and
Figure 8. Comparing Net10Q and Net10Q-NoPrune with perfect oracle for NF (each subfigure for a topology). Curves to the left are better. Net10Q outperforms in all topologies.

Figure 9. Performance of Net10Q with imperfect oracle ($p = 10$) for MCF, NF and OSPF on CWIX.

Figure 10. Performance of Net10Q under different level of inconsistency ($p = 0, 5, 10, 20$) on CWIX.

OSPF. While Net10Q shows some performance degradation at higher inconsistency levels ($p = 20$), it still achieved good solution quality.

C.3 Sensitivity to Size of Pre-Computed Pool
To examine how sensitive Net10Q is to the size of the pre-computed pool, we evaluated Net10Q with pools of different size for BW on CWIX, sampled from a larger pool of size...
Figure 11. Performance of Net10Q with different size of pre-computed pool for BW on CWIX.

(a) User background.
(b) User experience.
(c) Diversity of user policies.

Figure 12. User background and diversity of chosen policies.

Figure 13. Avg. time per query across users.

C.4 Additional Details Regarding User Study

Implementation. Our user study used an earlier version of Algorithm 1 implemented as an online web application. Specifically, the PCSes were generated on the fly, rather than pre-generated. To ensure responsiveness, the deployed algorithm set the threshold $\text{Thresh} = 2$. We note that the cloud application for our user study was developed and tested over multiple months, and in parallel to refinements we developed to the algorithm. We were conservative in deploying the latest versions given the need for a robust user-facing system, and to ensure all participants saw the same version of the algorithm.

User background. Fig 12a and 12b show the background of participants in the user study. 47% of the users are computer networking researchers while 41% of them are network practitioners (managers/engineers). 47% of the users have under 2 years of experience managing networks, while 24% of them have 2-5 years experience, and 29% of them have more than 5 years experience.

Diversity of user policies. In the post-study questionnaire, users were asked to characterize their policy by choosing how important it was to achieve each of three criteria below: (i) Balance, indicating allocation across classes is balanced; (ii) Priority, indicating how important it is to achieve a solution with more allocation to a higher priority class if a lower priority class does poorly; and (iii) No-Starvation, indicating how important it is to ensure lower priority classes get at least some allocation. Fig 12c presents a breakdown of user choices of policies. 70.6% of users indicated Balance were somewhat or very important. 82.3% of users indicated Priority were somewhat or very important, while 94.1% of users indicated No-Starvation was somewhat or very important. The results were consistent with the qualitative description each user provided regarding his/her policy. Overall, almost all users were seeking to achieve Balance and Priority avoiding the extremes (starvation) – however, they differed considerably in terms of where they lay in the spectrum based on their qualitative comments.

Time taken per response. Fig 13 shows a cumulative distribution across users of the average Net10Q time (i.e., the average time taken by Net10Q between receiving the user’s choice and presenting the next set of allocations). For comparison, the figure also shows a distribution of the average user think time (i.e., the average time taken by a user between when Net10Q presents the options and when the user submits her/his choice).