Composite Alternative Pareto Optimal Recommender System (CAPORS)

William Jeffries and Alexander Brodsky
George Mason University, 4400 University Drive 4A4, Fairfax, VA 22030, U.S.A.

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Abstract: We propose a methodology and present a system for generating composite alternative recommendations combining user-guided continuous improvement with Pareto optimal trade-off considerations. The system consists of (1) a model to generate the recommendation space; (2) metrics for measuring each recommendation; (3) an analytics function for computing composite alternative metrics and constraints; (4) system configuration settings; (5) an algorithm for calculating Pareto optimal curve of recommendations; (6) an algorithm for generating user-guided improvements using relaxed constraints; (6) charting functionality for plotting recommendations; (7) and a user interface for enabling users to accept or improve-upon selected recommendations.

1 INTRODUCTION

Composite alternative recommender systems recommend a combination of products and services, based on multiple criteria such as price, availability, and user ratings. They include recommenders for vacation packages, investment portfolios, healthcare plans, product bundles, and more.

Consider an example of a sourcing recommender. In this case, a recommendation is a set of orders, where an order contains a set of item quantities to be purchased from a particular supplier. Sourcing recommendations are associated with multiple criteria such as cost, carbon emissions, and fulfillment time. These recommendations are composite since they contain multiple suppliers with multiple items, and they are multi-criteria because of the three metrics mentioned previously. The result of generated recommendations must be Pareto-optimal.

There has been extensive research conducted on composite alternative recommenders in recent years. This research comprises proposed methods and presented systems, addressing both domain specific and domain-independent recommenders.

Interdonato et al (2013) propose a graph-based framework that uses Page Rank-style algorithm to learn packages that conform to a user preference model. The framework is ultimately based on user rankings and identifies domain-independence as its key feature. CARD (Brodsky, Henshaw and Whittle, 2008) is a proposed framework for generating optimal composite alternative recommendations. CARD utilizes a SQL-based data model for generating the recommendation space. It also extends the SQL language in order to provide diverse recommendations and to provide a mechanism for learning user preferences. CARD is a generic framework capable of being applied across domains. There is no current implementation of the CARD framework. FlexRecs (Koutrika, Bercovitz and Garcia-Molina, 2009) is a proposed framework for providing domain-independent recommendations. The recommendation space in FlexRecs is generated using workflows designed by system implementers. As with CARD, the FlexRecs framework is built on top of relational data models and extended relational operators.

These three frameworks address composite recommendations, but do not offer a system that implements the framework, nor use methodology on which the system functionality can be based.

Xie, Lakshmanan and Wood (2010) present a generic package recommender system that uses a variation of the knapsack problem to generate optimal top-k recommendations. The recommendation space in their system is generated using individual component recommenders. Furthermore, ratings are the only metric used to

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calculate recommendations. TopRecs+ (Khabbaz, Xie and Lakshmanan, 2011) is another generic package recommender that uses a variation of the knapsack problem to find optimal top-k package recommendations. As with Xie et al above, TopRecs+ leverages individual item recommenders to generate the composite alternative recommender space. CompRec-Trip (Xie, Lakshmanan and Wood, 2011) is a system for recommending travel packages by finding the optimal alternatives using user-supplied preferences and constraints. As Xie et al's other work mentioned above, the system uses component recommender systems for generating the recommendation space. The system is narrowly focused, but allows flexibility through interaction with the user.

These three systems generate composite recommendations by aggregating single-item recommenders. However, this aggregation does not take into account interaction among the components of the composite recommendation. Therefore, neither offers an integrated composite alternative methodology, which is often required when components have a non-trivial interaction among them. Also, in the case of CompRec-Trip, the system is domain-specific and not designed to accommodate general recommendation problems.

Ribeiro, et al (2015) propose two Pareto-efficient approaches for recommender systems. In both approaches, they propose using recommendation accuracy, novelty, and diversity as the objectives to consider when generating a Pareto-efficient list of recommendations. One approach creates a Pareto-efficient ranked list from multiple competing recommendation algorithms. Their second approach creates Pareto-efficient hybrid recommenders built from individual recommender algorithms. While both approaches apply Pareto-efficiency to their recommendations, it is limited to the criteria of accuracy, diversity, and novelty. However, many package recommendations require diverse user-defined criteria, such as cost, risk, benefit, etc., which is outside the scope of (Ribeiro et al, 2015). Neither approach considers continuous user feedback. Furthermore, both approaches are proposed algorithms that do not include a system to implement their methodology.

To our knowledge, there are no proposed recommender systems that combine Pareto optimal solutions for arbitrary user-defined criteria with continuous user guidance. Nor is there a system with this combination of features designed for composite alternatives that have complex interactions between them. Addressing these limitations is the exact focus of this paper.

First, we develop a methodology for recommending Pareto-optimal composite alternatives based on (1) multi-criteria optimization and (2) continuous user-guided feedback. The methodology first generates an initial set of recommendations based on Pareto-optimal curve for two selected criteria (such as cost and benefit). Then, the user iteratively improves the alternatives through critique of additional criteria and re-optimizations to iteratively generate a small subset of user-selected Pareto-optimal alternatives. Finally, the user extracts the final recommendation from this small set.

Second, we develop a system called CAPORS (Composite Alternative Pareto Optimal Recommender System) that implements the proposed methodology. CAPORS is implemented using a Decision Guidance Management System (DGMS) (Brodsky and Wang, 2008). In CAPORS (as well as the underlying DGMS), the description of all possible recommendation alternatives is captured by the concept of an Analytical Model. The Analytical Model formally describes (1) criterion of interest (such as cost, benefit, risk, etc.) as a function of recommendation control variables, and (2) feasibility constraints on possible composite recommendations. With the help of DGMS, CAPORS manages the workflow of recommendations improvement based on two key algorithms: (1) generation of Pareto-optimal curve for the recommendation Analytic Model along two selected criteria and (2) generation of Pareto-optimal improvement along the additional criteria that the user asks to improve.

Third, we develop these two key algorithms using DGMS.

Finally, as a case study to demonstrate applicability to a real world problem, we implement a sourcing recommender based on the domain-independent CAPORS system and methodology.

This paper is organized into the following sections. Section 2 demonstrates composite alternative recommendation using a supply chain sourcing example. Section 3 gives background on some of the technologies relevant to the system. Section 4 describes the core algorithms of the system. Section 5 details the system architecture and explains its various mechanics. Section 6 concludes and offers ideas for future extensions.

2 CAPORS FUNCTIONALITY BY SOURCING EXAMPLE

We explain the functionality of the system and related methodology through the use of a supply chain sourcing example, shown in Figure 1. Supply chain sourcing is the process of locating the sources of goods that a company needs to order. This process usually has the goal of finding an order configuration that meets the constraints set by the company and is optimized according to one or many criteria, such as cost, fulfillment time, and carbon emissions.

The components of supply chain sourcing are (1) a customer that needs to order items, (2) order constraints such as item demand and budget, (3) suppliers that offer items at a given price, and (4) an order that defines which items are ordered from which suppliers and in what quantities.

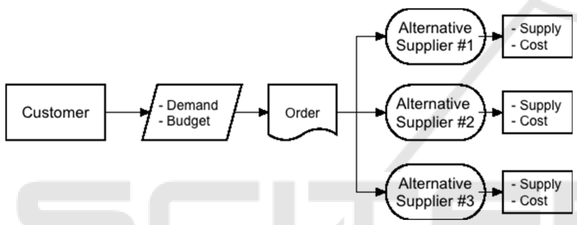


Figure 1: Supply Chain Sourcing.

Supply chains orders can potentially be configured in so many different ways as to be impractical for a human to thoroughly review and consider. One way for decision guidance systems to solve this issue is to simply optimize on a single metric (e.g. total cost) and produce the least expensive option. However, there may be other metrics that the user would want to optimize, even if it meant a supply chain configuration yielding a higher cost. For instance, fulfillment time might be a crucial metric to the user, so much so that they are willing to trade off some cost in order to get an alternative with a faster fulfillment time.

Consider the scenario of a small supply chain consisting of items, demand, and suppliers. The goal is to construct an order that will define which items will be ordered from which suppliers. The order must meet certain specified constraints, such as demand. Analysis is executed on the order to compute metrics, such as order cost, carbon emissions, and fulfillment time.

In this scenario, CAPORS can be used to generate a recommendation. A recommendation is a set of orders, with each order defined by (1) a supplier id representing a specific supplier, (2) an item id representing a specific item, and (3) quantity of ordered item.

Each recommendation is associated with a set of metrics: (1) cost per item, (2) carbon emissions produced for each item, and (3) fulfillment time, i.e. the time in days it will take to fulfill all items in the order.

The methodology used by CAPORS for generating the optimal recommended order is captured as a state-activity diagram, shown in Figure 2.

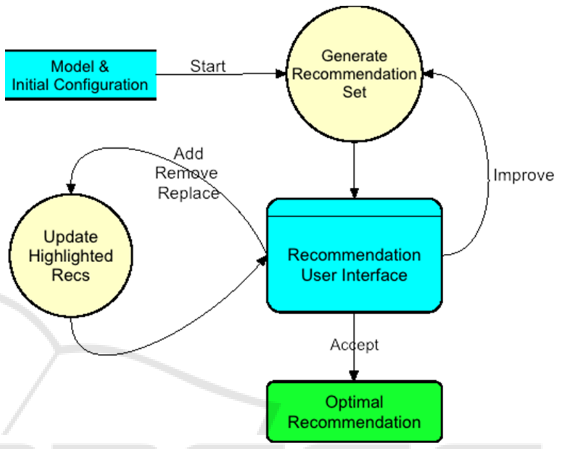

Model & Initial Configuration
Start
Generate Recommendation Set
Improve
Add
Remove
Replace
Update Highlighted Recs
Recommendation User Interface
Accept
Optimal Recommendation

Figure 2: CAPORS Methodology.

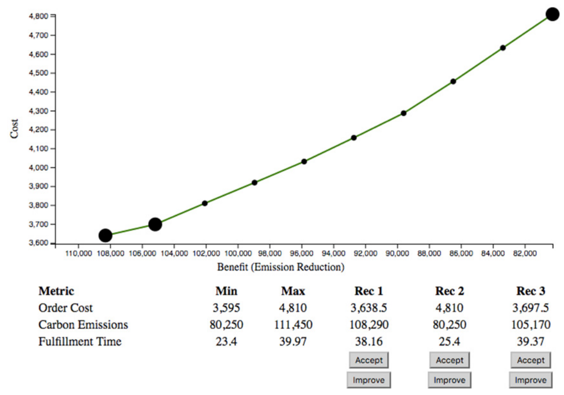
To generate an initial set of recommendations, the system needs two components: (1) an analytics model and (2) a set of configuration settings. The analytics model contains (1) data needed to generate the recommendation space, (2) order constraints, and (3) an analytics function for computing order metrics. The configuration settings include the number of recommendations to generate, metrics definitions, and the initial two metrics to consider for the first set of recommendations (defined as core cost and core benefit in the configuration settings). These settings are captured in the Model & Initial Configuration State, depicted in the upper left corner of Figure 2.

After CAPORS receives the analytics model and initial configuration, the system generates the first set of recommendations for the user to consider. Each recommendation consists of an order configuration and computed metrics. The computed metrics in this example are order cost, total amount of carbon emissions, and the time (in days) that it will take to fulfill the entire order. The Generate Recommendation Set activity (shown at the top middle of Figure 2) generates the information necessary to display in the Recommendation User Interface State (shown in the middle of Figure 2).

The Recommendation User Interface itself is shown in Figure 3. The Recommendation User Interface displays the recommendations using two main components: (1) line chart and (2) a table. The line chart shows all of the generated recommendations, which fall along a Pareto optimal curve. The recommendations are plotted along two axes: (1) cost along the y-axis and (2) benefit along the x-axis. In this example, the y-axis represents order cost and the x-axis represents carbon emission reduction. Each point on the displayed line chart is Pareto-optimal, that is there does not exist a recommendation that improves on one metric without sacrificing another.

For the initial recommendation set, the system automatically selects three recommendations to be part of the Closer Consideration Set displayed as a table at the bottom of Figure 3. The Closer Consideration Set contains recommendations that the user can interact with (described further below). The initial Closer Consideration Set contains (1) the recommendation with the minimal cost, (2) the recommendation with the maximal benefit, and (3) the recommendation with the greatest benefit/cost ratio, relative to the minimum cost recommendation (the leftmost point). The recommendations that belong to this set appear as bigger circles.

In addition to the line chart, the Recommendation User Interface also displays the Closer Consideration Set in a table underneath the chart. The table contains the following information: (1) list of metrics, (2) the overall minimum and maximum possible for each metric, as constrained by the user, (3) the metric values for each recommendation in the Closer Consideration Set, and (4) buttons for accepting or improving a recommendation.



Metric	Min	Max	Rec 1	Rec 2	Rec 3
Order Cost	3,595	4,810	3,638.5	4,810	3,697.5
Carbon Emissions	80,250	111,450	108,290	80,250	105,170
Fulfillment Time	23.4	39.97	38.16	25.4	39.37

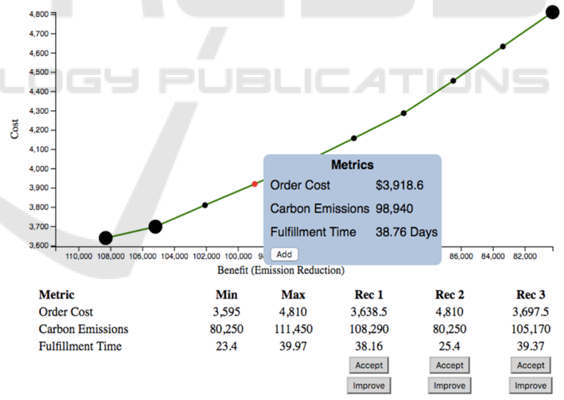
Figure 3: Recommendation User Interface.

After the Recommendation User Interface displays the line chart and Closer Consideration Set table, the user has three options: (1) accept one of the highlighted recommendations, (2) modify the Closer Consideration Set, or (3) request a new set of recommendations by improving upon one of the recommendations in the Closer Consideration Set.

The user can accept a recommendation by pressing the “Accept” button underneath the selected choice. This puts the system in the terminal Optimal Recommendation State (shown in bottom of Figure 2) as no further improvements are needed.

Before accepting or improving-upon one of the selections, the user can modify the Closer Consideration Set. Modification actions include (1) adding a recommendation to the Closer Consideration Set, (2) removing a recommendation from the Closer Consideration Set, and (3) replacing one of the recommendations in the Closer Consideration Set.

A user adds a recommendation by right-clicking on one of the small circles on the graph and pressing the “Add” button, as shown in Figure 4. The user interface then increases the size of the recommendation circle on the chart and adds the recommendation metrics to the Closer Consideration Set table beneath the chart.

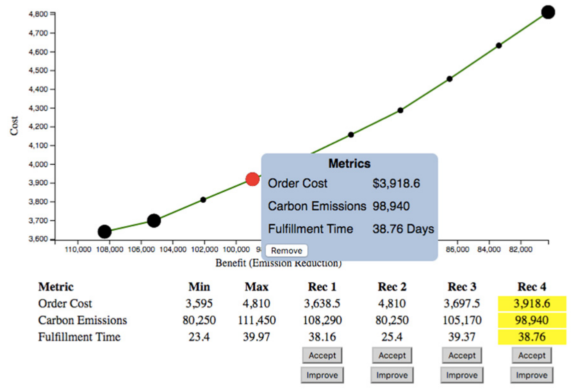


Metrics	
Order Cost	$3,918.6
Carbon Emissions	98,940
Fulfillment Time	38.76 Days

Metric	Min	Max	Rec 1	Rec 2	Rec 3
Order Cost	3,595	4,810	3,638.5	4,810	3,697.5
Carbon Emissions	80,250	111,450	108,290	80,250	105,170
Fulfillment Time	23.4	39.97	38.16	25.4	39.37

Figure 4: Add recommendation to Closer Consideration Set.

Similarly, a user removes a recommendation from the Closer Consideration Set by right-clicking and pressing “Remove” (shown in Figure 5). Again, the user interface reflects this new state by reducing the size of the recommendation circle and removing the recommendation from the table.



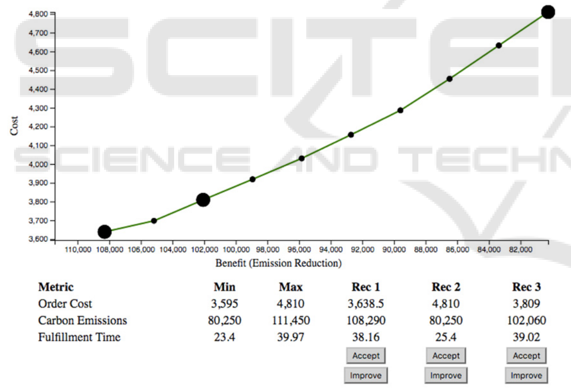
Metrics

Order Cost	$3,918.6
Carbon Emissions	98,940
Fulfillment Time	38.76 Days

Metric	Min	Max	Rec 1	Rec 2	Rec 3	Rec 4
Order Cost	3,595	4,810	3,638.5	4,810	3,697.5	3,918.6
Carbon Emissions	80,250	111,450	108,290	80,250	105,170	98,940
Fulfillment Time	23.4	39.97	38.16	25.4	39.37	38.76

Figure 5: Remove recommendation from highlighted subset.

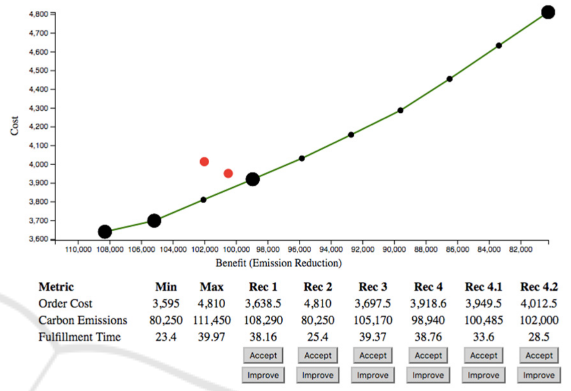
To replace a recommendation, the user simply drags the circle of the old recommendation over top the circle of the new recommendation on the chart. The recommendations' circle size change accordingly on the chart and the old recommendation is replaced in the table by the new recommendation (shown in Figure 6).



Metric	Min	Max	Rec 1	Rec 2	Rec 3
Order Cost	3,595	4,810	3,638.5	4,810	3,809
Carbon Emissions	80,250	111,450	108,290	80,250	102,060
Fulfillment Time	23.4	39.97	38.16	25.4	39.02

Figure 6: Replaced recommendation.

If one of the recommendations is not accepted as optimal, the user can generate additional recommendations by improving upon one of the recommendations in the Closer Consideration Set. To do that, the user clicks on the metric to be improved (Fulfillment Time, for example), chooses the most desirable recommendation, and presses the "Improve" button underneath its entry in the recommendation table. By using the selected recommendation as a starting point, a new set of recommendations is generated that improves the selected metric while relaxing the non-dominated constraints in the x and y dimensions (cost and emission reduction, for example). The new recommendation set is overlaid on the chart and displayed using red circles. The new recommendation set is also displayed in the highlighted table under the chart. The new recommendations are not automatically placed on the graph. But if the user decides to add to the Closer Consideration Set, then they are labelled using decimal numbers to indicate which original recommendation they were generated from, shown in Figure 7.



Metric	Min	Max	Rec 1	Rec 2	Rec 3	Rec 4	Rec 4.1	Rec 4.2
Order Cost	3,595	4,810	3,638.5	4,810	3,697.5	3,918.6	3,949.5	4,012.5
Carbon Emissions	80,250	111,450	108,290	80,250	105,170	98,940	100,485	102,000
Fulfillment Time	23.4	39.97	38.16	25.4	39.37	38.76	33.6	28.5

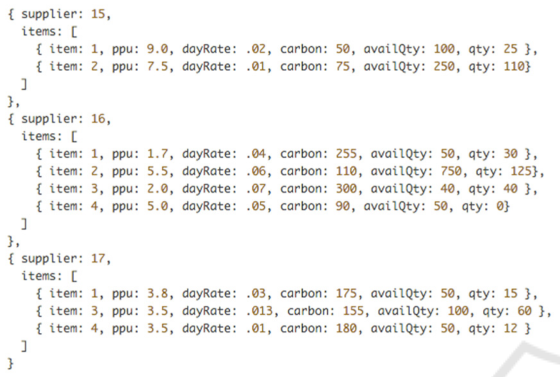
Figure 7: Improved recommendations.

3 RECOMMENDATION GENERATION

The implementation of system functionality described in Section 2 requires algorithms to compute the Pareto-optimal curve and the improved recommendations (Figure 7). These algorithms are detailed in Section 4. To support these algorithms, we need to be able to (1) represent a recommendation, (2) represent a set of all feasible recommendations, and (3) find an optimal recommendation in terms of one of the metrics when other metrics are constrained. In this section, we explain how these are done, using our example.

We represent a recommendation using a data structure expressed in JSON (JavaScript Object Notation, 2016). JSON is a minimal data structure that represents data as objects consisting of key/value pairs. In our sourcing example, a recommendation captures purchase quantities for each item and each supplier.

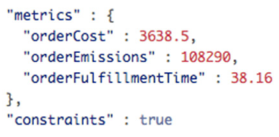
In Figure 8, each outer pair of curly braces defines the purchase items for a particular supplier. Each supplier is identified by a "supplier" field that denotes a specific supplier. Along with the "supplier" field is an array of items to be ordered from that supplier. Each item contains "item" to identify the item, "ppu" containing the price-per-item, "dayRate" defining the number of items that can be fulfilled per day by the supplier, "carbon" showing the amount of emissions per item, "availQty" for the available quantity for the item, and "qty" for the actual quantity to be ordered for the item.



```
{ supplier: 15,
  items: [
    { item: 1, ppu: 9.0, dayRate: .02, carbon: 50, availQty: 100, qty: 25 },
    { item: 2, ppu: 7.5, dayRate: .01, carbon: 75, availQty: 250, qty: 110}
  ]
},
{ supplier: 16,
  items: [
    { item: 1, ppu: 1.7, dayRate: .04, carbon: 255, availQty: 50, qty: 30 },
    { item: 2, ppu: 5.5, dayRate: .06, carbon: 110, availQty: 750, qty: 125},
    { item: 3, ppu: 2.0, dayRate: .07, carbon: 300, availQty: 40, qty: 40 },
    { item: 4, ppu: 5.0, dayRate: .05, carbon: 90, availQty: 50, qty: 0}
  ]
},
{ supplier: 17,
  items: [
    { item: 1, ppu: 3.8, dayRate: .03, carbon: 175, availQty: 50, qty: 15 },
    { item: 3, ppu: 3.5, dayRate: .013, carbon: 155, availQty: 100, qty: 60 },
    { item: 4, ppu: 3.5, dayRate: .01, carbon: 180, availQty: 50, qty: 12 }
  ]
}
```

Figure 8: Sourcing recommendation JSON.

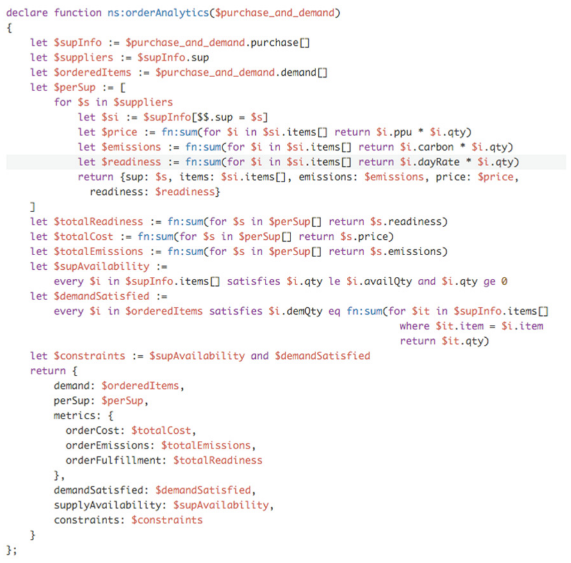
Every recommendation (as in Figure 8) is associated with metrics (orderCost, orderEmissions, orderFulfillment) and the key constraints that are true if all feasibility constraints for the order (such as satisfaction of demand and supply availability) are satisfied. These metrics and constraints are also expressed in JSON. For the recommendation shown in Figure 8, computed metrics and constraints are shown in Figure 9.



```
"metrics" : {
  "orderCost" : 3638.5,
  "orderEmissions" : 108290,
  "orderFulfillmentTime" : 38.16
},
"constraints" : true
```

Figure 9: Metrics and constraints.

The set of all feasible recommendations are represented implicitly by using the notion of an analytical model expressed in JSONiq (Fourny, 2013). JSONiq is an expressive functional language used to query and process JSON data. An analytical model is a function that describes how metrics and constraints are computed from a recommendation instance (like in Figure 8). For our sourcing example, the function is given in Figure 10. Given an analytical model, the set of feasible recommendations is the set of JSON inputs with all possible non-negative values for quantities that satisfy the constraints (i.e. return a value of true for the constraints variable computed by the analytical model).

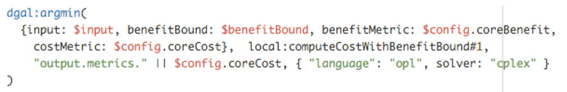


```
declare function ns:orderAnalytics($purchase_and_demand)
{
    let $supInfo := $purchase_and_demand.purchase[]
    let $suppliers := $supInfo.sup
    let $orderedItems := $purchase_and_demand.demand[]
    let $perSup := [
        for $s in $suppliers
            let $si := $supInfo[$$.sup = $s]
            let $price := fn:sum(for $i in $si.items[] return $i.ppu * $i.qty)
            let $emissions := fn:sum(for $i in $si.items[] return $i.carbon * $i.qty)
            let $readiness := fn:sum(for $i in $si.items[] return $i.dayRate * $i.qty)
            return {sup: $s, items: $si.items[], emissions: $emissions, price: $price,
              readiness: $readiness}
    ]
    let $totalReadiness := fn:sum(for $s in $perSup[] return $s.readiness)
    let $totalCost := fn:sum(for $s in $perSup[] return $s.price)
    let $totalEmissions := fn:sum(for $s in $perSup[] return $s.emissions)
    let $supAvailability :=
        every $i in $supInfo.items[] satisfies $i.qty le $i.availQty and $i.qty ge 0
    let $demandSatisfied :=
        every $i in $orderedItems satisfies $i.demQty eq fn:sum(for $it in $supInfo.items[]
                                                           where $it.item = $i.item
                                                           return $it.qty)
    let $constraints := $supAvailability and $demandSatisfied
    return {
        demand: $orderedItems,
        perSup: $perSup,
        metrics: {
          orderCost: $totalCost,
          orderEmissions: $totalEmissions,
          orderFulfillment: $totalReadiness
        },
        demandSatisfied: $demandSatisfied,
        supplyAvailability: $supAvailability,
        constraints: $constraints
    }
};
```

Figure 10: Analytical model.

Given an analytical model, one may want to find an input (the qty fields in Figure 8) that would optimize a metric. For example, one may want to minimize the orderCost metric while keeping the constraints satisfied and bounding another metric (e.g. orderEmissions <= x). This is done by invoking the function argmin (or argmax) of the Decision Guidance Analytics Language (DGAL) (Brodsky, Luo and Nachawati, 2015). DGAL is a language used to express tasks to be executed by a DGMS. DGAL tasks are expressed using JSONiq and operate on analytic models defined using JSON.

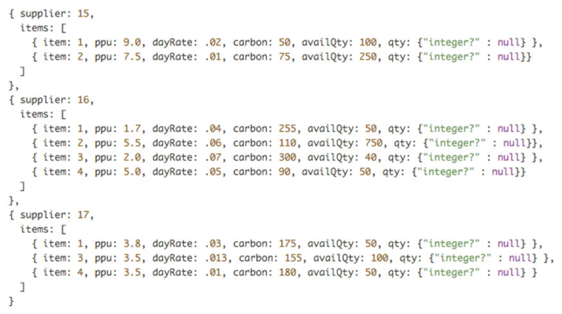
In our sourcing example, a DGAL expression is used to minimize and maximize specific metrics in order to construct recommendations. Figure 11 shows an example of using DGAL to express an argmin operation to produce an optimized order, given restraints.



```
dgal:argmin(
  {input: $input, benefitBound: $benefitBound, benefitMetric: $config.coreBenefit,
    costMetric: $config.coreCost},  local:computeCostWithBenefitBound#1,
    "output.metrics." || $config.coreCost, { "language": "opl", solver: "cplex" }
)
```

Figure 11: DGAL optimization expression.

For the optimization to work, the input to the argmin or argmax function of the DGMS must include parametrized fields in its input. These parameterized fields are decision variables that need to be optimized. In the sourcing example, we make the "qty" field parameterized, since this is the variable that we want to generate for the recommendations. Figure 12 shows an example of the parameterized input that is used for optimization.



```
{ supplier: 15,
  items: [
    { item: 1, ppu: 9.0, dayRate: .02, carbon: 50, availQty: 100, qty: {"integer?" : null} },
    { item: 2, ppu: 7.5, dayRate: .01, carbon: 75, availQty: 250, qty: {"integer?" : null}}
  ]
},
{ supplier: 16,
  items: [
    { item: 1, ppu: 1.7, dayRate: .04, carbon: 255, availQty: 50, qty: {"integer?" : null} },
    { item: 2, ppu: 5.5, dayRate: .06, carbon: 110, availQty: 750, qty: {"integer?" : null}},
    { item: 3, ppu: 2.0, dayRate: .07, carbon: 300, availQty: 40, qty: {"integer?" : null} },
    { item: 4, ppu: 5.0, dayRate: .05, carbon: 90, availQty: 50, qty: {"integer?" : null}}
  ]
},
{ supplier: 17,
  items: [
    { item: 1, ppu: 3.8, dayRate: .03, carbon: 175, availQty: 50, qty: {"integer?" : null} },
    { item: 3, ppu: 3.5, dayRate: .013, carbon: 155, availQty: 100, qty: {"integer?" : null} },
    { item: 4, ppu: 3.5, dayRate: .01, carbon: 180, availQty: 50, qty: {"integer?" : null} }
  ]
}
```

Figure 12: Parameterized optimization input.

The argmin function takes the analytical model (from Figure 10) and the parametrized input (from Figure 12) and returns a JSON structure containing a concrete recommendation (like the one shown in Figure 8) as well as computed metrics and constraints (as shown in Figure 9).

4 KEY CAPORS ALGORITHMS

CAPORS consists of two key algorithms: (1) Pareto-optimal chart algorithm, and (2) recommendation improvement algorithm.

The Pareto-optimal algorithm accomplishes the following: (1) accepts and verifies system input; (2) generates bounds for recommendations; (3) optimizes recommendations by integrating with a DGMS; (4) filters out recommendations that don't fall along Pareto-optimal curve; (5) outputs final recommendation set of points.

```
Function: Pareto-Optimal Recommendations
Input: M (analytic model), r (metrics), c
(configuration)
Output: Pareto-optimal recommendation points

/*find ranges for each metric using model */
ranges = calculateMetricsRanges(M, r)

/*find x-axis points from min to max */
benefitRange = ranges[benefitMetric]
n = c.numRecommendations
bPoints= computeBenefitPoints(benRange, n)

/* optimize cost at each benefit point */
costPoints = optimizeCost(M, bPoints)

/* remove points that don't improve */
finalCurve = filterCostPoints(costPoints)
```

The recommendation improvement algorithm is responsible for generating a set of recommendations that improve upon an existing recommendation using an alternative metric. This function calculates a set of relaxed bounds for which the DGMS can generate a new set of recommendations. The function computes improved values for the alternative metric and relaxed values for cost and benefit metrics. DGAL uses these new constraints to generate new composite alternatives.

```
Function: Recommendation Improvement
Input: M (analytic model), c
(configuration), R (starting recommendation
point), a (alternative metric)
Output: Pareto-optimal recommendation points

/*calculate alternative metric points */
altMetricPts = computeAltMetricPoints(R, a)

/*optimize cost at each altMetric point*/
n = c.numAltRecommenations
e = epsilon
newPoints = []
for i=1 to n do
  bounds = R.cost + (e * i)
  p = altMetricPoints[i-1]
  newRec = optimizeRelaxedCost(M, R, p,
bounds)
      newPoints.add(newRec)

/* remove points that don't improve*/
finalCurve = filterAltMetricPts(newPoints)
```

5 SYSTEM ARCHITECTURE

The system consists of two core internal components: (1) Recommendation Engine, which implements both the Pareto-optimal algorithm and the recommendation improvement algorithm, and (2) Recommendation User Interface for displaying results and enabling user-guided improvement of recommendations. The Recommendation Engine is further integrated with DGMS for: (1) generating recommendation space and computing metrics, and (2) executing argmin and argmax functions.

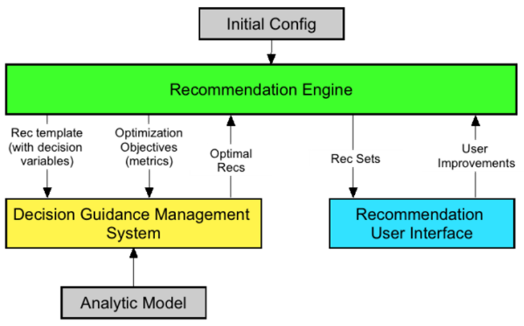

Initial Config
Recommendation Engine
Rec template (with decision variables)
Optimization Objectives (metrics)
Optimal Recs
Rec Sets
User Improvements
Decision Guidance Management System
Recommendation User Interface
Analytic Model

Figure 13: System Architecture.

The Recommendation Engine must be

configured with several elements, in order to generate the initial Pareto-optimal curve: (1) a data model used to generate the full recommendation space, (2) defined metrics for measuring each recommendation, and (3) other miscellaneous configuration points, such as number of recommendations to produce.

The Recommendation Engine integrates with a DGMS in order to generate the domain-specific recommendations based on the input model. Furthermore, the DGMS provides the capability of calculating metrics on each recommendation. Any DGMS can be seamlessly integrated into CAPORS simply by implementing a JSONiq function that conforms to a signature specified by CAPORS.

The JSON output of the recommendation engine is fed directly to the user interface. The user interface is written in HTML and JavaScript. The JavaScript functions of the user interface perform the following: (1) load the recommendation JSON records; (2) bind JSON data to D3JS (Data Driven Documents, 2016) charting library; (3) format the recommendation chart; (4) determine the initial Closer Consideration Set; (5) display Closer Consideration Set in a table; (6) draw improved recommendations onto chart; (7) handle all user interactions (add, remove, replace, improve, accept).

6 CONCLUSIONS

In this paper we proposed a methodology for generating composite alternative recommendations, based on Pareto-optimal trade-off consideration and continuous user feedback. The methodology improves upon earlier research by introducing the combination of optimized recommendations along a Pareto-optimal curve with the ability of users to repeatedly optimize an alternative metric until an optimal recommendation is generated and accepted.

Furthermore, we presented a system, CAPORS, which implements the proposed methodology. CAPORS utilizes existing technologies such as JSON, JSONiq, DGAL, and D3JS to provide a working framework for the proposed methodology. CAPORS is designed using abstractions such that the system is domain-independent, a big improvement over the majority of existing composite recommenders.

This work is a first step in our work towards a domain-independent, optimal, composite-alternative recommender system. In future work, we will extend the capabilities by introducing machine learning and data mining concepts to the methodology and system.

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